ABSTRACT

Title of Document: ESSAYS ON THE ROLE OF SPECIFIC HUMAN CAPITAL

Xiaohan Hu, Doctor of Philosophy, 2007

Directed By: Prof. Judith Hellerstein, Department of Economics

Human capital theory states that workers' knowledge and skills increase their productivity and thus raise their earnings. An important dimension of human capital theory distinguishes between general human capital and specific human capital. Chapter Two and Chapter Three of this dissertation examine two groups of individuals who encounter interruptions in their work careers and cannot completely transfer their specific human capital to their new jobs.

Chapter Two investigates displaced workers who lose jobs due to mass layoffs by their employers. Their success in job transition depends partially on the extent to which their human capital can be carried over across jobs. The Chapter Two analysis adds to the extensive literature on the earnings cost of displacement by distinguishing the earnings losses between high technology (hi-tech) displaced workers and low-tech displaced workers. Earnings losses are estimated using a generalized difference-in-difference model which compares the earnings patterns of displaced workers with a comparison group of non-displaced workers. The empirical results demonstrate that

earnings decline substantially upon displacement and then recover gradually. Hi-tech displaced workers suffer larger initial earnings losses and have faster recoveries than other displaced workers.

Chapter Three examines female immigrants to the U.S. whose entry wages fall short of those of comparable natives because their human capital accumulated in foreign countries is not completely transferable to the U.S. labor market. The entire literature on immigrant skills has focused almost exclusively on male immigrants. Chapter Three extends the previous research to the population of female immigrants by examining changes across cohorts in their labor market skills, as measured by their English proficiency, educational attainment and wages. The results show that, across successive cohorts of female immigrants, English proficiency at entry stays constant and average education level increases. After controlling for human capital and demographic characteristics, predicted wages are lower for female immigrants upon entry relative to female natives. Compared to male immigrants in the same period, female immigrants exhibit faster growth across cohorts in educational attainment and in predicted wages.

Overall, this dissertation provides further evidence of the role of specific human capital in explaining multiple dimensions of workers' earnings patterns.

ESSAYS ON THE ROLE OF SPECIFIC HUMAN CAPITAL

By

Xiaohan Hu

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2007

Advisory Committee:
Professor Judith Hellerstein, Chair
Professor Seth Sanders
Professor Mahlon Straszheim
Dr. Douglas Meade
Professor John Robinson

Dedication

To my husband, Xiaoxue He, who contributed to this dissertation in countless ways. Without your continual support and understanding, it would have been much harder to complete this research.

To my mother, father, and grandfather, who gave me the passion and courage to pursue this difficult but fascinating path.

To my aunt, uncle, and brother, who provided tremendous help and support throughout this endeavor.

Acknowledgements

I owe a huge debt to my advisor, Judith Hellerstein, for continually providing valuable comments on this dissertation. I am grateful to Seth Sanders, who shared many interesting insights, and to Mahlon Straszheim, who gave wonderful advice on writing about economics. I also want to thank all of my committee members for reading the draft and offering helpful suggestions.

I appreciate as well the comments of participants in the Microeconomics workshop at the University of Maryland and participants in the Population Association of America (PAA) conferences. I am especially indebted to David Stevens and John Janak of the Jacob France Institute at the University of Baltimore and to Bernie Antkowiak of the Division of Workforce Development at the State of Maryland Department of Labor, Licensing and Regulation, who provided data on displaced workers.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

Human capital theory[1] states that resources embodied in people, such as knowledge, skills and health, contribute to increases in earnings in the same way that physical capital raises output and income. Activities such as education, on-the-job training and medical care affect individuals' future earnings through the accumulation of human capital and are thus called investments in human capital. Although human capital theory originally was focused on explaining the substantial income growth in the U.S. even after controlling for growth in physical capital and labor, it also helps explain many aspects of workers' earnings over their lifetimes. Workers' earnings increase with age at a decreasing rate. This positive and concave age-earnings profile can be explained by a lifetime human capital accumulation process in which investments are mostly concentrated at workers' younger ages. Investments in human capital when workers are young provide a longer period to recoup the returns, and such investments are less costly earlier in life because the opportunity costs of investing in human capital are lower when earnings are lower. Human capital theory also provides important insights into the patterns and changes in the distribution of earnings across workers. Differences in schooling and labor market experience explain a significant fraction of the inequality in earnings. The explanatory power of the human capital model is even stronger when quality of schooling and the amount of on-the-job training are included in the analysis.

[1] See Becker (1993), Mincer (1974), Ben-Porath (1967).

An important dimension of human capital theory is its distinction between general and specific human capital. General training increases a worker's marginal productivity by the same amount in the firm providing the training as in other firms. By contrast, specific training increases productivity more in the firm providing the training than when the worker is employed by another firm. For example, a training program of communication skills is general training because it raises trainees' productivity in all firms that require a similar level of communication at work; on the other hand, a course in a specific software used only by firm X is specific training because it does not contribute much, if any, to the trainee's productivity increase in firms other than X.

The distinctions between general training and specific training depend on the nature of training and on the extent to which employers require specific skills and training. For example, medical skill is specific human capital to the medical industry but general human capital to all hospitals. A mastery of Danish language is specific human capital to the Danish labor market but general human capital to all the firms in Denmark. If different countries are considered separate labor markets, even schooling, a typical general human capital in most cases, could become specific human capital. Knowledge about a country's language, history and institutions is often of little value in another country.

General human capital can be carried over across jobs easily while specific human capital is less portable. A specific skill used in a certain labor market (a firm, an industry or a country) would contribute less to production, and thus be less valued, in other labor markets. Since workers' earnings depend on the stock of human capital, the extent to which specific human capital could be transferred to a new job has a crucial impact on the wage received in the new job.

This dissertation considers the work and earnings experience of workers with an interruption in their work careers. A central issue in this examination is the extent to which interrupted workers lose the benefits of accumulated specific human capital. The two groups of workers studied in the following two chapters have this in common: They both encounter an interruption in their work career and are confronted with the issue of transferring existing human capital to a new job. Chapter Two investigates the differential earnings losses between high technology (hi-tech) displaced workers and other displaced workers. Displaced workers are workers who lose jobs involuntarily because of economic reasons rather than incompetence or misconduct. Chapter Three examines differences in skills across successive cohorts of female immigrants. Cohorts are defined by the arrival years of immigrants. These two groups of subjects differ in one important respect: Displaced workers lose their jobs because of an exogenous economic shock, while most immigrants (except refugees and those seeking asylum) choose to migrate voluntarily. However, both groups of workers face the reality that their specific human capital cannot be completely transferred to their new jobs and both will experience a process of adapting to new job environments.

The earnings effect of displacements has been one of the central issues in the economic analysis of job displacements. A large body of previous evidence has shown that displaced workers suffer substantial long-term earnings losses post-displacement (e.g. Ruhm 1991, Jacobson et al. 1993, Stevens 1997). One of the theoretical reasons for this earnings effect is the loss of human capital specific to the old job[2]. (This lost skill could be either industry-specific human capital or firm-specific human capital.) Empirical evidence supporting this hypothesis includes the findings that displaced workers reemployed within their pre-displacement industries have smaller earnings losses than those who switch industries (Carrington 1993, Ong and Mar (1992)) and that displaced workers with longer tenure on the old job tend to suffer greater earnings losses (Hamermesh (1987), Topel (1990)).

By accumulating job-specific skills in their new positions, displaced workers experience earnings recoveries. But, despite relatively fast earnings growth after displacement, displaced workers' earnings still do not catch up with the level of comparable non-displaced workers. An explanation proposed in Stevens (1997) is an unstable recovery process interrupted by additional job losses in subsequent years.

A similar process affects immigrants to the United States, who often earn lower wages on arrival than natives with similar measurable characteristics (e.g. Chiswick 1977, 1978), indicating that not all human capital accumulated in the home country can be transferred to the U.S. labor market. Evidence demonstrates that the greater the economic and social distance between home country and the U.S., the larger the human capital devaluation. Chiswick (1977) shows that immigrants experience an occupational downgrading on arrival in the U.S., and that this downgrading is smallest among immigrants from English-speaking countries,

[2] Earnings losses upon displacement could also be explained by other theories. For example, workers may receive wages lower than their marginal productivity in the early phase of a job in return for higher wages later (Lazear 1981). This tilted wage profile could lead to a wage loss upon displacement if workers are displaced during the stage when their old wages are higher than their marginal productivity.

followed by those from other developed countries, and is largest from developing countries.

Following the initial earnings drop at entry, immigrants have higher earnings growth than the native-born with comparable characteristics (Chiswick 1978, 1980, Duleep and Regets 1997)[3]. Several factors explain this pattern (Duleep and Regets 1997). First, immigrants accumulate U.S.-specific labor market skills, which are complementary to the human capital they bring from their home countries. For example, improving English proficiency or obtaining U.S. professional certificates could presumably boost the rental price of their total human capital. Second, with lower earnings at entry than natives, immigrants have relatively lower opportunity costs for investing in human capital and thus a larger incentive to undertake more investment. The investment could take the form of participating in more on-the-job training or changing jobs more frequently.

For both displaced workers and immigrants, the initial wage drop and subsequent earnings recovery reflect a process of devaluation and then subsequent restoration in human capital. Mincer and Ofek (1982) argue that the productivity, and thus the market value, of the "deficient" human capital declines greatly even if only small parts of the total human capital are lost. Put in terms of the Ben-Porath human capital production model, the deficiency of human capital reduces its market productivity to a greater extent than its ability to reproduce itself. Therefore, the opportunity costs of reproducing human capital for the interrupted workers are lower than for stayers (non-displaced workers in the case of displaced workers and natives

[3] There is little consensus in the literature on whether the wages of immigrants could eventually converge to those of ethnically similar natives. See a summary in Borjas (1994) Page 1680.

in the case of immigrants), leading to larger investments and steeper wage growth among the interrupted workers than among the stayers. This model in Mincer and Ofek (1982) explains the wage changes of female workers after an extended period of withdrawl from the labor force; therefore, it suggests skill erosion from disuse as the cause of human capital depreciation. By contrast, displaced workers and immigrants tend to have very brief interruptions so the devaluation of human capital for these two groups is driven by a different factor - untransferrability of human capital from the old job to the new job.

The effects of job displacement and immigration on earnings and human capital are two widely studied topics in Labor Economics. This dissertation focuses on two specific issues in these two areas. The first issue is whether hi-tech displaced workers suffer different earnings losses compared to other displaced workers. The second issue is whether the labor market skills of female immigrants have changed across successive cohorts in recent decades.

Extending the large literature on the earnings consequences of job displacement, Chapter Two investigates whether hi-tech displaced workers suffer different earnings losses than other displaced workers. This study is mainly motivated by the increase of job losses in hi-tech industries during the past decade. Economic theories suggest that displacement might have different earnings consequences for hi-tech displaced workers than other displaced workers. On the one hand, hi-tech workers may have more opportunities in the labor market because their higher skills are better suited to an economy that rewards skills and education. On the other hand, hi-tech workers may have more difficulties in transferring their skills to new jobs and thus encounter greater human capital devaluation. The obstacle to skill transfer could result from the "niche" labor market of hi-tech industries, where skills useful in one job may not be valued in another (Meares (1999), Violante (2002)), or from the tendency in hi-tech industries to abolish positions associated with obsolete skills. Workers with very specific or outdated skills would have more trouble moving smoothly to a new job.

An extensive panel data set of individual workers is used to estimate job displacement effects in the period 1989-2005. A cohort of individual workers are observed repeatedly every quarter, with information on their quarterly earnings, firm code, industry code and employer size available. The longitudinal feature of this data set permits examination of the long term earnings effects of displacement and helps to control for unobserved individual characteristics using workers' earnings history. To identify hi-tech workers, industry-level technology measures are linked to individual workers using each firm's industry codes. With no occupation information available, income rankings are used as a proxy for workers' occupations. Exploiting the information on firm code and employer size in each quarter, this study defines displaced workers as those who leave a job as part of a mass layoff. This definition of job displacement ensures that voluntary job quitters or fired workers are not misclassified as displaced workers.

The empirical results of Chapter Two show that displaced workers' earnings decline substantially on job loss and then recover gradually. This finding is consistent with results in previous research and is consistent with the human capital devaluation and restoration hypothesis proposed by Mincer and Ofek (1982). One of the principal contributions of Chapter Two to the literature is the finding that hi-tech displaced workers suffer greater earnings losses upon displacement and have faster earnings recoveries than other displaced workers. This difference in earnings trend between the two groups is consistent with the theory that hi-tech workers have a larger fraction of specific human capital. The larger loss of the specific skills leads to the larger earnings drop during job transition, and the greater accumulation of new job-specific skills contributes to the steeper earnings growth on the new job.

Similar to an involuntary job loss, migrating to a new country is another typical example of interruption in a work career. The U.S. has received a large number of immigrants, and the proportion of immigrants in the U.S. population has increased dramatically in recent decades. The quality of immigrants' labor market skills is an important concern in assessing how much recent immigrants contribute to the U.S. economy. The literature has focused almost exclusively on male immigrants, despite the fact that female immigrants constitute about 50 percent of the immigrant population. The important role female immigrants play in the host country economy has been illustrated by the Family Investment Model (Duleep and Sanders 1993) which demonstrates that wives in immigrant families participate in the U.S. labor market to finance their husbands' initial investments in U.S.-specific human capital to maximize the family's permanent income. Examination of the quality changes across female immigrant cohorts facilitates comparisons of the labor market performance of female immigrants and male immigrants, which is studied far less than the gender earnings differentials among the native-born. In addition, the investigation of female immigrants' skill changes over time is important in assessing the validity of estimating assimilation rates (the wage effects of years since migration) using cross-sectional data. Borjas (1985) documented that skill declines across immigrant cohorts would generate an upward bias in the assimilation rates estimated using cross-sectional data.

Changes in the labor market skills of immigrants could be driven by changes in the U.S. demand for immigrants, reflected in changes in immigration laws, as well as changes in the supply of immigrants in home countries. Immigration laws in favor of visas issued for family reunification relative to skill-based visas presumably would decrease the average immigrant's skills. On the contrary, policies strengthening the control of illegal immigrants would lower the number of unauthorized immigrants, who are usually less skilled than legal immigrants, and would raise the average immigrant's skills. On the supply side, immigrants are a self-selected group who choose to migrate only when the migration costs, including physical and psychic costs, can be fully compensated by greater income in the U.S. Therefore, any factor affecting the migration costs or earnings expectation in the U.S. and the home country could affect which groups of immigrants are drawn to the U.S.

Labor market skills of female immigrants are measured in Chapter Three by three indicators: English proficiency, educational attainment and earnings capacity. The first two measures are directly compared across immigrant cohorts using raw data from the U.S. Census. Earnings capacity is compared both in raw terms and after controlling for education, experience, marital status, etc. The analysis of "residual" earnings provides insights into trends in the unobserved dimensions of immigrants' productivity, such as quality of schooling, innate ability and self-motivation.

The results in Chapter Three show that, across successive cohorts of female immigrants, English proficiency at entry stays constant and average education level increases. Regression-adjusted wages are lower for female immigrants at entry compared to natives, indicating a devaluation of immigrants' human capital brought from the home country.[4] The unobserved dimension of labor productivity increases for many female immigrants from 1970 to 1980, contrary to the quality decline of male immigrants in the same period documented in Borjas (1985). From 1980 to 1990, Asian and Mexican immigrants both experienced skill declines but the reasons vary. Overall, the skill change is becoming more stable, with a smaller degree of skill change in the most recent decade.

The following two chapters are two illustrations of the manifestation of human capital through workers' labor market experiences. These two investigations provide further evidence of the importance of specific human capital in explaining multiple dimensions of workers' earnings patterns.

[4] Language ability, educational attainment and earnings capacity all increase with years of stay in the U.S., reflecting the assimilation, or human capital restoration, process. Although some results regarding the assimilation process are presented, Chapter Two focuses on changes in immigrants' skills measured on migration rather than after a lengthy stay in the U.S.

Chapter 2: Technology and Displaced Workers' Earnings Losses

2.1 Introduction

The employment and earnings consequences of job displacement have long been an important dimension in labor economics research, and concerns about earnings declines after job losses have led to many policy initiatives to assist displaced workers. Initially, the focus was on manufacturing and blue collar workers, where large-scale job displacements took place in the 1970s and 1980s. Over the last decade, an increased number of displacements occurred in high technology (hi-tech) industries, which employ many highly educated and skilled employees.

In this chapter, hi-tech industries are defined as industries with intensive computer usage, with a large fraction of investment in hi-tech equipment, or with a high concentration of scientists and engineers. Some examples of hi-tech industries are communication, professional services, machinery manufacturing, and chemicals and allied products manufacturing. Displacements increased markedly in many hi-tech industries from the early 1990s to the beginning of the new century. For example, between 1993 and 2001, the displacement rate increased from eight percent to 12 percent in the communication industry, from 11 percent to 20 percent in the machinery manufacturing industry, and from 10 percent to 14 percent in the business services industry, calculated using data from the Displaced Worker Surveys (DWS)[5]. During this time period, the displacement rate remained constant or declined in most

[5] The displacement rate is calculated by the same approach as in Farber et al 1997.

low-tech industries where computer usage and concentration of scientists and engineers is low.

Increases in displacement in hi-tech industries are driven by several forces. The rapid expansion in the IT sector followed by the “dot-com bubble burst” in 2000 increased the number of displacements among hi-tech workers. According to the Bureau of Labor Statistics (BLS) Mass Layoff Statistics, the number of mass layoff events in the IT sector tripled between 2000 and 2001, compared to an average of 38 percent growth for all sectors. Other hi-tech industries also experienced above average increases in mass layoffs during this period. For example, mass layoffs increased by 86 percent in the chemical manufacturing industry, by 70 percent in professional and technical services, and by 49 percent in the finance and insurance industry. The 2000-2001 recession was followed by a period of only moderate employment growth, with employment in professional and business services, finance, and information sectors in 2003 at the same levels as in the 2000 pre-recession peak.

Even before the “dot-com bubble burst”, rapid growth of innovation and the recurrent closing of startup firms contributed to the rising number of displaced hi-tech workers. Compared to the total private sector, the information industry had a 20 percent higher annual rate of establishments closing between 1996 and 2004, according to the author’s calculation using business employment dynamics data from the BLS. Moreover, the recent upsurge in outsourcing also increases the risk of displacement in hi-tech sectors. With improvements in communication technology, more and more firms move jobs such as computer programming or call-center operations to lower-wage countries. This trend of increased outsourcing is evident in trade flow data which shows that imports of computer and information services[6] as a share of total private services imports in 2003 is more than five times larger than that in 1998, more than twice the rate of growth of their counterpart in exports during this period. The number of domestic job losses due to outsourcing is estimated to range from 34,000 to 72,000 per year in IT sectors after 2000.[7]

This paper explores the differential earnings consequence of displacement between hi-tech displaced workers and other displaced workers. There are several reasons why hi-tech displaced workers might face different earnings losses than other displaced workers. Hi-tech workers could have more opportunities than other workers in the labor market because their higher skills are better suited to an economy that rewards skills and education. However, hi-tech displaced workers may suffer larger earnings losses because their human capital depreciates faster. Hi-tech industries may intend to displace workers whose skills are obsolete, creating a barrier to re-enter a job with similar pay.

Another reason for different displacement costs between hi-tech workers and other workers is the different skill transferability across jobs. Theory provides ambiguous predictions on the sign of the relationship between skill transferability and technology. On the one hand, the hi-tech labor market is called a “niche” labor market where skills useful in one job may not be valued in another job (Meares 1999, Violante 2002). This feature makes it difficult for hi-tech workers to transfer skills to new jobs or to form another good match after job loss. On the other hand, information technology (IT), an important component of current hi-tech industries, is called a

[6] Computer and information services imports include computer and data processing services and database and other information services. Data are from Bureau of Economic Analysis.
[7] See Bednarzik 2005.

“general purpose” technology which spreads to most sectors (Bresnahan and Trajtenberg 1995, Jovanovic and Rousseau 2005, Aghion, Howitt and Violante 2002). For example, programming skills can be used in various sectors and jobs. This feature facilitates skill transfers across jobs. It thus remains an empirical question as to which of these two features dominates the skill transferability of hi-tech workers.

This paper examines the long-term earnings consequences of displacement, applying a generalized difference-in-difference model that compares the earnings patterns of displaced workers with a comparison group of non-displaced workers. Data used in this paper are drawn from Maryland Unemployment Insurance wage records, linked with several industry-level technology measures. The longitudinal feature of this data set provides information on the long term effects of displacement and also helps to control for worker heterogeneity. The results demonstrate that the initial earnings losses after displacement are higher for hi-tech displaced workers than for other displaced workers. But in the long run, hi-tech displaced workers experience faster earnings recovery and the earnings loss differences between hi-tech and low-tech workers tend to disappear. Industry-level technology is measured by several alternative indicators: the fraction of employees using computers at work, the fraction of investment in hi-tech equipment, and the fraction of scientists and engineers in the industry’s workforce.

The question of whether hi-tech displaced workers have higher earnings losses than other displaced workers is important to both policymakers and researchers. In order to design effective programs to assist displaced workers, policymakers need information on the distribution and magnitude of earnings losses associated with displacement. To the extent that hi-tech workers are found to have larger earnings losses because of displacement, government assistance programs could be designed to reflect these differences. If displacement costs are higher for hi-tech workers, this potential uncertainty might discourage people from investing in hi-tech skills, and in turn reduce long-term economic growth. Assistance programs from the government such as retraining or employment services could alleviate this risk associated with investing in hi-tech skills.

For researchers, information about earnings patterns of hi-tech displaced workers adds to knowledge of displacement costs and the impact of technology on the labor market. Identifying the differences in earnings losses between hi-tech displaced workers and other displaced workers is the first step toward studying the channels through which technology affects displaced workers' earnings losses.

2.2 Literature Review

An extensive literature on displaced workers has examined earnings losses and the subsequent employment experience of workers with different demographic characteristics, industry categories, and occupations. Previous papers have found that displaced workers suffer substantial long-term losses, regardless of gender, age, or race (Ruhm 1991, Jacobson, LaLonde and Sullivan 1993, Schoeni and Dardia 1996, Ann Huff Stevens 1997, Kletzer and Fairlie 2003). For example, Jacobson et al. (1993) shows that high-tenure displaced workers suffer 25 percent earnings losses even six years after displacement. The literature also shows that some displaced workers suffer larger earnings losses than others. For example, earnings losses are positively related to displaced workers' tenures on the old jobs (Hamermesh 1989, Topel 1990); workers who switch industries after displacement tend to lose more (Podgursky and Swaim 1987, Addison and Portugal 1989, Carrington 1993, Neal 1995); and, displaced workers' earnings losses also depend on the general conditions of their industries or local labor market (Howland and Peterson 1988).

Recent evidence has shown that job loss rates have declined in manufacturing industries and increased in services industries, and displacements have been spreading across various occupations, rather than concentrating in blue-collar, production occupations (Kletzer 1998, Farber et al. 1997, Fallick 1996). Using very recent data through 2003, Farber (2005) found that there was an upward trend in job loss rates for more educated workers in the early and mid-1990s and again after 2000, and earnings losses have been larger for displaced workers who have attended college than for workers with less education since the end of 1990s.

Relatively little work has examined workers displaced in hi-tech industries. Addison, Fox and Ruhm (2000) examined the relationship between technology and the probability of job displacement. They found that the risk of job loss is relatively high for workers employed in industries with high investment in computer technologies and with high fraction of scientists and engineers in the workforce. Papers studying the consequences of hi-tech displaced workers focused on whether displaced workers remaining in hi-tech industries fared better than those switching to non hi-tech industries. Ong and Mar (1992) found that displaced workers in Silicon Valley's semiconductor industry suffered large earnings losses if they were reemployed outside hi-tech sectors, but that there were small losses or no losses at all if workers were reemployed in similar industries. Dardia et al. 2005 and Hotchkiss 2005 found that workers who switched from IT-producing industries to other industries after displacement suffered larger earnings losses than those who stayed in IT-producing industries. Since these papers examine different samples and cover different time periods than Jacobson et al., the results are not comparable enough to address adequately the issue of whether hi-tech displaced workers have different earnings losses than other displaced workers, a question that this paper attempts to answer.

2.3 Data

2.3.1 MD UI Data

Data used in this paper are drawn from the Unemployment Insurance (UI) wage records of Maryland (MD) extending from 1989 through 2005. The UI dataset is an administrative dataset compiled by the state government for the purpose of collecting unemployment insurance contributions from employers. In each quarter, employers report to the state government how much they pay to each employee. MD UI data cover more than 90 percent of the MD workforce. Workers who are not included in this dataset are mainly federal government employees, self-employed individuals, and workers in small agricultural enterprises.

This study draws a 10 percent random sample of all Maryland workers who were working in the first quarter of 1992 (1992:1).[8] The sample is restricted to

[8] By using this fixed cohort of workers, I miss workers who entered labor market after 1992:1. However, Census data from 1990 and 2000 show that the composition of Maryland workers did not change much between 1990 and

workers in firms with more than 50 workers in 1992:1. With this restriction, there is a 99.5 percent probability that at least one worker is sampled from each firm. In the baseline sample, only workers who have positive earnings in each calendar year are included since it is not known what workers with missing earnings were doing. This sample selection criterion eliminates 60 percent of workers, with 40 percent permanently disappearing from the data and the remaining 20 percent temporarily disappearing. The statistical results will be affected by this sample selection if hi-tech and low-tech workers with missing earnings data are systematically different. Possible biases due to missing earnings are investigated in Section V.3. To reduce the computational burden, a 15 percent random sample is drawn for non displaced workers.

The resulting baseline sample analyzed has 4,547 workers displaced between 1992:1 and 2004:3 and 5,995 workers who are never displaced. For each displaced worker, up to 41 quarters are included in the sample, from the 20th quarter before job loss, or the beginning of the sample period, to the 20th quarter after job loss, or the end of the sample period. For non-displaced workers, there are up to 67 quarters from 1989:1 to 2005:3 recorded for each person. The total number of person-quarter records analyzed is 576,400.

The MD UI data provide information on the workers and the firms. For each worker, the data report the quarterly earnings and the employer identification number (EIN) in each quarter. For workers who hold more than one job in a given quarter, the job that pays the most is used to define the employer and the worker's earnings. For

---

2000. See Appendix Table A1.

each firm[9], the data reports the industry code by the U.S. Standard Industrial Classification (SIC) system (before 2001) or the North American Industry Classification System (NAICS) (since 2001) in each quarter, and the quarterly employment level for the firm (the number of wage records). By linking the firm's information to workers, every worker's quarterly earnings, industry, and firm size in each quarter can be identified.

The use of MD UI data instead of other national representative datasets offers a number of advantages. MD UI data cover almost the entire MD workforce and have a large sample of displaced workers. This linked employer-employee data set allows precise identification of job separations and subsequent employment and earnings consequences. As an administrative data set, it reports more accurate information on displacements and earnings than survey data. The UI data avoid the problems of other national representative datasets that have the disadvantages of smaller samples and biases associated with imperfect recall by survey participants of their job histories.[10]

Finally, while the Maryland data are not representative of the whole nation, the industry distribution in Maryland is broadly similar to that in the whole U.S., with the principal exception that Maryland has larger fraction of workers in services and public administration and a smaller fraction of workers in manufacturing (Table 2.1). Also, employment changes in Maryland over time mimic those in the U.S., as shown in Figures 2.1a through 2.1d. Figure 2.1a demonstrates that the employment changes

[9] More than 90% of the reporting employing units have a single establishment, but some reporting units have multiple establishments. For example, a chain supermarket may have separate EINs for each of the store, or it may combine all the stores into a single EIN. Since the majority of the reporting units have single establishment, I use employer, firm, and establishment interchangeably in this paper.
[10] The National Longitudinal Survey of Youth (NLSY) and the Panel Study of Income Dynamics (PSID) have small samples of displaced workers. The number of displaced workers is in hundreds in these two datasets. DWS has a severe problem of recall bias as documented in Topel 1990. For more information on the problems and benefits of using DWS and UI data to study displaced workers, see Hildreth, Wachter, and Handwerker 2005.

in all private sectors are similar between Maryland and the U.S. Figures 2.1b through 2.1d demonstrate that three typical hi-tech industries have employment trends in Maryland that are very similar to those for the entire U.S.

However, there are two limitations to the Maryland UI data. The reasons workers drop out of the data are unknown. Workers who leave the dataset all have missing earnings after they disappear. Some of them actually have positive earnings if they are reemployed outside of Maryland or become federal government employees, while others who remain non-employed have zero earnings. This attrition would bias the estimated earnings losses differential between hi-tech and low-tech workers if hi-tech "disappearers" are more likely to have positive earnings. For example, if the majority of the hi-tech workers who leave the dataset on displacement are reemployed in other states while the majority of the low-tech workers who leave the dataset on displacement have long spells of unemployment, then the estimates would overstate the earnings losses of hi-tech displaced workers compared to those of low-tech workers. This potential attrition bias will be analyzed in the next section. A second shortcoming of this data is the lack of demographic information on workers that is typically used in studies of labor market outcomes. As a remedy, this chapter employs individual fixed effects to control for time-invariant person specific characteristics, such as gender, race, education and innate ability.

2.3.2 Measures of Technology

Since there is no perfect measure of industry level technology, several alternative measures are used in the analysis. The use of computer and related equipment is frequently used as a measure of technology (Autor, Levy and Murnane 2003, Autor, Katz and Krueger 1998, Bartel and Sicherman 1999, Bartel and Sicherman 1998, Addison, Fox and Ruhm 2000). The first indicator, therefore, is the fraction of workers using computers at work in each industry, obtained from the Current Population Survey (CPS) Computer and Internet Usage Supplement in 1997 and 2001. However, this indicator ignores the technology content of computers. For example, a computer used for bookkeeping has a lower technology content than a computer used for software development. A second indicator based on the value of computers and other hi-tech equipment reflects the degree of sophistication of the equipment. This second measure is the fraction of new investment in hi-tech equipment, obtained from Bureau of Economic Analysis (BEA)'s capital flow data for 1992 and 1997. Hi-tech equipment includes computers and peripheral equipment, communication equipment, photocopy and related equipment in 1992. In 1997, hi-tech equipment includes the above three categories plus software.

Some hi-tech industries are not characterized by intensive utilization of computers, so two other technology measures are introduced. One is R&D expenditure as a share of total sales, obtained from the 1988-2001 National Science Foundation (NSF) R&D tables. The other is fraction of scientists and engineers in the workforce, calculated from CPS 1994, 1998 and 2002. Selected values for these four technology measures by industry are presented in Appendix Table A2.2. These industry-level technology measures are linked to each person-quarter observation by the industry where the individual works in a quarter. Details of the linking process are discussed in Appendix 2B.

Correlation coefficients are calculated for these four measures of technology across industries, using values in 1997 or 1998 (applying industry aggregation as necessary to make industry definitions across the four measures comparable). The correlation coefficient is 0.58 between the first indicator and the second indicator, 0.29 between the first indicator and the third indicator, 0.57 between the first and the fourth and 0.31 between the third and the fourth. The positive correlation coefficients are consistent with the fact that industries ranked high by one technology measure are also ranked high by another measure in most cases. The low correlation coefficients between the R&D indicator and other indicators suggest that the R&D indicator may measure a different aspect of technology than the other three measures. Using alternative technology measures in the analysis increases the robustness of results.

2.4 Definition of Displacement and Stylized Facts

Displaced workers are defined as workers leaving a firm as part of a mass layoff, where more than 30 percent of employment is reduced across consecutive quarters.[11] This same definition was used in earlier papers by Jacobson, LaLonde and Sullivan (1993) and Lengermann and Vilhuber (2002). Because the Maryland UI data do not have information on the reason a worker leaves a job, using mass-layoff to define displacement avoids the potential biases of including discharges for cause and

[11] I tested an alternative definition of displacement based on plant closing (where workers leaving a job due to plant closing are defined as displaced workers). The short term results are the same as those presented in this paper. In the longer term, hi-tech displaced workers show better recovery, probably because plant closing captures lots of startup firm closings which displace young workers with frontier technology. Or it could be because plant closing mainly captures seasonal jobs since there is strong seasonality in the earnings trend of workers displaced from closing plants (see Appendix Figure 1).

quits as displacements. Although some separators in this mass-layoff sample may be quitters or fired workers, the majority is displaced for economic reasons.

Displaced workers are identified in the following procedure. First, a firm with more than 50 workers is recorded as having a displacement in quarter t if its employment level is reduced by more than 30 percent from t to t+1 and remains low for three more quarters.[12] In cases in which more than 30 percent of a firm's workers move to the same new firm in the following quarter, it is assumed that a merger or a split has occurred, and the original firm is recorded as not having a displacement in this quarter. Second, based on this definition of firm mass-layoff, any given worker is defined as displaced if this worker leaves a firm in the quarter when the firm has a mass-layoff, and does not return to this firm within four quarters. This procedure for defining displaced workers therefore includes workers who lose their jobs involuntarily and permanently due to economic reasons rather than their own misbehavior. To avoid the effects of multiple displacements, only the first observed displacement is included in the analysis.

To illustrate the earnings losses from displacement, earnings between 1994:4 and 2004:4 are drawn in Figure 2.2 for workers displaced in 1999:4, a quarter with a relatively large number of displacements, as well as for workers who are never displaced as a reference group. To show the role of technology in earnings losses, Figure 2.2a presents earnings of workers in industries with above median computer usage and Figure 2.2b presents earnings of workers in industries with below median computer usage. A comparison between Figure 2.2a and 2.2b suggests that hi-tech

[12] Requiring three more quarters of low employment avoids the effects of measurement errors and seasonal employment changes.

workers suffer larger earnings losses upon displacement. For hi-tech workers, earnings drop about $6000, or 75 percent, from pre-displacement levels; while for low-tech workers, the drop is about $3000, or 50 percent.

Figure 2.2 shows that there are systematic differences between displaced and non-displaced workers, and between hi-tech and low-tech workers. These heterogeneities must be taken into account to get unbiased estimates of differential displacement effects between hi-tech and low-tech workers, especially when no controls for human capital variables are available in the data. Another point worth noting from Figure 2.2b is that earnings start to decline before displacement. Therefore, it is important to pick a time period several quarters before displacement as a reference period in estimating total earnings losses to avoid underestimating earnings losses.[13]

The simple illustration in Figure 2.2 highlights the basic feature of earnings losses differential between hi-tech versus low-tech workers. However, it only portrays a snapshot of a particular cohort of displaced workers in a 10-year window. A comprehensive statistical analysis aggregating all displaced workers and spanning the entire sample period is presented in the following section.

2.5 Empirical Specification and Results

2.5.1 Empirical Specification

Displaced workers' overall earnings losses are the summation of actual earnings losses and the foregone earnings they could have earned in the absence of

[13] Pre-displacement losses are also documented in Jacobson et al 1993.

displacements. Actual earnings declines after job loss are equal to earnings in the post-displacement periods minus pre-displacement earnings in some base period when the effects of displacement had not yet begun. In summary, displaced workers' earnings losses at a post-displacement time t can be written as:

$$(\text{Earnings}_{D,t} - \text{Earnings}_{D,0}) - (\text{Earnings}_{N,t} - \text{Earnings}_{N,0}).$$

The term in the first parenthesis calculates displaced workers' actual earnings change from a base period (period 0) to some post-displacement period (period t). The term in the second parenthesis calculates non-displaced workers' earnings changes between time 0 and time t, which is used as a proxy for displaced workers' hypothetical earnings growth in the absence of displacement. Examining pre-displaced earnings in the UI data shows that earnings between displaced workers and non-displaced workers are not significantly different three years before the job loss, so the base period is chosen as 12 quarters before displacement.

Overall earnings losses are estimated using a generalized difference-in-difference framework as in Jacobson, LaLonde and Sullivan 1993:

$$Y_{it} = \sum_{-12 \le k \le 20} D_{it}^{k} \delta_k + \alpha_i + \sum_{t=1}^{67} Q_t \gamma_t + \varepsilon_{it}, \qquad (1)$$

where Y_{it} is person i's earnings in quarter t;[14] the individual fixed effect α_i controls for time-invariant person specific characteristics; the set of quarterly dummies Q_t control for changes in the macroeconomic environment; and D_{it}^{k} are dummy variables representing the event of displacement, where k stands for the number of quarters after (before) displacement if k is positive (negative). For example, if person i is

[14] The reason why earnings levels is used instead of log earnings is because log transformation can not properly deal with zero earnings in the regression.

displaced in 1998:3, then his/her D_{it}^{1} is equal to 1 in 1998:4 and his D_{it}^{-2} is equal to 1 in 1998:1. K ranges from -12 to 20, so coefficients δ_k on the dummy variables capture earnings effects of displacement from up to 12 quarters before the job loss to up to 20 quarters after the job loss.[15]

To examine whether displacement effects vary between hi-tech workers and low-tech workers, the industry-level technology measure is interacted with each of the displacement dummies in equation (1):

$$Y_{ijt} = \sum_{-12 \le k \le 20} D_{it}^{k}\delta_k + \sum_{-12 \le k \le 20} (D_{it}^{k} * Tech_{jt})\theta_k + \alpha_i + Q_t\gamma + (Tech_{jt} * Q_t)\varphi + \varepsilon_{it} \quad (2)$$

where $Tech_{jt}$ is the technology measure of industry j where person i works in quarter t. $Tech_{jt}$ varies by industry and over time. The coefficients θ_k measure the differential displacement effects in industries with different levels of technology. If θ_k is estimated to be negative, that means hi-tech displaced workers suffer larger earnings losses in the k_{th} quarter after displacement than low-tech workers. The technology variable is also interacted with quarterly dummies so that quarterly effects are allowed to be different between hi-tech workers and low-tech workers. Including the fixed effect α_i avoids the potential bias which may arise if hi-tech workers have systematically higher earnings levels than low-tech workers, or if displaced workers have systematically different earnings levels than non-displaced workers.

[15] To identify coefficients on the displacement dummy variables, earnings must be observed more than 12 quarters before displacement for some workers. In my sample, workers are displaced between 1992:1 and 2004:3 and their earnings are observed from 1989:1 to 2005:3.

2.5.2 Baseline Results

Figures 2.3a through 2.3d present graphically the estimated results from equation (2), using the four alternative technology indicators. Lines labeled “hi-tech” depict the predicted quarterly earnings of a typical hi-tech displaced worker, who has the median level of technology of all hi-tech workers. Similarly, lines labeled “low-tech” depict the predicted quarterly earnings, assuming the technology variable is equal to the median technology of all low-tech workers. For example, in Figure 2.3a, a typical hi-tech displaced worker loses $980 while a typical low-tech displaced worker loses $560 in the fourth quarter after displacement, relative to non-displaced workers. The pre-displacement average quarterly earnings are $7100 and $5600 for hi-tech and low-tech workers respectively, so their percentage earnings losses are 14 percent and 10 percent respectively. Hi-tech workers’ earnings losses are four percentage points higher than low-tech workers in the fourth quarter after job loss.

Shaded areas in Figures 2.3a denote time intervals where the corresponding coefficients of θ_k, the coefficient on the interaction terms between the technology variables and the displacement dummies, are statistically significantly different from zero at the five percent level, [16] in other words the displacement effects are statistically significantly different between hi-tech workers and low-tech workers in these quarters. Statistical significance exists both before and after displacement, indicating that hi-tech workers start to lose more than low-tech workers even before separating from the job. Possible reasons include that workers displaced are less skilled than their non-displaced counterparts and this difference is larger among hi-

[16] Standard errors are clustered at the level of an individual.

tech workers than among low-tech workers, or that the conditions of hi-tech firms ultimately experiencing displacements deteriorate to a greater extent than low-tech firms[17]. Since individual fixed effects are controlled in the model, time-invariant worker characteristics are ruled out as an explanation for the earnings differences before displacement. But time-varying worker characteristics could contribute to the earnings gap before job loss. For example, firms in hi-tech industries may tend to displace workers whose skills become obsolete and earnings trend down.

Similar patterns also appear when other technology indicators are used, except in Figure 2.3c where hi-tech workers measured by R&D expenditures tend to suffer smaller earnings losses compared to low-tech workers. As indicated above, the R&D measure has a low correlation with other technology measures, suggesting that this measure may capture a different aspect of technology, such as the degree of innovation in the future rather than the current period.[18] A comparison between Table A2.2c and A2.2d shows that many industries with a high fraction of scientists and engineers do not have intensive R&D activities. Examples include the transportation equipment manufacturing industry and the communication industry. This evidence suggests that the R&D measure only partially captures the technology level of an industry's workers. Since computer usage, hi-tech equipment investment, and concentration of scientists and engineers are more directly related to the amount of workers involved in hi-tech jobs in an industry, results generated from these three

[17] Lengermann and Vilhuber (2002) states that earnings declines before displacement could be attributed to differences in unobserved characteristics between the ultimately displaced workers and the comparison group, or to differences in the productivity of the firms that ultimately displace workers.
[18] I also use percentile ranking rather than real values of R&D to estimate equation (2), but the estimated earnings losses differential between hi-tech and low-tech workers are similar to what Figure 3c shows. It is not the skewness of R&D measures that drive the results in Figure 3c.

measures are taken as a better estimate of the earnings losses of hi-tech displaced workers.

Figures 2.3a and 2.3b are very similar, both in the magnitude of earnings losses differentials and in the time intervals in which the differentials are significant. Using hi-tech investment as the technology measure, earnings losses are $620 (nine percent) for hi-tech workers and $290 (five percent) for low-tech workers in the fifth quarter after displacement. Disparities in earnings losses between hi-tech and low-tech displaced workers are concentrated in the second and third year after the job loss and gradually diminish in the long run. In the fifteenth quarter after job loss, the earnings losses are $490 (seven percent) for hi-tech workers and $330 (six percent) for low-tech workers in Figure 2.3b, and the difference is statistically insignificant. The convergence between two lines of predicted earnings in the longer run in Figures 2.3a and 2.3b suggests that hi-tech displaced workers experience faster earnings growth, which is likely the result of accumulation of new skills in a new position.[19]

Figure 2.3d shows similar patterns of earnings losses as in Figures 2.3a and 2.3b except in the fourth and fifth year after displacement. In Figure 2.3d, the earnings losses of hi-tech workers and low-tech workers do not tend to converge in the long run, contrary to what is shown in Figures 2.3a and 2.3b. This may be because workers displaced in industries with a large fraction of scientists and engineers have fewer opportunities or lower incentives to reinvest in new skills when reemployed,

[19] Since the sample period ends at 2005:3, only workers displaced before 2000:3 have observed earnings in all the twenty quarters post displacement. The long-run earnings losses after job loss are thus estimated by a different sample, which includes only workers displaced in early years, than the short-run earnings losses upon displacement, where the sample includes workers displaced in all years between 1992:1 and 2004:3. To test whether this difference in sample composition affects the baseline results, Equation (2) is re-run for displaced workers who lose jobs before 2000:3 and the results are presented in Appendix Figure 2. The qualitative result replicates the baseline result in Figure 3a.

either because training is emphasized less in these industries or because these workers are older on average. The different paths of skill accumulation on the new job could lead to distinct long-term effects of displacement.

2.5.3 Biases due to Missing Data

The baseline results shown in Figure 2.3 are based on a sample of workers who do not have missing earnings for more than four continuous quarters and quarters with missing earnings are simply dropped from the analysis. As a result, the substantial earnings losses of workers not immediately reemployed after displacement are not included in the estimation. Figure 2.4 shows that for this baseline sample the fraction of workers with non-missing earnings after displacement is higher for hi-tech than for low-tech workers. The differences are statistically significant. To investigate whether earnings losses are still larger for hi-tech workers after taking into account workers not immediately reemployed after displacement, Equation (2) is estimated again on the baseline sample but with missing earnings replaced by zeros. The results are presented in Figures 2.5a-2.5d. The earnings losses are still larger for hi-tech workers, although the coefficients of θ_k are less significant in Figures 2.5a-2.5d than in Figures 2.3a-2.3d. Again, three of the four technology indicators generate similar results, whereas the results are again somewhat different when technology measure used is R&D.

Since the technology measure of computer usage is relatively well-correlated with the measure of hi-tech investment and the fraction of scientists and engineers, for the sake of brevity, only results from regressions where technology is measured by computer usage are presented below.

As mentioned previously, workers with continual missing earnings for more than one year are excluded from the baseline analysis. This exclusion would bias the baseline results if hi-tech workers drop out of the data for different reasons than low-tech workers. As an example, assume that hi-tech displaced workers are likely to be reemployed in other states, receiving positive earnings, while low-tech displaced workers are likely to be in long spells of unemployment or to withdraw from the labor market. In that case, excluding observations on these workers would overstate the earnings losses of hi-tech displaced workers, and understate the earnings losses of low-tech displaced workers.

Table 2.2 displays the extent of attrition by showing the number of disappearing workers and the average quarterly earnings of the whole sample period for three exclusive categories of workers: permanent "disappearers" who disappear from the data at some point and never return to the data thereafter, temporary "disappearers" who have missing earnings for at least one calendar year and then return to the data, and stayers who have positive earnings for at least one quarter in each calendar year. Only workers in the third category are used in the baseline analysis. Temporary disappearers are excluded from the baseline analysis because these workers may be in long spells of non-employment before being reemployed, or they may be working in another state after leaving Maryland and then return to Maryland workforce again. According to Table 2.2, 60 percent of workers drop from the data either permanently or temporarily and their earnings are lower than stayers on average. Earnings differentials between disappears and stayers are smaller among displaced workers than among non-displaced workers. These patterns are similar between hi-tech workers and low-tech workers, as shown in the lower two panels in Table 2.2. The similar patterns of attrition between hi-tech and low-tech workers imply that excluding disappearers may not affect the estimates of earnings losses differentials between hi-tech and low-tech displaced workers. Two formal tests below confirm that this conjecture is true.

The first test takes advantage of the UI Data Exchange Program between Maryland and neighbor states. This program provides information on workers who once worked in Maryland and are now working in Washington D.C., Virginia, Delaware, Pennsylvania, New Jersey, Ohio or West Virginia. Earnings of these workers are observed quarterly between 2004:3 and 2006:2 in the neighboring states. Among all displaced workers who permanently drop out from the MD UI wage data, about 16 percent are currently working in these eight neighbor states. This fraction is very similar between hi-tech workers and low-tech workers: 16.34 percent for hi-tech workers and 16.02 percent for low-tech workers[20]. The difference in this fraction between the two groups is not statistically significant.

Displaced workers who are now working in neighbor states have higher earnings between 2004:3 and 2005:3 than displaced workers who are working in Maryland in these five quarters, as shown in Column (1) of Table 2.3. However, Column (2) of Table 2.3 shows that the pre-displacement average quarterly earnings

[20] Hi-tech (low-tech) workers are defined as those spending more than half of their working life in industries with above (below) median level of computer usage. Using the other three technology measures, the fraction of reemployment in neighbor states are 17.26, 16.78 and 16.05 for hi-tech workers and 15.20, 18.61 and 16.82 for low-tech workers. None of the differences in this fraction between hi-tech and low-tech workers are statistically significant.

do not differ much between workers currently working in Maryland and those currently working in neighbor states, indicating that workers who move to work in other states are not a selected group of especially productive individuals. The higher post-displacement earnings of workers moving out of Maryland may be because they can take advantage of higher wage offers in other states by having fewer location restrictions. Comparing the upper and lower panels of Table 2.3 shows that these earnings trends of stayers and movers are similar between hi-tech workers and low-tech workers.

To confirm that workers who move to work outside Maryland after displacement do not affect the baseline results presented in the previous section, these workers who are now working in neighbor states were added to the original Maryland UI data and the regressions were rerun. Their missing earnings between the quarter when they disappear from the Maryland UI data and the quarter they are observed again in other states are calculated in the following way. Earnings in the four quarters before they disappear are averaged as "starting earnings" and earnings between 2004:3 and 2005:3 are averaged as "ending earnings". Earnings growth calculated from the "starting earnings" and "ending earnings" is then used to extrapolate earnings in between.[21] The results of rerunning the regressions using this expanded data set are shown in Figure 2.6a. The earnings trends of hi-tech and low-tech displaced workers in Figure 2.6a are almost identical to those in Figure 2.3a,

[21] Extrapolating earnings in this way would underestimate earnings losses of displaced workers if workers rehired in neighbor states suffer earnings drop upon displacement. But as long as this unobserved earnings drop is similar between hi-tech and low-tech workers, this extrapolation would not affect the estimation of different earnings losses between the two groups. An approach to get around the problem of not knowing workers' earnings between the time they drop out from MD data and the time their earnings are observed in neighbor states is to limit the "rehired worker" sample to workers who drop out from MD data in more recent years. Among workers dropping out from MD data in 2003, the fraction of being observed in neighbor states after 2004:3 is slightly higher than among workers who drop out from MD data in earlier years, with the former equal to 16.6% and the latter equal to 14.1%.

suggesting that disappeared workers who are rehired in other states after displacement do not affect my baseline results.

Unlike the 16 percent disappearing workers who are reemployed in neighbor states, other workers who drop out from the Maryland UI data cannot be tracked. Without knowing the actual values of their missing earnings, there is no way to estimate the true earnings losses of these workers. To get around this problem, an upper bound of the earnings losses differential is estimated as a second test for the attrition bias. For hi-tech displaced workers who drop out from the data, their missing earnings are replaced by their usual positive earnings, as described in Appendix 2C; for low-tech displaced workers who drop out from the data, their missing earnings are replaced by zeroes. Such an imputation exaggerates the earnings losses of low-tech workers and shrinks the earnings losses of hi-tech workers. If the upper bound earnings losses differential estimated in this way is still negative, then it is assured that the estimated larger earnings losses of hi-tech displaced workers in the baseline results are not driven by excluding workers disappearing from the data.

The attrition bias test is conducted for both permanent "disappearers" and temporary "disappearers". A detailed discussion of how the earnings are imputed is presented in Appendix 2C. After making the imputations, equation (2) is estimated again and the results are shown in Figures 2.6b through 2.6c. In Figure 2.6b, where permanent "disappearers" are brought back to the original data set, hi-tech workers still show larger earnings losses in the first two years after displacement, although most quarters have insignificant coefficients. In Figure 2.6c, it is shown that the baseline results are also preserved after temporary disappearers' missing earnings are imputed. These findings confirm that patterns in Figures 2.3 are not spurious results driven by excluding large number of disappearers from the data.

2.5.4 Controlling for Earning Ranks

Ideally, hi-tech workers should be identified by both their industries and occupations because some workers in hi-tech industries do not hold hi-tech occupations. Unfortunately, information on occupations is unavailable in the MD UI data, so workers' earnings are used to define their occupations.[22] Workers with earnings higher than the 75th percentile of their industry's earnings distribution are very likely to be chief executives or senior managers. On the other end, workers with earnings below the 25th percentile of their industry's earnings distribution are mostly administrative workers or blue-collar workers. Therefore, workers are divided into a high-earnings group, a mid-earnings group, and a low-earnings group, using the 75 percentile and the 25 percentile of the industry earnings distribution as cutoffs.[23]

Equation (2) is estimated separately for these three groups and results are shown in Figures 2.7a-2.7c. Among high-earners, hi-tech displaced workers suffer smaller earnings losses than low-tech workers, but the differences are not statistically significant in almost all quarters. Post-displacement earnings of hi-earners in hi-tech industries fully recover in about one year after job loss. These results are consistent

[22] An alternative is to constrain the sample to workers in hi-tech industries only and define workers with earnings above a certain level as hi-tech workers. The problem with conducting such an exercise is that hi-tech workers are defined by a dummy variable rather than a continuous variable. There is not much variation in such a dummy variable within person and even in cases where within-person variation does exist, it is likely to be due to measurement error and may not reflect a true switch between hi-tech and low-tech position. Considering that within-person variation is used for identification in fixed effect model, this alternative approach is not useful for estimating hi-tech displaced workers' earnings losses relative to low-tech displaced workers.

[23] In defining these three groups, workers' earnings are compared with their industry earnings in each quarter. If a worker is a high-earner in more than half of the time during the sample period, then this worker is defined as a high-earner. The same approach applies to mid-earners and low-earners.

with the hypothesis that managers have larger fractions of general human capital which can be carried over across jobs more easily.

Among mid-earners and low-earners, hi-tech displaced workers suffer larger overall earnings losses after job loss. The result for low-earners is contrary to expectations because low-earners in hi-tech industries are likely to do non-hi-tech jobs and should mainly have general human capital. A closer examination of Figure 2.7b and Figure 2.7c reveals that earnings of hi-tech workers and low-tech workers tend to eventually converge among mid-earners, while this convergence in earnings does not happen for low-earners. If hi-tech workers' larger earnings losses are due to human capital depreciation or low transferability of skills, then we should observe earnings to recover gradually after displacement with the accumulation of new skills in the new job and therefore the earnings losses should gradually converge between hi-tech and low-tech workers. The lack of convergence in earnings losses among low-earners suggests that the reasons underlying the earnings losses differentials might differ for low-earners than for mid-earners. What low-earners lose after displacement in hi-tech industries may be a wage premium that is not associated with higher labor market skills. Employers in hi-tech industries may be more willing to pay such wage premiums to lower the probability of worker turnover or to avoid shirking. An examination of the Census 2000 data shows that secretaries and receptionists in the IT industry have higher annual earnings as well as higher hourly wages than secretaries and receptionists in other industries. This industry wage premium is not driven by higher education or more potential experience (age-6-years of education) because the wage premium remains the same even after these two variables are used as controls.

2.6 Reasons for Hi-Tech Displaced Workers' Larger Earnings Losses

2.6.1 Is it driven by the 2000-2001 recession?

The dot-com bubble burst in 2000 marked the end of the boom in many hi-tech industries. From 2000 to 2003, average employment decreased by 21 percent in IT manufacturing industries and by 17 percent in IT services industries; while the employment drops in non-IT manufacturing and non-IT services industries were two percent and 0.5 percent respectively.[24] Other hi-tech industries also experienced large job losses in the 2000-2001 recession and many of them had only moderate employment recoveries in the post-recession period.[25]

To examine whether the baseline results are driven by the 2000-2001 recession and the following sluggish employment growth, equation (2) is estimated separately for person-quarter observations during 1989-1999 and person-quarter observations during 2000-2005. The results are presented in Figures 2.8a and 2.8b. Hi-tech displaced workers have significantly larger earnings losses in periods before 2000 but not after. This result is likely explained by the fact that non-displaced hi-tech workers have steeper earnings growth before 2000 than after 2000, resulting in workers displaced in the 1990s suffering larger foregone earnings than workers displaced after 2000. These results suggest that the baseline results are not driven by the weaker labor market in hi-tech sectors after 2000.

[24] These numbers are from Hotchkiss (2005).
[25] See Groshen and Potter (2003).

2.6.2 Job Mobility following Displacement

Stevens (1997) and Schoeni and Dardia (1996) found that displaced workers who change jobs more frequently after displacement have larger earnings losses because their earnings recovery process is interrupted. In the Maryland UI data, a review of the number of job changes after displacement shows that hi-tech workers have fewer job changes than low-tech workers. The former has an average of 3.4 job changes while the latter has an average of 4.1 job changes. Therefore, hi-tech workers' greater earnings losses cannot be explained by more frequent job mobility after displacement.

2.7 Conclusion

This chapter explores whether hi-tech displaced workers have larger earnings losses than low-tech displaced workers. Using individual-level longitudinal data set linked with industry level technology measures, this study finds that initial earnings losses after job loss are greater for hi-tech workers than for low-tech workers. In the long run, earnings recover faster in post-displacement period for hi-tech displaced workers when technology is measured by computer usage or hi-tech equipment investment.

The kind of government assistance program most helpful to hi-tech displaced workers depends on the reasons for their larger losses. For example, training programs may be more helpful than financial support, if hi-tech displaced workers lose earnings because their skills depreciate. Job search services may be more desirable if hi-tech skills are too specific to be easily transferred to new jobs or good matches are hard to find. Future research, both theoretical and empirical, should explore the explanations for hi-tech workers' larger earnings losses.

Chapter 3: Skill Changes of Female Immigrants to the United States, 1970-2000

3.1 Introduction

Compared to many other countries in the world, the U.S. population has included a relatively large proportion of immigrants and this proportion has increased dramatically in recent decades. In 1970, 9.6 million persons, or 5 percent of the U.S. population were foreign-born; whereas in 2000, 32.9 million U.S. people, or 11.7 percent of the population were foreign-born. The labor market skill of immigrants is an important concern in assessing the overall contribution of immigrants to the U.S. economy.

Skills of female immigrants are measured along both observed and unobserved dimensions in this chapter. Observed skills include English proficiency and educational attainment, two major components of human capital that affect immigrants' performance in the US labor market. Unobserved skill is estimated using regression-adjusted wages, controlling for education, experience, health, marital status, and residence area. Based on the assumption of perfectly competitive labor markets, the wage is equal to the marginal productivity of labor. This implies that regression-adjusted wages capture workers' unobserved characteristics that affect their productivity. Examples of these characteristics include quality of schooling, self-motivation, and commitment to work. Quality changes of female immigrant cohorts over time are measured by comparing the quality, either directly observed or indirectly estimated, of immigrant cohorts who arrived in the U.S. in different time periods.

A great deal of literature has examined the quality changes of male immigrant cohorts. Early research, such as Borjas (1985, 1995), Funkhouser and Trejo (1995) and Yuengert (1994), has shown that the skills of male immigrants decreased across successive cohorts from the 1950s to the 1980s. One major contributing factor to the quality decline of male immigrants is the shift of origin country from Europe to Asia and Latin America. Borjas (1992) and LaLonde and Topel (1991) demonstrate that, after controlling for changes in source country composition, all quality declines disappear. Using more recent data, Jasso, Rosenzweig and Smith (1998) and Lubotsky (2000) show that the secular decline in skills of male immigrants halted in the mid-1980s and that male immigrants exhibited a rise in quality from the late 1980s through the 1990s.

Little attention has been devoted to female immigrants' earnings or skill changes, probably because of a lack of information on women's real working experience. As far as I know, the only research studying female immigrants' skill changes is Funkhouser and Trejo (1998), which shows no quality decline across successive cohorts of female immigrants, after controlling for education, experience, marital status, etc. Despite the few studies on labor market skills of female immigrants, the important role female immigrants play in the host-country economy has been emphasized in the Family Investment Model (Duleep and Sanders 1993). Their research demonstrates that wives in immigrant families work to finance their husbands' initial investments in U.S.-specific human capital during their first few years in the U.S. to maximize the family permanent income. This view of immigrants' earnings from a family perspective illustrates that female immigrants' human capital is a critical component affecting immigrants' contribution to the U.S. economy.

The analysis presented here of skill changes among female immigrants is helpful in addressing a number of issues. Examination of the labor market skills of female immigrants facilitates comparisons of human capital between female immigrants and male immigrants. Using the same data and measurement methods as Borjas (1985) provides a consistent basis for comparing the quality changes of female immigrants with those of male immigrants studied in Borjas's work. Earnings differentials by gender among immigrants have been studied far less than those among the native-born.

The study of female immigrants' quality changes across cohorts is important in helping to interpret the cross-sectional data analysis that is often used to estimate immigrants' assimilation rates, namely the wage growth rate with years of stay in the U.S. Because of the lack of longitudinal data sets for immigrants, most research studying immigrants uses cross-sectional data. As noted most importantly by Borjas (1985), cross-sectional analyses would lead to biased estimates of the assimilation rate if immigrants' skills change across cohorts. For example, if immigrants arriving in 1985 have higher skills than those arriving in 1995, an analysis using Census 2000 alone would show that immigrants with 15 years of stay in the U.S. have better labor market performance than those with five years of stay in the U.S., even if there is no assimilation at all. The methodology and estimates presented here on changing patterns across cohorts of female immigrants can be helpful in assessing to what extent cross-sectional estimation of the assimilation rate is biased for female immigrants.

Many factors may contribute to changes in the human capital of immigrants to the U.S. Quality changes across cohorts of female immigrants could be driven by changes in the U.S. demand for immigrants as well as changes in the supply of immigrants in their countries of origin. Immigration laws in the U.S. affect the kinds of immigrants selected into the U.S. and thus affect the average quality of certain immigrant cohorts. For example, under the Immigration and Naturalization Act of 1965, individual visas were granted giving priority to family reunification. Immigrants who could not migrate to the U.S. under an occupational visa could then enter on the basis of kinship. This kind of change in the law would presumably decrease the skill level of immigrants. In 1986, the Immigration Reform and Control Act (IRCA) was passed to control unauthorized immigration to the United States. This act reduced the number of illegal immigrants who are usually lower-skilled workers and would therefore have a positive effect on average immigrant skills. The impact of these laws may vary across different groups of immigrants. For example, IRCA (1986) may have the greatest impact on Mexican immigrants.

On the supply side, trends in immigrant quality across cohorts are related to the economic incentives for migration. Individuals choose to migrate only when the difference between their expected earnings in the U.S. and those in their home countries could compensate for migration costs. Lower transportation costs and simpler procedures for applying to go abroad as some countries open their doors wider reduce the overall migration costs and make migration profitable for a greater number of low-earning individuals. In addition, the kind of individuals within a home country who choose to migrate depends on the skill price in the home country relative to that in the U.S. As discussed in Borjas (1987), immigrants are mainly drawn from the upper end of the earnings distribution in the home country if the destination country has a larger variance in earnings than the home country, everything else being equal, and vice versa. This is because countries with low earnings variance tend to tax high-earners to subsidize low-earners, which drives high-earners to a destination country with a higher earnings variance to benefit from the higher skill premium. More immigrants coming from countries with greater income inequality than that of the U.S. would decrease average immigrant quality because more lower-end individuals would be included. In summary, the quality of immigrants in the U.S. would change over time because of changes in migration-related costs or changes in the earnings dispersion in the home country and in the U.S.

Because the supply-side and demand-side influences on immigrants may be offsetting, theory does not offer an unambiguous prediction on the direction of immigrants' quality changes. Therefore, the net result of these factors on the changes of female immigrant human capital is an empirical question.

This paper examines changes across cohorts in female immigrants' labor market skills using data from the U.S. Decennial Censuses of 1970, 1980, 1990 and 2000. Census data shows that, across cohorts of female immigrants, English proficiency at entry has not changed and average years of education has increased. To estimate unobserved quality changes, differences in regression-adjusted wages are calculated between successive cohorts of female immigrants using the methodology in Borjas (1985). His regression model is extended somewhat to address the potential estimation biases caused by women's discontinuous work history. The empirical results show that, unlike male immigrants whose unobserved skills declined across successive cohorts from the 1960s to the 1970s, the skills of successive cohorts of many female immigrant increased during this period. From the 1970s to the 1990s, Asian and Mexican female immigrants both show quality declines but the reasons vary. Finally, the skills of new cohorts of female immigrants have not changed much in the most recent decade.

3.2 Changes in Observed Dimensions of Human Capital

3.2.1 English Proficiency

The English proficiency of immigrants is a critical component of human capital for success in the U.S. labor market. Previous research has shown that immigrants who are proficient in the dominant language of the host country have higher earnings than those who are not (McManus, Gould and Welch (1983), Dustmann (1994), Chiswick and Miller (1995), Carliner (1996), Berman and Lang (2000)). For example, Chiswick and Miller (1995) found that English fluency is associated with five percent higher earnings among immigrants in Australia. This positive correlation is higher for immigrants from non-English speaking countries and is increasing over time. Carliner (1996) shows that better English skill is rewarded by higher earnings in the U.S. at a similar rate as the return to additional years of education. All else being equal, male immigrants who speak English “very well” earn

9.6 percent more than those who speak English well and male immigrants with 12 years of schooling earn 8 percent more than those with 11 years of schooling.

Information on the English proficiency of female immigrants in this paper is taken from the U.S. Decennial Censuses of 1980, 1990 and 2000. Immigrants are defined as individuals who are born outside the United States[26]. English proficiency is measured using a self-rated[27] response to the Census question "How well does the respondent speak English?" Responses fall into one of five categories: "only speaking English", "speaking English very well", "speaking English well", "speaking English not very well", and "not speaking English at all". Table 3.1 presents two indicators of English proficiency: fraction of immigrants speaking only English or speaking English very well and fraction of immigrants not speaking English at all. All results in this paper are weighted by person weights provided by the Census Bureau.

Census measures of the English proficiency for female immigrants by race and ethnicity are presented in Table 3.1, for the period 1980 – 2000. Among immigrants who have been in the U.S. for five years or less, 36.5 percent spoke English at least very well in 1980, with this number increasing only slightly over time (37.9 percent in 1990 and 38.9 percent in 2000). The lower panel of Table 3.1 shows the other end of the distribution – the percentage of female immigrants not speaking

[26] This definition of immigrant is widely used in the literature on immigrants' economic performance in the U.S. Another definition of immigrant, used by the U.S. Immigration and Naturalization Service (INS), is all legal permanent residents. The latter definition can not be used with Census data because information on legal status is not available. Besides, the INS defined immigrants do not include foreign students and recent refugees, who are very likely to become permanent residents later.

[27] There is evidence that self-reported second language skills are highly correlated with other more objective measures (Spolsky (1989) and Le Blank and Painchard (1985)) and are powerful predictors of immigrants' labor market performance (Carliner (1996), Berman and Lang (2000)), which suggests that they can capture the real language ability of immigrants. This self reported English skill in the Census is widely used in the literature of immigrants' language assimilation (Carliner (1996), Carliner (2000), Chiswick et al. (1995), Chiswick et al. (2006)). However, Anderson (1982) found that the correlation of self-assessment with object test scores differs by country of origin and Shuy (1981) reported that some respondents may be unable to assess language issues precisely.

English at all. About 17 percent of female immigrants with five years or less of residence in the U.S. do not speak any English. This proportion also stays almost the same from 1980 to 2000. The seemingly stable trends in language ability hide large variations across ethnic groups. Row two through Row five in the upper and lower panels of Table 3.1 present the different trends in English proficiency for four groups: White immigrants (non-Hispanic, non-Asian), Black immigrants (non-Hispanic, non-Asian), Asian immigrants and Mexican immigrants. Asian and Mexican immigrants exhibit steadily increasing language ability, reflected by both increasing fractions of people speaking English at least very well and decreasing fractions of people speaking no English. By contrast, Black immigrants show a constant decline in English ability. There is no obvious trend for White immigrants.

By comparing the language ability of immigrant cohorts who have been in the country different lengths of time, the changes over time in language ability – the language assimilation process – can be determined.[28] According to Figure 3.1, 37 percent of immigrants who arrived in the U.S. during 1975-79 spoke only English or spoke English very well during their first five years in the U.S., while the fraction for this cohort increased to 55 percent after 10 years and to 57 percent after 20 years. This language adaptation process is faster for earlier cohorts of immigrants than for more recent cohorts. The dotted line in Figure 3.1 shows that the cohort arriving during 1985-89 experienced a 14 percentage point increase in English proficiency over 10 years, while the solid line shows that the cohort arriving during 1975-79 had

[28] This is based on the assumptions that immigrants who migrate out from this country have similar language skills on average as those who stay and that self-reporting norms do not change with lengths of stay in the U.S. Stevens (1994) and Chiswick et al. (2006) have provided evidence that immigrants returning to their home countries have similar language abilities as those staying in the U.S.

an increase of 18 percentage points. This slowing down of language assimilation rate is also true for other cohorts not shown Figure 3.1.

3.2.2 Educational Attainment

Another critical factor affecting immigrants' quality is educational attainment. Table 3.2 shows the changes over time in educational attainment of female immigrants and natives. Because educational attainment has increased for women in almost all countries in recent decades, educational attainment of the native born is reported as a benchmark. The sample is restricted to individuals older than age 24, an age at which most people have completed their college education, if any, so that changes in the distribution of age at migration would have a minimal effect on changes in educational attainment across cohorts.

The top panel in Table 3.2 presents the percentage of high school dropouts among immigrant and native women over time. In 1980, 45 percent of newly arrived female immigrants were high school dropouts. By 2000, only 28 percent of female immigrants did not have a high school diploma. The percentage of high school dropouts decreased by more than one-third over these two decades. Among female natives, there is a smaller proportion of high school dropouts, with only 13 percent lacking a high school diploma. Moreover, natives experienced a 60 percent decline in high school dropouts from 1980 to 2000, a much higher rate than that of the immigrants during the same time period. The relatively slow decline of high school dropouts among immigrants may be driven by the rapid increase of Mexican immigrants with low levels of education on average. As shown in the top panel of

Table 3.2, the percentage of high school dropouts among Mexican immigrants is more than twice as large as that of other immigrants, and the number of Mexican immigrants in 2000 is more than four times the number in 1980. All three other immigrant groups exhibit a similar decline rate of high school dropouts as that of natives.

Although immigrants have a larger fraction of high school dropouts and this fraction has declined more slowly for immigrants than for natives, immigrants' educational attainment at the other end of the education ladder – college graduation – is as good as, if not better, than for natives, at least on average. The middle panel of Table 3.2 shows that, among newly arrived immigrants, the fraction with a college degree is higher than that of natives and the growth rate of this fraction is similar between immigrants and natives. The high fraction of college graduates among immigrants is driven by highly educated white and Asian immigrants. In contrast, the growth rate in the fraction of college graduates among black and Mexican immigrants is faster than that of natives, although their levels have remained below that of natives.

Most immigrants migrate at relatively young ages, so the population of newly arrived immigrants has a larger fraction of young people than the native population, which may drive up the average educational attainment of immigrants relative to the natives due to the secular increase in college enrollment rates. To control for this difference in age composition, the native sample is reweighted using the age distribution of the newly arrived immigrants and the weighted average of educational attainment calculated for the native sample. The last row in the middle panel of Table 3.2 shows the results of this adjustment. Immigrants still exhibit a higher fraction of college graduates and a similar growth rate over time compared to the natives, when the age distribution of the immigrant sample is imposed on natives.

The top two panels of Table 3.2 demonstrate that, in terms of educational attainment, recently arrived immigrants are worse than natives at the low end of the education distribution and better than natives at the high end. The bottom panel of Table 3.2 complements the upper two panels by depicting an overall picture of the average educational attainment between immigrants and natives. This bottom panel shows that average years of education[29] attained by immigrants is lower than that of the natives but the growth rate across cohorts is similar between the two groups. Asian female immigrants stand out by showing a remarkable improvements in education across cohorts, starting at a lower than native educational attainment in 1980 and ending at a much higher level than natives in 2000. This improvement in education among Asian immigrants offsets the negative effects on immigrants' average education caused by the increase of Mexican immigrants.

Compared to the educational attainment changes for male immigrants in Table 3.2 in Borjas (1995), female immigrants studied in this paper show a larger decline across cohorts in the fraction who are high school dropouts and faster growth in the fraction who are college graduates from 1980 to 1990.[30] As presented in Figures 3.2 and 3.3, male immigrants show no decline in high school dropouts and a flatter growth in college graduates than male natives. These differences in trends result in a

[29] "Years of education" is established based on the education attainment variable in Census. The recoding mechanics are described in Appendix 3A.
[30] The sample in Borjas (1994) Table 4 is not exactly the same as that in my Table 2. Borjas only studied men aged 25-64, who work in the civilian sector, who are not self-employed, and who do not reside in group quarters; while the sample in my Table 2 are women aged older than 24. However, fraction of respondents in military, reporting self-employed, and residing in group quarters is so small that it may not affect the comparison. Moreover, there is only little difference in age distribution at ages older than 64 across Census years so the different age ranges between my sample and Borjas' sample may not matter as well.

larger improvement across cohorts of education among female immigrants than their male counterparts, relative to respective U.S.-born individuals.

3.3 Changes in Unobserved Dimensions of Human Capital

3.3.1 Framework

Language proficiency and educational attainment are important components of human capital affecting the wage of immigrants, and measures of these factors are included in the Census data. There are, however, other unobserved factors determining how well immigrants perform in the US labor market, such as schooling quality, self-motivation and other personal characteristics. This section investigates the trend in these unobserved dimensions of immigrant quality. A measure of these unobserved effects is based on regression-adjusted wages, which are predicted wages after controlling for observed factors such as education and experience, as developed by Borjas (1985). This approach makes it possible to compare the predicted wages of two cohorts, holding everything else equal. Implementing this approach requires the use of multiple years of Census data. The repeated cross-sectional data permits a comparison between two cohorts that have the same length of stay in the U.S. For example, to examine the quality changes between people migrating during 1965-1969 versus those migrating during 1975-1979, an estimate of the earlier cohort's predicted wages in 1970 is compared to an estimate of the later cohort's predicted wages in 1980. Both cohorts will have at most five years of residence in the U.S. when observed in each respective Census. Specific cohorts of immigrants are compared between Census 1970 and Census 1980, between Census 1980 and Census 1990, and between Census 1990 and Census 2000. The following introduction of the estimation framework describes the comparison between Census 1970 and Census 1980 as an example. Comparisons of later cohorts using later years of Census data replicate the same logic.

Immigrants are categorized as cohorts by their arrival years reported in Census. In Census 1970, all immigrants can be grouped into four cohorts: arrivals in 1965-69, arrivals in 1960-64, arrivals in 1950-59 and immigrants arriving prior to 1950. In Census 1980, two more cohorts are added: arrivals in 1975-79 and arrivals in 1970-74. Using dummy variables to indicate these cohorts, two regressions are estimated for Census 1970 and Census 1980 respectively:

$$\ln w_{70} = X\beta_{70} + \alpha_{70,65}D_{65} + \alpha_{70,60}D_{60} + \alpha_{70,50}D_{50} + \alpha_{70,40}D_{40} + \varepsilon_{70,} \qquad (1)$$

$$\ln w_{80} = X\beta_{80} + \alpha_{80,75}D_{75} + \alpha_{80,70}D_{70} + \alpha_{80,65}D_{65} + \alpha_{80,60}D_{60} + \alpha_{80,50}D_{50} + \alpha_{80,40}D_{40} + \varepsilon_{80,} \quad (2)$$

where the subscripts 70 and 80 indicate the Census year. The dependent variable is log wage in the year before Census, calculated as annual earnings divided by total hours worked last year. Total hours worked last year is a multiplication of weeks worked last year and hours worked per week[31]. X is a vector of explanatory variables including education, potential work experience (equal to age-6-years of education), potential work experience squared, marital status, number of own children in the household, marital status interacted with potential experience, marital status interacted with potential experience square, health, and residence area.

[31] Hours worked per week is reported as weekly working hours in the Census week in Census 1970 and is reported as usual hours worked in the past year in Census 1980 through 2000. Hours worked per week and weeks worked last year are coded as intervals in Census 1970. Mid points of these intervals are used in calculation. A detailed discussion of the definitions of all dependent and independent variables is in Appendix 3A.

Since women often have interrupted work histories (Mincer and Polachek 1974), the potential work experience calculated as "age-6-years of education" does not measure accurately the actual amount of work experience of women. The variable "number of children" is included to proxy the amount of time women stay out of the labor force. Marital status is interacted with potential work experience to allow for different wage effects of potential experience based on marital status, further controlling for the possible difference in labor market attachment between married women and single women. Arriving cohorts are indicated by the set of dummy variables D_k. For example, D_{65}=1 if an immigrant migrated during 1965-69. All the four cohorts in Census 1970 and all the six cohorts in Census 1980 are captured in equations (1) and (2). Intercepts are omitted in the regressions so that coefficients of all the cohort dummies are identified.

Using estimated coefficients from regressions (1) and (2), predicted wages for each cohort are generated. Three pairs of across-cohort comparisons are conducted between Census 1970 and 1980. Cohorts 65-69, 60-64 and 50-59 in Census 1970 are compared with cohorts 75-79, 70-74 and 60-69[32] in Census 1980. Considering the comparison between cohort 65-69 and cohort 75-79 as an example, their predicted log wages are calculated as:

$$\ln \hat{W}_{70,65} = \overline{X}\hat{\beta}_{70} + \hat{\alpha}_{70,65}, \qquad (3)$$

$$\ln \hat{W}_{80,75} = \overline{X}\hat{\beta}_{80} + \hat{\alpha}_{80,75}. \qquad (4)$$

By definition, cohort 65-69 in Census 1970 and cohort 75-79 in Census 1980 both have zero to five years of residence in the U.S. Other explanatory variables are

[32] The cohort 50-59 is at a ten-year interval while cohorts 60-64 and 65-69 are two five-year intervals. To facilitate the comparison between Census 1970 and 1980, a predicted wage is calculated for cohort 60-69 by averaging the predicted wage of cohort 60-64 and cohort 65-69.

held constant for these two cohorts by imposing the same $\overline{X}$ in the calculation. The $\overline{X}$ used in equations (3) and (4) is the average of the $\overline{X}$ of cohort 1965-69 in Census 1970 and the $\overline{X}$ of cohort 1975-79 in Census 1980[33]. Using the same $\overline{X}$ and holding constant the length of stay in the U.S. assures that the differences between two cohorts' predicted wages are not driven by observed factors included in X.

Changes in macroeconomic conditions (which may also lead to a difference between $\ln \hat{W}_{70,65}$ and $\ln \hat{W}_{80,75}$) are controlled for by comparing immigrants' wages to native workers' wages. For example, a higher return to education throughout the overall labor market in 1980 than in 1970 would make the predicted wage of a worker in 1980 higher than that of a worker in 1970, even if the two workers are exactly the same in both the observed and the unobserved dimensions of human capital. To remove this effect of changes in overall labor market condition, native workers are used as a benchmark group (Borjas 1985), based on the assumption that the wage effects of human capital variables change in the same way between immigrants and natives[34]. The change in unobserved human capital between cohort 65-69 and cohort 75-79 is thus defined as:

$$\begin{aligned}&(\ln \hat{W}^{I}_{80,75} - \ln \hat{W}^{N}_{80}) - (\ln \hat{W}^{I}_{70,65} - \ln \hat{W}^{N}_{70})\\&= [(\overline{X}\hat{\beta}^{I}_{80,75} + \hat{\alpha}^{I}_{80,75}) - (\overline{X}\hat{\beta}^{N}_{80} + \hat{\alpha}^{N}_{80})] - [(\overline{X}\hat{\beta}^{I}_{70,65} + \hat{\alpha}^{I}_{70,65}) - (\overline{X}\hat{\beta}^{N}_{70} + \hat{\alpha}^{N}_{70})], \qquad (5)\end{aligned}$$

[33] X means of other samples are also tried. Setting X means equal to X means of cohort 1965-69 measured in Census 1980 (as used in Borjas 1985) leads to similar results.

[34] The estimated returns to observed human capital characteristics may change differently between immigrants and natives. For example, wages of nurses have increased over time, so predicted wages of Filipino women who are largely concentrated in nursing jobs would increase over time even if their skills do not improve. Another example is that the different labor market effect of economic recession between immigrants and natives could lead to different estimated returns. To pin down the extent to which differences in predicted wages are caused by differences in the quantity of human capital rather than the price of human capital, one could perform decomposition as in Juhn, Murphy and Perce (1989). This is left for future research.

where the superscripts I and N stand for immigrants and natives respectively.[35] Predicted wages of native workers are obtained using the same $\overline{X}$ described as above, together with the estimated coefficients from the regressions of native worker samples[36]:

$$\ln w_{70}^{N} = X\beta_{70}^{N} + \alpha_{70}^{N} \cdot \text{intercept} \qquad (6)$$
$$\ln w_{80}^{N} = X\beta_{80}^{N} + \alpha_{80}^{N} \cdot \text{intercept} \qquad (7)$$

3.3.2 Data

The data used in the following regressions are drawn from the 1970, 1980, 1990 and 2000 U.S. Census. The sample selection criteria require that: (1) the individual was between the ages of 18[37] and 64; (2) the information on weeks worked last year and hours (or usual hours) worked per week was not missing; (3) the individual was not self-employed or out of the labor force; (4) the individual did not reside in group quarters. Table 3.3 shows the fraction of individuals excluded from the following regressions because of the above sample selection criteria. Fewer immigrants than natives are excluded for not belonging to the working age range – ages 18 to 64 – because younger and older people are less likely to migrate. Immigrants are more likely than natives to be self-employed or not participating in the labor force.[38] But among those who work and receive positive wages, immigrants

---

[35] Changes in immigrants' predicted wages relative to those of natives are also influenced by changes in discriminatory attitudes against immigrants and changes in the composition of ethnical groups.

[36] An alternative method to estimate the predicted wages by cohorts is to pool data of immigrants and natives from all four Census years and to run a single regression which includes on the right hand side native dummies, cohort dummies, and length of stay in the U.S. Such a single regression constrains that the coefficients on X are all the same across Census years and between immigrants and natives. Adding interaction terms between duration of stay and cohort dummies allows the cohort effects to differ by length of stay.

[37] Eighteen instead of twenty four is used as the lower bound of the age restriction so that the newly arrived high school dropouts are captured.

[38] The sample used for regression includes working women only. Women's self-selection into the labor force is

are less likely to have missing information on working weeks or hours. On average, working women with no information on working weeks or hours are less educated and younger than other working women. Wages for all years are defined in 2000 dollars, by converting nominal wages in 1970, 1980 and 1990 into 2000 dollars by the Consumer Price Index. Workers with wages lower than $1 per hour or higher than $200 per hour are excluded. These outliers constitute less than one percent of the sample.

Immigrants from different countries of origin have very different socioeconomic status and there is evidence that the shift of immigrant composition from white European immigrants to Asians and Mexicans is a major contributor to the change of male immigrant quality over time (Borjas (1992), LaLonde and Topel (1991)). To single out the across-cohort quality changes due to changes in country of origin mix, the following analysis examines female immigrants separately for four major immigrant groups[39]: White immigrants (non-Hispanic, non-Asian), Black immigrants (non-Hispanic, non-Asian), Asian immigrants and Mexican immigrants. Immigrants are compared to their native counterparts in the same ethnic groups. For example, Asian immigrants are compared with natives reporting Asian race and Mexican immigrants are compared with natives of Mexican origin.[40]

---

investigated using Heckman's two-step model (Heckman 1979). However, the lack of valid exclusion restriction from the Census data introduces large noises into the estimation and leads to unreliable results.

[39] These four groups are generated by aggregating immigrants from very different countries into specific ethnic groups. Changes in the origin country composition within each group could affect estimated changes in immigrant quality. This issue is particularly severe for the Asian group because Asian countries are very diverse, ranging from developed countries such as Japan and Singapore to less developed countries such as Vietnam and the Philippines.

[40] There is debate in the literature as regard to whether immigrants should be compared to white natives (the typical native US individual) or to natives with the same ethnicity. My paper studies immigrants' wages, with natives used as a control group to account for the general macroeconomic effects. So I think it is more appropriate to compare immigrants with the most similar natives, the natives with the same ethnicity, considering the large difference in socioeconomic statuses between ethnic groups even among natives.

Figures 3.4a through 3.4d present raw log wages measured after at most five years in the U.S. for immigrant cohorts 1965-69, 1975-79, 1985-89, 1995-99, together with raw log wages of female natives who are in the labor market during the same time periods. White and Black immigrants show higher wages than their native counterparts while Asian and Mexican immigrants have lower wages than their native counterparts. All four immigrant groups had lower wages among cohort 1975-79 than among cohort 1965-69. From cohort 1975-79 to cohort 1995-99, wages become higher for White, Black and Asian immigrants, and the rate of wage increase is similar to their native counterparts.

Figure 3.4 confirms that different ethnic and country groups have quite different wage levels. Mexican immigrants have the lowest average wages among all immigrants in all Census years. Asian immigrants' average wage is higher than that of Black immigrants and Mexican immigrants but is lower compared to that of native Asians. The language barrier is a possible reason. The large linguistic distance between English and most Asian languages is a hurdle limiting Asian immigrants' assimilation into the U.S. labor market while language is not an obstacle for Asian natives.

3.3.3 Empirical Results

Table 3.4 presents estimated coefficients in wage regressions of immigrants and natives in Census 1970 and 1980 (Equations (1), (2), (6) and (7)). Two findings from the regressions are consistent with previous results in papers such as Chiswick (1978), Borjas (1985) and Duleep and Regets (1997). First, the wage returns to education and experience are higher for native women than for immigrant women. For example, in Census 1980, one additional year of education increases the wage of natives by five to seven percent, but only increases the wage of immigrants by two to five percent. Second, immigrants who have been in the U.S. for a longer period of time have significantly higher wages than those who have just arrived, as indicated by the cohort dummy coefficients being larger for earlier cohorts than for more recent cohorts. This positive correlation between wages and length of stay in the U.S. is presumably a combination of assimilation effects and cohort effects.

Regressions presented in Table 3.4 expand the wage equation in Borjas (1985) to include number of own children in the household and interactions between marital status and potential experience variables. Results show that there is a negative wage effect of number of children – one more child is associated with a two percent wage decline in for white female natives in 1970. This finding is consistent with the hypothesis that women with more children tend to spend more time out of the labor force and therefore have a smaller incentive to invest in labor market human capital and also a shorter period of time to accumulate human capital. Coefficients on interactions between marital status and potential experience indicate that most married women have smaller returns to potential experience than single women (except for Asian natives in Census 1970 who have negative wage effects of potential experience among singles). This presumably reflects the fact that potential experience is a more upward biased measure of true experience for married women than for single women. Number of children and the interaction between marital status and experience may change over time, so failing to control for them in the regressions would cause their changes to be captured as part of the unobserved quality change.[41]

Unobserved dimensions of quality differences across female immigrant cohorts are calculated by applying estimated coefficients in Table 3.4 and the mean values of independent variables calculated from appendix Table A3.4 to the formula in equation (5). The results are reported in Tables 3.5a through 3.5c, which present the quality comparisons between Census 1970 and 1980, between Census 1980 and 1990, and between Census 1990 and 2000 respectively. Most of the quality difference estimates are statistically significant. According to Table 3.5a, white immigrants who migrated during 1975-79 have a predicted wage after at most five years in this country that is 39 percent[42] lower than those who migrated during 1965-69. For native whites, their predicted wage is 26 percent lower in 1980 than in 1970. Therefore, relative to natives, the predicted wage of cohort 1975-79 is lower than cohort 1965-69 by 13 percentage points among white immigrants. For Asian and Mexican female immigrants, the unobserved quality of cohort 1975-79 is higher than that of cohort 1965-69. The magnitudes of the relative quality improvement are 1.8 percentage points for Asian immigrants and 8.3 percentage points for Mexican immigrants. Cohorts migrating during 1960-64 and during 1950-59 are observed in Census 1970 with six to 20 years of residence in the US. These cohorts' predicted wages are measured after a relatively lengthy exposure to the US economy and thus capture the across-cohort differences in both entry wages and wage growth rates after arrival. For

[41] Although not reported here, regressions results from Census 1990 and 2000 show similar patterns as discussed above.

[42] A decrease in predicted log wage by X is approximately equal to a decrease of predicted wage by X*100 percent. This is because: log(w1)-log(w2)=log(w1/w2)=log(w1/w2-1+1)=log((w1-w2)/w2+1), which is approximately equal to (w1-w2)/w2 when (w1-w2)/w2 is small. Numbers in Column 3 of Table 5 are calculated as Column 1 (percentage) minus Column 2 (percentage) so they are in percentage points.

all immigrant groups, the predicted wages are higher for cohort 1970-74 than for cohort 1960-64, and lower for cohort 1960-69 than for cohort 1950-59.

Figure 3.5 presents a comparison of estimated quality differences between female and male immigrants, based on results from Table 3.5a in this paper and those from Table 5 in Borjas (1985). For Asian and Mexican immigrants, there is a quality decline from cohort 1965-69 to cohort 1975-79 among male workers but a quality increase among female workers. For Black immigrants, both male and female workers experience decreased predicted wages from cohort 1965-69 to cohort 1975-79 but the magnitude of the decline is smaller for female immigrants. White immigrants are the only group where female immigrants fared worse than male immigrants during this period. So overall, the unobserved dimensions of human capital increase more among female immigrants than among male immigrants from cohort 1965-69 to cohort 1975-79.

Quality differences across cohorts in later years are presented in Tables 3.5b and 3.5c. From cohort 1975-79 to cohort 1985-89, white and black female immigrants exhibit quality increases across cohorts while Asian and Mexican female immigrants show quality declines. The underlying reasons for the quality decline are different between Asian and Mexican immigrants. Asian natives experience healthy wage increases from Census 1980 to 1990 but the wage differences between cohort 1975-79 and 1985-89 among Asian immigrants do not catch up with their native counterparts, resulting in quality declines among Asian immigrants relative to natives. By contrast, the experiences of Mexicans different. Both Mexican immigrants and natives of Mexican origin had low wage growth between Census 1980 and 1990, compared to other ethnic groups and compared to their own historical experience. One possible explanation is the increasing return to education over the 1980s. White natives, on average, have higher levels of education than natives of Mexican origin. When the return to education increases, white natives on average benefit more from the higher return to education than natives of Mexican origin, leading to larger average wage increases for White natives. Since Mexican immigrants have even lower educational attainment than natives of Mexican origin, their predicted wage growth is even lower, leading to an observed relative quality decline of Mexican immigrants from 1980 to 1990.

Results from the most recent two decades are presented in Table 3.5c. Although the most recent cohorts of female immigrants have lower predicted wages than those who arrived ten years before, the magnitude of the quality decline is smaller than those in Tables 3.5a and 3.5b. This is similar to what has been found for male immigrants in Borjas and Friedberg (2006) and Bohn (2007).

Some cohorts are observed across multiple years, which allows one to examine cohort quality at different positions along their duration in the U.S. For example, cohort 1965-69 in Census 1970 and cohort 1975-79 in Census 1980 can be compared in terms of wages at entry, and can also be compared in Census 1980 and Census 1990, 10 to 15 years after entry. For White immigrants, the predicted wage at entry is 13 percentage point lower for cohort 1975-79 than for cohort 1965-69. After ten more years of residence in the US, cohort 1975-79 has a wage 6.3 percentage point higher than cohort 1965-69, as shown in Table 3.5b. The faster assimilation rate of cohort 1975-79 than cohort 1965-69 has contributed to the takeover.

Analogous to Figure 3.4, which depicts *raw* log wages across cohorts, Figure 3.6 portrays *predicted* log wages across cohorts. Since the same X means are used in the calculation of predicted wages for both immigrants and natives, the difference in predicted wages between immigrants and natives is a "residual" wage difference not explained by the Xs in the wage equation. For all four immigrant groups, predicted wages of immigrants lie below those of natives, indicating that newly arrived immigrants have wage disadvantages compared to natives with similar characteristics. This finding is consistent with the hypothesis that skills brought by immigrants from home countries are not valued as much as skills hold by native workers in the U.S. labor market. The wage gap between immigrants and natives is especially large for Asian and Mexican immigrants. Similar to the trends in raw wages, predicted wages are lower for cohort 1975-79 than for cohort 1965-69 among all immigrants, and are higher for cohort 1995-99 than for cohort 1985-89 among all immigrants except Blacks.

The one caveat to the above analysis is that it is based on a sample of working females only. Since human capital variables affect wages as well as selection into the labor force, failing to control for this self-selection into labor force would bias the estimate of wage returns to human capital. For example, the probability of being employed is positively associated with the level of education, so the wage effect of education would be underestimated if only working women are used in the wage regression. Without controlling for self-selection, a wage regression using working women only shows that the wage return of one additional year of education is 3.2 percent for Asian immigrants in 1970 (Table 3.4a). After controlling for self-selection using the Heckman two-step model and “number of children under age five” as an exclusion restriction, the wage effect of education increases to 5.8 percent for the same sample. If labor force selection patterns change over time, failing to control for this selection would affect the differences in predicted wages across cohorts. For example, an increasing fraction of working women would push up the coefficient of education and lead to a higher predicted wage for the more recent cohort.

A possible approach to control for self-selection into labor force is to implement a Heckman two-step model. This model requires a valid exclusion restriction term which affects wages only through the labor market participation choice and has no direct impact on wages. However, such an exclusion restriction is virtually impossible to find.

3.4 Conclusion

This chapter examines the quality differences across successive cohorts among female immigrants along both observed and unobserved dimensions of human capital. Observed skills include English proficiency and educational attainment. English proficiency at entry does not change across successive cohorts of female immigrants. Educational attainment increases across cohorts and the increase is larger among female immigrants than among male immigrants. The patterns of these skill changes vary across racial and ethnic groups. The upward shift of high school dropouts due to a rising fraction of less educated Mexican immigrants is offset by the increase of college graduates among female immigrants, especially Asians.

Differences in predicted wages across cohorts reflect the differences in unobserved dimensions of human capital across cohorts. This “residual” wage is positive for many cohorts of female immigrants from 1970 to 1980, unlike the quality decline Borjas (1985) found for male immigrants in the same period. From 1980 to 2000, the quality across successive cohorts of recent Asian and Mexican immigrants both declined, but the underlying reasons for the declines vary. Asian immigrants suffered quality declines across cohorts because they did not keep up with the large wage increases of Asian natives. On the other hand, Mexican immigrants and natives both show smaller wage increases than other ethnic groups, and Mexican immigrants fared even worse than native Mexicans. Mexicans, both native born and foreign, have lower educational attainment on average than people in other racial groups, which could lead to a relatively low wage increase when returns to education are rising.

Chapter 4: Conclusions

Specific human capital is an important component of human capital that affects worker productivity and returns in the labor market. Two examples of the role of specific human capital analyzed here are the earnings effects when workers experience involuntary job loss and the labor market consequences of migration. Workers who lose their jobs involuntarily experience an earnings shock partly because of a loss in specific human capital. In the case of immigrants, both general and specific human capital is depreciated when a worker migrates. This analysis of human capital of immigrants focuses on how the labor market values the human capital of successive cohorts of female immigrants to the United States.

The existing literature on the earnings effects of job displacement demonstrates significant earnings losses post-displacement. The analysis here examines whether earnings costs differed across workers in high-tech versus low-tech industries. An extensive panel data set of individual workers' earnings in the state of Maryland is used to estimate job displacement effects for the period 1989-2005. The analysis of earnings focuses on workers who lost their jobs but were subsequently reemployed, with any change in earnings interpreted as reflecting the effect of lost specific human capital. Workers in high-tech industries suffered larger initial earnings losses of approximately 14 percent one year after displacement, relative to the earnings losses of 10 percent for low-tech workers. Post displacement earnings recovery is faster for workers in high-tech industries than for workers in low-tech industries, with disparities in earnings losses of high-tech versus low-tech workers disappearing in the long run.

Much of the earnings loss of workers in high-tech industries is traceable to a subset of workers with earnings below the 75th percentile of their industry earnings distribution. Among workers with earnings above the 75th percentile, who are most likely managers, there is no statistically significant difference in earnings losses between hi-tech and low-tech displaced workers. In contrast, workers earnings below the 75th percentile experienced larger earnings losses in hi-tech industries than in low-tech industries. For those workers between the 25th and 75th percentile of their industry earnings distribution, initial earnings losses are larger in hi-tech industries than low-tech industries, but earnings losses between the two groups converge over time as displaced workers in hi-tech industries experience faster wage growth. This suggests that the specific human capital these hi-tech workers lost upon displacement is recovered over time through returns to new specific human capital investments that are made in new jobs. In contrast, workers in the lowest quartile of the earnings distribution experience persistent earnings loss disparities between hi-tech and low-tech industries even several years after job loss. For these low-earning workers, who are likely to do predominantly non-technology related jobs (even in hi-tech industries), those in hi-tech industries do not experience faster earnings recovery than those in low-tech industries. This is probably because what is lost with displacement for these workers is not specific human capital but rather a wage premium not correlated with labor market skills.

These findings reflect wage adjustments over the entire sample period from 1989 to 2005 rather than just during the most recent years following the dot-com bubble burst. The examination of earnings patterns for the two time periods pre- and post-2000 reveal that earnings losses were greater for high-tech workers in the pre-2000 period than after. This is likely because of a downward adjustment in wages throughout the high-tech sector after 2000 (hence affecting the earnings of the non-displaced workers who serve as a reference group to estimate displacement costs). Therefore, the results here reflect wage patterns beyond those of the dot-com bubble and collapse.

The results appear robust to a number of plausible assumptions about the subsequent earnings experience of displaced workers who "disappear" from the state of Maryland data after their initial job losses. While some of these workers may have left the work force or were unemployed, a significant number were likely working in other states. Approximately one sixth of the "disappearing" workers in the Maryland file have joined the labor force in a number of states surrounding Maryland, appearing in a data file of earnings histories recently obtained from neighboring states covering the 2004-2006 time period.

To test for the possible effects of attrition in the Maryland data, the analysis was repeated by including those workers employed in other states in the period since 2004. There is no difference in the percentages of high-tech and low-tech workers who reappeared working in nearby states. Adding these workers employed outside Maryland to the original data set of workers remaining in Maryland throughout the entire period yielded virtually identical statistical results.

Immigrants to the United States face the challenge of entering labor markets in a new country where both general human capital may not be highly valued and where some specific human capital may also be lost with relocation. Immigrants suffer a wage disadvantage on arrival compared to natives with similar skills. A great deal of empirical literature describes the decline in skills of male immigrants to the United States in successive cohorts from the 1960s to the 1980s, with the most pronounced declines caused by changes in county of origin from Europe toward Asian and Latin America. The analysis here refines and extends this analysis, focusing on changes in the human capital of female immigrants to the United States.

Measuring changes in the human capital of female immigrants considers both observed characteristics such as English proficiency and education, as well as other unobserved factors that are reflected in market wages. The English proficiency of female immigrants has remained stable across successive cohorts from the 1970s to the 1990s. Educational attainment (years of school) has increased across successive cohorts, although there remains a gap between education of immigrants and natives. Much of the advance in the education of immigrants reflects increases in college degrees among white and Asian immigrants. While the education level of Mexican immigrants has risen significantly since 1960, it remains far below that of other immigrant groups or natives at present. Across all immigrant groups, the education gap between immigrants and natives among females has declined significantly, whereas the education gap for male immigrants relative to natives has increased sharply since 1980, much of it traceable to the disproportionate growth in Mexican immigrants who have lower education levels.

In the period 1970 to 2000, white and black female immigrants have higher raw wages than their native counterparts, whereas Asian and Mexican immigrants have lower wages than their native counterparts. After holding constant the human capital variables, predicted wages are lower for all groups of immigrants than for their native counterparts, indicating a wage disadvantage among newly arrived immigrants. Across all immigrant groups, both raw and predicted wages are lower among cohort 1975-79 than among cohort 1965-69. From cohort 1975-79 to cohort 1995-99, raw wages become higher for white, black and Asian immigrants, and the rate of wage increase is similar to their native counterparts.

Estimation of market wages for immigrants and natives follows the usual human capital approach, using age-6-education as a proxy for potential experience. Including marital status and the presence of children in the wage regressions provides a means of accounting for the effect on wages of time that child-bearing women spend out of the workforce. This non-labor-market experience is not reflected when using potential experience as a measure of real working experience. Unmeasured dimensions of human capital, such as innate ability, self-motivation, and types of experience also are reflected in market wages. Comparisons of predicted market wages of immigrants across successive cohorts of female immigrants provides a measure of changes in unobserved dimensions of human capital as reflected in market valuations.

Changes in unmeasured dimensions vary by cohort and race/ethnicity. Measured within five years after arrival in the U.S., the predicted wages of cohort 1975-79 are higher than those of cohort 1965-69 for Asian and Mexican female immigrants. This result is in stark contrast to what Borjas (1985) found for male immigrants, who experienced substantial quality declines between the same two cohorts among Asian and Mexican immigrants. For white and black female immigrants, the quality declined between these two cohorts but the magnitude of decline is smaller for black female immigrants than for black male immigrants.

Compared to cohort 1975-79, predicted wages of cohort 1985-89 are lower for Asian and Mexican female immigrants. The underlying reasons for this vary between these two groups. Asian immigrants suffer relative wages declines because they could not keep up with the high wage growth of Asian natives during this period; in contrast, both Mexican immigrants and natives experience wage declines from the late 1970s to the late 1980s, probably because of their low education levels and the increasing return to education. From the late 1980s to the late 1990s, the magnitude of predicted wage changes becomes smaller for all groups, indicating a trend towards fewer unobserved quality differences across the two most recent cohorts of immigrants.

There are many possible avenues of future research that can be explored following this dissertation. As discussed in Chapter One, the incentive to invest in human capital, especially specific human capital, decreases with age. The tendency of younger workers to accumulate more new skills would affect the wage patterns for displaced workers after job loss and for immigrants after arriving in the U.S. The data set used in Chapter Two to study displaced workers does not contain information on age, but it would be interesting to exploit other data sets to investigate the differential earnings recoveries across age groups among hi-tech displaced workers. Similarly, it would be interesting to conduct formally the analysis in Chapter Three disaggregating the results by age where sample sizes allow.

The results in Chapter Two show that displaced workers in hi-tech industries began to experience lower earnings than other displaced workers even before displacement occurred. It would be interesting to examine the pre-displacement earnings histories in more detail. By taking advantage of this data set in which workers in the same firm can be identified, one could investigate whether workers remaining in firms with mass layoffs also suffer earnings decline before the layoffs occur. This could further distinguish whether the pre-displacement earnings drop of displaced workers is the result of the worsening firm conditions or of the human capital deterioration of workers who are ultimately displaced.

Finally, with the rapid and tremendous changes in the U.S. economy, particularly the fast advances in technology and increases in immigrant flows, it will be important and interesting to reexamine the two issues studied here using future data. Further developments in high technology may lead to more specific skills associated with various jobs, while the expansion of cutting-edge technologies to more firms may ease transitions from job to job. Both of these two circumstances would affect the displacement costs for hi-tech workers. As the fraction of immigrants rises in the U.S. population, their wage disadvantage may shrink as a result of a more ethnically diversified labor market. On the other hand, increasing competition among immigrant workers may have a negative impact on wages of immigrants, as discussed in Bohn (2007). Future research will have to tease out the impacts of all of these varying forces on the future fortunes of workers in the United States.

Appendices

Appendix 2A Worker Composition

The sample used in this paper follows a fixed cohort of workers who were working in 1992:1. Therefore, workers who entered the labor market in Maryland after 1992:1 are missed. However, the composition of workers did not change much between 1990 and 2000. Table A2.1a presents the educational and demographic composition of Maryland workers in four typical hi-tech industries and in all other industries in 1990 and 2000, as calculated using data from the 1990 and 2000 Public Use Microdata from the U.S. Census. Educated workers and Asian workers increased by a larger extent in hi-tech industries than in other industries between 1990 and 2000. But overall, the changes in worker composition did not differ much between hi-tech industries and other industries. Table A2.1b shows that the whole nation's worker composition and its change over time do not differ much from Maryland, except that Maryland has more educated workers and more non-White workers.

Appendix 2B Technology Measures

The first technology indicator is the fraction of workers using computer at work, calculated from the CPS 1997 Computer Ownership/Internet Supplement, and the CPS 2001 and 2003 Internet and Computer Use Supplement. When linking this indicator to individuals, the 1997 value for the 1989-1998 period, the 2001 value for the 1999-2002 period, and the 2003 value for the 2003-2005 period are used.[43] Links

[43] Using the computer usage average from 1997, 2001 and 2003 generates similar results.

of the first two periods are based on the industries' SIC codes, and links of the last period are based on NAICS codes.

The second indicator is the fraction of new investment in hi-tech equipment, calculated from the BEA's capital flow table of 1992 and 1997. The 1992 value for the 1989-1996 period based on SIC codes is used, as well as the 1997 value for the 1997-2005 period based on NAICS codes.

The third measure is company and other (except Federal) industrial R&D funds as a percent of net sales, obtained from the National Science Foundation (NSF). Values are available from 1988 to 2001 for manufacturing industries and from 1995 to 2001 for non-manufacturing industries. Missing values are replaced by those available in adjacent years. For example, values of manufacturing industries in 1994 are equal to their corresponding values in 1995. Then values in each year are linked to individuals, using SIC codes for 1989-1998 and NAICS for 1999-2005.

The fourth indicator is the fraction of scientists and engineers in the workforce in each industry, calculated from the CPS 1994, 1998 and 2002. The 1994 value is used for the 1989-1995 period, the 1998 value is used for the 1996-2000 period, and the 2002 value is used for the 2001-2005 period, all based on SIC codes.

In the MD UI data, industry codes are reported by SIC 1987 system during 1989-2000 and by NAICS 2002 system during 2001-2005. In order to match to the industry level technology indicators, sometimes it is necessary to convert between SIC and NAICS codes using the correspondence table at the Census Bureau.

Appendix 2C Impute Earnings for Disappearers

Earnings are imputed for disappearers to obtain an upper bound of earnings losses differentials between hi-tech and low-tech workers. The imputation is conducted for both permanent disappearers and temporary disappearers. For hi-tech permanent disappearers, earnings in the first four quarters after a worker disappears are equal to this worker's average quarterly earnings in the six years[44] before he/she drops out from the data. For example, if a worker disappears from the data in the second quarter of a certain year, then the earnings in the third quarter of this year is set to be the average third quarter earnings from his earnings history during the six years before he/she drops out from the data. Earnings in the fifth quarter and forward following his disappearance are determined using earnings in the first four quarters following his disappearance and the annual earnings growth rate calculated from his earnings history. Projecting earnings in this way takes into account the seasonal effects and the person specific earnings growth rate. For hi-tech temporary disappearers, the consecutive missing earnings are replaced by the first non-missing earnings that come after the missing earnings quarters for hi-tech displaced workers. For low-tech disappearers, missing earnings in quarters after the worker drops out from the data are replaced by zeros. Missing technology values associated with these missing earnings are replaced by non-missing technology values in the preceding quarters.

[44] This long time period is used because earnings in years immediately before displacement are very low relative to workers' normal earnings prior to displacement (the "Ashenfelter dip"). To implement this calculation, workers who disappear from the data in the first six years of the sample period are dropped.

Appendix 3A: Definition of variables in the regressions

Dependent variable:

lwage=log(annual earnings/weeks worked last year/hours worked per week)

Mid-points are taken when hours/weeks are reported as intervals in Census 1970:

weeks=8.1 if wkswork2=1-13

weeks=20.8 if wkswork2=14-26

weeks=33.1 if wkswork2=27-39

weeks=42.4 if wkswork2=40-47

weeks=48.3 if wkswork2=48-49

weeks=51.8 if wkswork2=50-52

hours=8.8 if hrswork2=1-14

hours=20.9 if hrswork2=15-29

hours=31.2 if hrswork2=30-34

hours=36.5 if hrswork2=35-39

hours=40 if hrswork2=40

hours=45.2 if hrswork2=41-48

hours=51.9 if hrswork2=49-59

hours=67.5 if hrswork2=60+

Independent variables:

Educ=years of education

(1st to 4th grade = 2.5 years;

5th to 8th grade = 6.5 years;

1 to 3 years of college = 14 years;

4+ years of college = 18.1 years.

According to 1990 Census (Census 1970 and 1980 do not have information on type of degrees), among immigrants with 4+ years of college, 59% are bachelor, 24% are master, 10% are professional, and 7% are Ph.D. So the weighted average years of education corresponding to “4+ years of college” is calculated as: 59%*16+24%*18+10%*18+7%*22=18.1)

Exper=Age-6-Educ

Mar=1 if married and spouse present; =0 otherwise

Hlth=1 if disability affects work; =0 if no disability that affects work

Smsa=1 if in metro area; =0 otherwise

Nchild= number of own children in the household

Nchilt5=number of own children under age 5 in the household

Appendix 3B: Replication of Borjas (1985)

Using Borjas's framework introduced in section 3.3.1, I obtain very similar results as in his work. The data are drawn from the 1970 and 1980 census and the sample is restricted to men ages 18-54 in 1970 and 28-64 in 1980. The sample selection criteria are similar to those for female immigrants except the age range.

Based on equations (1), (2), (6) and (7), I run the cross-section regressions for native people and immigrants, for t=1970 and t=1980, respectively. For some large groups (e.g., white natives in both 1970 and 1980, black and Mexican natives in 1980, etc.), random samples are drawn from the census data. Because of this randomness and the fact that there are some unknown sample selection criteria in Borjas' work, my sample cannot be exactly the same as his. Therefore my estimated coefficients are slightly different from his. The results of the regressions are presented in Table A3.1.

The mean values of the socioeconomic characteristics for each cohort are used in the process of decomposing cross-section growth into within-cohort and across-cohort components. Table A3.2 presents these mean values $\overline{X}_k$ as of 1980. Again, because of the difference in sample selection, the mean values are slightly different from those in Borjas' work.

Based on the numbers in Table A3.1 and A3.2 and the following regression equations, I can obtain the predicted log wage of a worker who is statistically similar to the average immigrant from cohort k:

$$\hat{y}_{70,k} = \overline{X}_k \hat{\beta}_{70} + \hat{\alpha}_{70,k}$$
$$\hat{y}_{80,k} = \overline{X}_k \hat{\beta}_{80} + \hat{\alpha}_{80,k}$$
$$\hat{y}_{80,k+10} = \overline{X}_k \hat{\beta}_{80} + \hat{\alpha}_{80,k+10}$$
$$\hat{y}_{70,n} = \overline{X}_k \hat{\delta}_{70,n} + \hat{\lambda}_{70,n}$$
$$\hat{y}_{80,n} = \overline{X}_k \hat{\delta}_{80,n} + \hat{\lambda}_{80,n},$$

where y is log (wage rate/10) and X includes education, experience (age-6-education years), experience squared, marital status, health, residence in SMSA.

The cross-section growth is decomposed into two parts:

Cross-section growth = (within-cohort growth) + (across-cohort-growth).

Based on the above predicted values, the decomposition can be obtained by:

$$(\hat{y}_{80,k} - \hat{y}_{80,n}) - (\hat{y}_{80,k+10} - \hat{y}_{80,n}) \ = [(\hat{y}_{80,k} - \hat{y}_{80,n}) - (\hat{y}_{70,k} - \hat{y}_{70,n})] + [(\hat{y}_{70,k} - \hat{y}_{70,n}) - (\hat{y}_{80,k+10} - \hat{y}_{80,n})]$$

The results the decomposition are presented in Table A3.3.

Table 2.1 Industry Distribution of Maryland and the U.S.

Industry	MD	US
Goods Producing-Agricultural Services	0.2%	0.8%
Goods producing-Other Agricultural	0.1%	1.7%
Mining	0.0%	0.6%
Construction	3.5%	6.4%
Mfg-Lumber & Wood Prods, Ex Furniture	0.1%	0.6%
Mfg-Furniture & Fixtures	0.2%	0.5%
Mfg-Stone, Clay, Concrete, Glass Prods	0.5%	0.5%
Mfg-Primary Metals	0.8%	0.6%
Mfg-Fabricated Metals	0.5%	1.0%
Mfg-Machinery, Ex Electrical	0.9%	1.9%
Mfg-Electrical Machinery,equip Supplies	0.8%	1.7%
Mfg-Motor Vehicles & Equip	1.0%	2.0%
Mfg-Professional & Photo Equip, Watches	1.6%	0.6%
Mfg-Misc & Nec Mfg Industries	0.1%	0.4%
Mfg-Food & Kindred Prods	1.7%	1.6%
Mfg-Tobacco Prods	0.0%	0.0%
Mfg-Textile Mill Prods	0.1%	0.5%
Mfg-Apparel & Other Finished Textile Pr	0.5%	1.0%
Mfg-Paper & Allied Products	0.7%	0.6%
Mfg-Printing, Publishing & Allied Inds	1.5%	1.6%
Mfg-Chemicals & Allied Prods	1.0%	1.1%
Mfg-Petroleum & Coal Prods	0.0%	0.1%
Mfg-Rubber & Misc Plastic Prods	0.6%	0.6%
Mfg-Leather & Leather Prods	0.1%	0.1%
Transportation	2.6%	4.2%
Communications	2.3%	1.4%
Utilities & Sanitary Services	1.5%	1.3%
Wholesale Trade	3.8%	3.9%
Retail Trade	18.6%	20.1%
Banking And Other Finance	3.4%	3.7%
Insurance And Real Estate	3.4%	1.0%
Private Household Services	0.0%	4.2%
Business Services	7.1%	1.5%
Automobile And Repair Services	0.3%	2.9%
Personal Serv Exc Private Households	0.0%	1.7%
Entertainment & Recreation Services	2.8%	3.9%
Health Services	9.2%	12.2%
Educational Services	12.5%	2.3%
Social Services	2.0%	4.6%
Other Professional Services	4.4%	0.1%
Forestry & Fisheries	0.0%	1.6%
Justice, Public Order & Safety	1.5%	0.6%
Admin Of Human Resource Programs	1.2%	0.6%
National Security & Internal Affairs	0.0%	1.6%
Other Public Administration	5.3%	0.1%

Data source: numbers of MD are calculated from MD UI data 1992:1; numbers of US are calculated from CPS 2000.

Table 2.2 Average Quarterly Earnings and Number of Observations: "Disappearers" vs. "Non-disappearers"

	Displaced Workers		Non-Displaced Workers	
	Earnings	N	Earnings	N
All workers				
Permanently Disappearers	$6,819	4459(37%)	$8,119	5488(44%)
Temporarily Disappearers	$6,413	2871(24%)	$7,349	2013(16%)
Stayers	$7,128	4588(39%)	$9,107	4918 (40%)
Total	$6,840	11918	$8,386	12419
Hi-tech workers				
Permanently Disappearers	$7,758	1937(38%)	$8,838	3784(43%)
Temporarily Disappearers	$7,248	1149(22%)	$8,282	1397(16%)
Stayers	$7,949	2033(40%)	$9,753	3636(41%)
Total	$7,720	5119	$9,127	8817
Low-tech workers				
Permanently Disappearers	$5,978	2321(37%)	$6,510	1695(47%)
Temporarily Disappearers	$5,836	1610(26%)	$5,233	616(17%)
Stayers	$6,226	2338(37%)	$7,272	1281(36%)
Total	$6,034	6269	$6,563	3592

Note: Average quarterly earnings are calculated using only non-missing earnings, for the whole sample period from 1989:1 to 2005:3.

Table 2.3 Average Quarterly Earnings before and after Displacement, by Current Working States

	Current working states	N	Ave qrt earnings 2004:3-2005:3 (1)	Ave qrt earnings pre-displacement (2)	Earnings change (1)-(2)
Low-tech	MD	3463	7111	6105	1006
	neighbor states	524	8316	6116	2200
Hi-tech	MD	4283	8265	6932	1333
	neighbor states	594	9798	6870	2989

Table A2.1a Worker Composition in 1990 and 2000, MD

	Computer product		Communication		Finance& insurance		Drugs		Other industries	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Education										
less than HS	6.4%	3.2%	3.2%	1.7%	3.1%	1.3%	5.7%	3.9%	13.2%	9.8%
HS graduate	28.0%	19.0%	31.9%	24.1%	29.4%	22.4%	21.8%	15.1%	32.8%	29.2%
some college	27.4%	28.5%	41.0%	41.3%	35.0%	36.8%	25.7%	23.5%	26.9%	28.7%
above college	38.2%	49.3%	23.8%	32.9%	32.5%	39.6%	46.8%	57.6%	27.1%	32.3%
Age										
25-34	38.8%	19.2%	35.6%	32.9%	41.8%	30.1%	34.1%	40.6%	35.7%	26.4%
35-44	28.9%	37.7%	34.7%	32.2%	31.6%	33.6%	34.0%	34.6%	31.5%	33.3%
45-54	21.9%	28.7%	20.4%	29.9%	17.8%	25.9%	19.2%	18.4%	21.3%	27.0%
55-64	10.4%	14.4%	9.3%	5.1%	8.8%	10.4%	12.7%	6.4%	11.5%	13.4%
Race										
white	81.9%	76.8%	73.2%	63.7%	78.9%	75.1%	78.5%	71.1%	77.1%	73.4%
black	14.4%	14.0%	25.8%	32.4%	18.4%	21.1%	18.8%	19.3%	20.0%	22.3%
asian	3.6%	9.2%	0.9%	3.6%	2.4%	3.6%	2.8%	8.4%	2.7%	4.0%

Sources: 1990, 2000 Census, MD weighted population.

Table A2.1b Worker Composition in 1990 and 2000,US

	Computer product		Communication		Finance& insurance		Drugs		Other industries	
	1990	2000	1990	2000	1990	2000	1990	2000	1990	2000
Education										
less than HS	12.6%	9.5%	5.1%	2.9%	3.4%	2.4%	8.1%	4.1%	42.9%	39.6%
HS graduate	32.8%	28.9%	35.3%	24.1%	30.4%	23.2%	26.9%	17.2%	25.2%	24.3%
some college	29.8%	31.0%	38.2%	40.9%	36.3%	37.3%	25.1%	24.6%	18.6%	20.4%
above college	24.8%	30.6%	21.4%	32.2%	30.0%	37.0%	40.0%	54.1%	13.3%	15.8%
Age										
25-34	36.3%	25.9%	33.4%	32.4%	40.1%	31.2%	31.5%	28.5%	33.6%	26.3%
35-44	29.6%	34.4%	35.1%	30.0%	29.6%	32.6%	33.6%	36.1%	29.4%	31.0%
45-54	20.3%	27.0%	19.5%	27.8%	18.6%	23.9%	19.4%	24.0%	20.0%	25.8%
55-64	13.8%	12.8%	12.1%	9.7%	11.8%	12.3%	15.5%	11.4%	17.0%	17.0%
Race										
white	85.7%	78.7%	85.0%	79.9%	87.3%	84.8%	86.7%	80.8%	84.3%	81.9%
black	7.6%	8.3%	12.3%	15.3%	9.1%	10.2%	10.1%	9.9%	12.1%	13.2%
asian	6.3%	12.3%	2.2%	4.4%	3.2%	4.7%	3.1%	9.2%	2.9%	4.0%

Sources: 1990, 2000 Census, U.S. weighted population.

Table A2.2 Technology Measures by Industry

Table A2.2a Fraction of Workers Using Computers at Work, by Industry

	1997	2001
	%	%
Goods Producing-Agricultural Services	20.1	30.6
Goods producing-Other Agricultural	11.3	19.5
Mining	42.9	42.4
Construction	18.8	24.0
Mfg-Lumber & Wood Prods, Ex Furniture	16.9	24.9
Mfg-Furniture & Fixtures	28.3	32.0
Mfg-Stone, Clay, Concrete, Glass Prods	31.6	37.0
Mfg-Primary Metals	42.9	45.0
Mfg-Fabricated Metals	36.4	44.6
Mfg-Machinery, Ex Electrical	54.1	53.9
Mfg-Electrical Machinery,equip Supplies	58.7	56.9
Mfg-Motor Vehicles & Equip	42.5	39.9
Mfg-Aircraft & Parts	71.2	65.0
Mfg-Other Transportation Equipment	55.5	55.6
Mfg-Professional & Photo Equip, Watches	63.4	68.7
Mfg-Toys,amusement & Sporting Goods	46.3	44.3
Mfg-Misc & Nec Mfg Industries	35.0	40.4
Mfg-Food & Kindred Prods	25.9	31.2
Mfg-Tobacco Prods	67.1	27.8
Mfg-Textile Mill Prods	30.7	27.7
Mfg-Apparel & Other Finished Textile Pr	16.2	24.7
Mfg-Paper & Allied Products	45.0	46.3
Mfg-Printing, Publishing & Allied Inds	58.6	59.5
Mfg-Chemicals & Allied Prods	65.4	68.2
Mfg-Petroleum & Coal Prods	67.4	81.1
Mfg-Rubber & Misc Plastic Prods	38.7	45.3
Mfg-Leather & Leather Prods	23.6	46.9
Transportation	38.2	38.7
Communications	79.4	77.1
Utilities & Sanitary Services	57.5	59.6
Wholesale Trade	51.8	55.3
Eating And Drinking Places	15.6	21.2
Other Retail Trade	40.2	42.0
Banking And Other Finance	85.2	83.1
Insurance And Real Estate	71.6	73.7
Private Household Services	3.1	8.6
Business Services	57.3	59.5
Automobile And Repair Services	28.5	35.3
Personal Serv Exc Private Households	26.5	33.0
Entertainment & Recreation Services	33.0	40.5
Hospitals	66.9	70.5
Health Services, Exc. Hospitals	44.8	52.4
Educational Services	60.7	67.8
Social Services	32.1	41.9

Other Professional Services	73.9	77.6
Forestry & Fisheries	29.6	40.5
Justice, Public Order & Safety	65.2	66.6
Admin Of Human Resource Programs	76.5	79.5
National Security & Internal Affairs	81.7	76.3
Other Public Administration	75.6	74.0
mean	45.3	48.2
25% quartile	29.1	34.2
median	42.9	45.0
75% quartile	64.3	65.8

Source: CPS 1997, 2001.

Table A2.2.b Fraction of New Investment in Hi-tech Equipments

Industry	1997 %
Crop production	2.43
Animal production	2.74
Forestry and logging	4.10
Fishing, hunting and trapping	16.87
Agriculture and forestry support activities	8.75
Oil and gas extraction	24.86
Coal mining	3.99
Metal ores mining	13.53
Nonmetallic mineral mining and quarrying	15.06
Support activities for mining	17.20
Power generation and supply	18.80
Natural gas distribution	38.35
Water, sewage and other systems	12.54
New and maintenance and repair construction	13.44
Food manufacturing	19.01
Beverage manufacturing	17.60
Tobacco manufacturing	43.68
Textile mills	9.86
Textile product mills	22.11
Apparel manufacturing	20.55
Leather and allied product manufacturing	20.00
Wood product manufacturing	13.11
Pulp, paper, and paperboard mills	13.74
Converted paper product manufacturing	20.09
Printing and related support activities	25.73
Petroleum and coal products manufacturing	22.31
Basic chemical manufacturing	33.42
Resin, rubber, and artificial fibers manufacturing	34.75
Agricultural chemical manufacturing	29.98
Pharmaceutical and medicine manufacturing	46.71
Paint, coating, and adhesive manufacturing	37.07
Soap, cleaning compound, and toiletry manufacturing	34.12
Other chemical product and preparation manufacturing	33.87
Plastics and rubber products manufacturing	8.64
Nonmetallic mineral product manufacturing	17.76
Iron and steel mills and manufacturing from purchased steel	14.58
Nonferrous metal production and processing	23.25
Foundries	18.82
Forging and stamping	17.33
Cutlery and handtool manufacturing	17.53
Architectural and structural metals manufacturing	25.40

Boiler, tank, and shipping container manufacturing	20.22
Ordnance and accessories manufacturing	33.33
Other fabricated metal product manufacturing	21.05
Agriculture, construction, and mining machinery	25.20
Industrial machinery manufacturing	28.23
Commercial and service industry machinery	38.18
HVAC and commercial refrigeration equipment	25.93
Metalworking machinery manufacturing	39.27
Turbine and power transmission equipment manufacturing	25.29
Other general purpose machinery manufacturing	30.54
Computer and peripheral equipment manufacturing	66.02
Audio, video, and communications equipment manufacturing	50.38
Semiconductor and electronic component manufacturing	20.00
Electronic instrument manufacturing	56.13
Magnetic media manufacturing and reproducing	52.48
Electric lighting equipment manufacturing	22.87
Household appliance manufacturing	21.84
Electrical equipment manufacturing	30.49
Other electrical equipment and component manufacturing	23.16
Motor vehicle manufacturing	21.36
Motor vehicle body, trailer, and parts manufacturing	23.64
Aerospace product and parts manufacturing	48.78
Other transportation equipment manufacturing	28.41
Furniture and related product manufacturing	17.48
Medical equipment and supplies manufacturing	38.03
Other miscellaneous manufacturing	24.02
Wholesale trade	35.31
Retail trade	31.43
Air transportation	44.44
Rail transportation	12.53
Water transportation	52.17
Truck transportation	12.87
Transit and ground passenger transportation	21.38
Pipeline transportation	71.44
Scenic and sightseeing transportation and support activities for transportation	36.84
Couriers and messengers	27.02
Warehousing and storage	29.40
Newspaper, book, and directory publishers	47.79
Software publishers	89.16
Motion picture and sound recording industries	53.95
Radio and television broadcasting	81.51
Cable networks and program distribution	91.07
Telecommunications	82.59
Information services	69.81
Data processing services	87.82

Monetary authorities, credit intermediation and related activities	72.96
Securities, commodity contracts, investments	77.77
Insurance carriers and related activities	65.32
Funds, trusts, and other financial vehicles	88.83
Real estate (and owner occupied dwellings)	20.47
Automotive equipment rental and leasing	2.70
Consumer goods and general rental centers	23.96
Machinery and equipment rental and leasing	35.79
Lessors of nonfinancial intangible assets	86.26
Legal services	71.48
Accounting and bookkeeping services	77.05
Architectural and engineering services	78.28
Specialized design services	33.11
Computer systems design and related services	90.66
Management and technical consulting services	70.73
Scientific research and development services	68.61
Advertising and related services	59.76
Other professional and technical services	56.92
Management of companies and enterprises	73.68
Employment services	66.35
Travel arrangement and reservation services	74.41
All other administrative and support services	42.90
Waste management and remediation services	24.67
Educational services	46.19
Ambulatory health care services	32.45
Hospitals	22.05
Nursing and residential care facilities	24.50
Social assistance	44.66
Performing arts, spectator sports, museums, zoos, and parks	45.55
Amusements, gambling, and recreation	14.49
Accommodation	16.16
Food services and drinking places	8.86
Automotive repair and maintenance	8.47
Electronic, commercial, and household goods repair	24.34
Personal and laundry services	39.14
Religious, grantmaking and giving, and social advocacy organizations	40.12
Civic, social, professional and similar organizations	56.64
mean	36.0
25% percentile	19.5
median	28.4
75% percentile	48.3

Source: BEA capital flow tables 1997.

Table A2.2c R&D Funds as a Percent of Net Sales in R&D, by Industry

Industry	1995	1996	1997	1998
	%	%	%	%
Manufacturing	2.9	3.3	3.3	3.2
Food, kindred, and tobacco products	0.5	0.4	0.5	0.4
Textiles and apparel	0.9	0.8	0.9	1.1
Lumber, wood products, and furniture	0.7	1.4	0.9	0.8
Paper and allied products	1.0	1.2	1.1	1.0
Chemicals and allied products	4.7	5.3	5.3	6.4
Industrial chemicals	3.9	3.7	3.5	5.1
Drugs and medicines	10.4	10.1	10.5	10.6
Other chemicals	1.4	2.7	2.1	2.5
Petroleum refining and extraction	0.7	0.7	0.6	0.8
Rubber products	1.6	1.8	1.4	2.1
Stone, clay, and glass products	1.5	1.2	1.8	1.4
Primary metals	0.5	0.6	0.6	0.6
Ferrous metals and products	0.3	0.4	0.6	0.5
Nonferrous metals and products	0.7	1.0	0.6	0.8
Fabricated metal products	1.1	1.4	1.5	1.4
Machinery	3.6	5.1	5.6	5.1
Office, computing, and accounting machines	8.1	9.9	9.2	9.2
Other machinery, except electrical	2.4	2.9	3.0	3.1
Electrical equipment	5.4	6.1	5.7	6.6
Radio and TV receiving equipment	1.6	2.0	2.6	2.9
Communication equipment	8.0	8.5	8.0	11.2
Electronic components	8.0	8.5	8.1	8.4
Other electrical equipment	2.5	2.6	2.7	2.8
Transportation equipment	3.6	4.1	3.8	2.5
Motor vehicles and motor vehicles equipment	3.6	4.2	3.8	2.2
Other transportation equipment	0.9	1.2	2.2	2.3
Aircraft and missiles	4.2	4.5	3.9	3.3
Professional and scientific instruments	7.3	7.7	7.7	8.0
Scientific and mechanical measuring instruments	6.6	6.7	6.5	6.5
Optical, surgical, photographic, and other instruments	8.0	8.6	8.9	9.2
Other manufacturing industries	1.2	2.5	2.0	2.0
Nonmanufacturing	2.4	2.2	2.2	2.9
Transportation and Utilities	1.1	1.0	0.4	0.5
Communications	2.2	1.9	0.7	0.9

Telephone communications	2.1	1.9	0.7	0.9
Other communications	3.0	1.3	0.7	1.0
Electric, gas, and sanitary services	0.2	0.2	0.1	0.1
Other transportation and utilities	0.1	0.3	0.3	0.4
Trade	2.4	2.3	2.4	3.6
Finance, insurance, and real estate	0.7	0.4	0.7	0.4
Services	5.9	6.8	8.6	9.2
Business services	9.5	9.9	10.8	10.3
Computer and data processing services	11.1	12.4	13.3	12.4
Other business services	0.9	1.1	1.1	1.4
Health services	5.2	5.9	5.2	8.4
Offices and clinics of medical doctors, hospitals, medical and dental labs	5.3	6.1	…	8.7
Other health services	2.4	3.4	…	5.9
Engineering and management services	4.1	6.1	10.8	13.4
Engineering, architectural, and surveying	2.0	2.5	2.6	2.7
Research, development, and testing	7.2	9.7	38.5	50.8
Other engineering and management services	1.7	1.3	2.8	3.4
Other services	0.6	0.7	1.0	0.7
Other nonmanufacturing industries	0.8	2.5	2.9	6.8
mean	3.18	3.51	4.46	5.12
25% percentile	0.85	1.05	0.90	0.95
median	2.00	2.00	2.60	2.70
75% percentile	4.75	5.30	6.95	7.40

Source: NSF R&D Table 1995-1998.

Table A2.2d Fraction of Scientists and Engineers, by Industry

	1994	1998	2002
	%	%	%
Goods Producing-Agricultural Services	0.6	1.0	1.0
Goods producing-Other Agricultural	0.1	0.1	0.1
Mining	10.0	9.4	8.3
Construction	1.4	1.3	1.2
Mfg-Lumber & Wood Prods, Ex Furniture	1.2	0.8	0.9
Mfg-Furniture & Fixtures	1.4	1.9	1.5
Mfg-Stone, Clay, Concrete, Glass Prods	2.8	2.7	1.8
Mfg-Primary Metals	5.3	4.6	5.0
Mfg-Fabricated Metals	3.1	4.0	2.7
Mfg-Not Specified Metal Industries	0.0	0.0	0.0
Mfg-Machinery, Ex Electrical	9.9	9.7	10.6
Mfg-Electrical Machinery,equip Supplies	13.1	16.1	16.2
Mfg-Motor Vehicles & Equip	6.3	7.2	7.4
Mfg-Aircraft & Parts	20.5	18.4	20.7
Mfg-Other Transportation Equipment	20.7	20.4	17.4
Mfg-Professional & Photo Equip, Watches	12.5	14.2	14.6
Mfg-Toys,amusement & Sporting Goods	0.7	3.9	1.1
Mfg-Misc & Nec Mfg Industries	1.5	1.6	2.8
Mfg-Food & Kindred Prods	1.9	1.8	2.1
Mfg-Tobacco Prods	2.3	6.1	7.7
Mfg-Textile Mill Prods	0.7	1.5	1.6
Mfg-Apparel & Other Finished Textile Pr	0.6	0.7	0.8
Mfg-Paper & Allied Products	4.5	3.1	4.0
Mfg-Printing, Publishing & Allied Inds	0.8	1.5	1.7
Mfg-Chemicals & Allied Prods	11.6	11.7	13.6
Mfg-Petroleum & Coal Prods	12.0	11.9	13.1
Mfg-Rubber & Misc Plastic Prods	4.1	3.1	4.2
Mfg-Leather & Leather Prods	1.9	1.6	0.6
Transportation	1.0	0.9	1.1
Communications	7.4	7.9	9.2
Utilities & sanitary services	8.8	8.7	7.4
Wholesale trade	1.2	1.4	1.7
Eating and drinking places	0.0	0.0	0.0
Other retail trade	0.3	0.3	0.5
Banking and other finance	2.1	2.4	3.3
Insurance and real estate	1.8	2.0	1.9
Private household services	0.0	0.0	0.0
Business services	6.8	10.4	11.8
Automobile and repair services	0.3	0.3	0.3
Personal serv exc private households	0.1	0.3	0.4
Entertainment & recreation services	0.5	0.5	0.9

Hospitals	1.1	1.7	1.4
Health services, exc. hospitals	0.5	0.5	0.9
Educational services	1.4	1.4	1.5
Social services	0.3	0.2	0.3
Other professional services	9.7	10.3	10.5
Forestry & fisheries	11.0	8.8	10.7
Justice, public order & safety	0.6	0.5	0.6
Admin of human resource programs	3.1	3.8	4.2
National security & internal affairs	14.4	15.9	12.7
Other public administration	9.1	9.9	10.4
Armed Forces	0.0	0.0	0.0
mean	4.6	4.9	5.0
25% percentile	0.7	0.8	0.9
median	1.9	2.0	1.9
75% percentile	8.1	8.7	8.7

Source: CPS 1994, 1998, 2002.

Table 3.1 English Proficiency of Female Immigrants with Zero to Five Years of Residence in the U.S.

	1980			1990			2000		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Fraction of immigrants speaking English at least very well									
All	16029	0.365	(0.481)	21545	0.379	(0.485)	33121	0.389	(0.488)
White	3151	0.599	(0.490)	3449	0.632	(0.482)	6038	0.594	(0.491)
Black	1096	0.818	(0.385)	1273	0.793	(0.405)	2114	0.740	(0.439)
Asian	5876	0.321	(0.467)	7122	0.355	(0.478)	8980	0.415	(0.493)
Mexican	3017	0.124	(0.329)	4891	0.171	(0.376)	9679	0.185	(0.389)
Fraction of immigrants not speaking English at all									
All	16029	0.174	(0.380)	21545	0.175	(0.380)	33121	0.173	(0.378)
White	3151	0.085	(0.278)	3449	0.060	(0.238)	6038	0.064	(0.245)
Black	1096	0.016	(0.124)	1273	0.019	(0.136)	2114	0.022	(0.148)
Asian	5876	0.109	(0.312)	7122	0.101	(0.302)	8980	0.088	(0.283)
Mexican	3017	0.389	(0.488)	4891	0.377	(0.485)	9679	0.343	(0.475)

Table 3.2 Educational Attainment of Female Immigrants with Zero to Five Years of Residence in the U.S. and of Female Natives, Age>24

	1980			1990			2000		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Fraction of high school dropouts									
Immigrants:									
All	8316	0.45	(0.50)	11971	0.34	(0.47)	19058	0.28	(0.45)
White	1881	0.31	(0.46)	2121	0.15	(0.36)	3841	0.10	(0.30)
Black	477	0.41	(0.49)	663	0.24	(0.43)	1144	0.19	(0.39)
Asian	3351	0.35	(0.48)	4542	0.26	(0.44)	5947	0.15	(0.36)
Mexican	1095	0.84	(0.37)	1980	0.69	(0.46)	4475	0.62	(0.49)
Natives:	643675	0.33	(0.47)	766662	0.20	(0.40)	775559	0.13	(0.34)
Fraction of college graduates									
Immigrants:									
All	8316	0.18	(0.39)	11971	0.23	(0.42)	19058	0.30	(0.46)
White	1881	0.24	(0.43)	2121	0.32	(0.47)	3841	0.41	(0.49)
Black	477	0.09	(0.29)	663	0.12	(0.33)	1144	0.20	(0.40)
Asian	3351	0.26	(0.44)	4542	0.35	(0.48)	5947	0.48	(0.50)
Mexican	1095	0.02	(0.16)	1980	0.05	(0.22)	4475	0.06	(0.23)
Natives:	643675	0.13	(0.34)	766662	0.18	(0.38)	775559	0.23	(0.42)
Natives with age distribution of immig		0.16			0.21			0.27	
Average years of education									
Immigrants:									
All	8316	10.61	(5.27)	11971	11.42	(5.45)	19058	12.43	(5.03)
White	1881	12.12	(4.75)	2121	13.62	(4.03)	3841	14.36	(3.87)
Black	477	10.99	(3.94)	663	11.91	(3.93)	1144	12.63	(4.08)
Asian	3351	11.68	(5.36)	4542	12.54	(5.62)	5947	14.34	(4.51)
Mexican	1095	6.19	(4.26)	1980	7.49	(5.07)	4475	8.64	(4.66)
Natives:	643675	11.76	(3.60)	766662	12.82	(3.38)	775559	13.51	(3.22)
Natives with age distribution of immig		12.50			13.41			14.01	

Table 3.3 Fraction of Individuals Excluded from Regressions due to Sample Selection Criteria

	Immigrants %	Natives %
Age<18 or age>64	29.5	41.7
Self-employed	4.02	2.91
Working but missing hour or week information	22.8	43.6
Not working	46.5	33.8

Table 3.4 Coefficients of Wage Regressions, Female Immigrants and Natives, Y=log(wagerate)

Table 3.4a Coefficients of Wage Regressions, Female Immigrants and Natives, Census 1970. Y=log(wagerate)

	White	Black	Asian	Mexican
		Natives		
Education	0.0721	0.0816	0.0646	0.0482
	(0.0001)**	(0.0002)**	(0.0011)**	(0.0007)**
Experience	0.0188	0.0066	-0.001	0.0159
	(0.0001)**	(0.0002)**	-0.001	(0.0008)**
Experience squared	-0.0003	-0.0001	0.0001	-0.0004
	(0.0000)**	(0.0000)**	0	(0.0000)**
Marital status	0.1245	0.1287	0.0644	0.1039
	(0.0010)**	(0.0037)**	(0.0132)**	(0.0101)**
Marital status *Experience	-0.0136	-0.0047	0.0018	-0.0172
	(0.0001)**	(0.0004)**	-0.0016	(0.0011)**
Marital status *Experience squared	0.0003	0	-0.0001	0.0005
	(0.0000)**	(0.0000)**	(0.0000)*	(0.0000)**
Number of children	-0.0219	-0.0088	0.0089	0.0053
	(0.0002)**	(0.0004)**	(0.0026)**	(0.0014)**
Observations	9605800	1220600	49900	128200
R-squared	0.11	0.16	0.11	0.06
		Immigrants		
Education	0.082	0.0859	0.0719	0.0748
	(0.0003)**	(0.0013)**	(0.0007)**	(0.0011)**
Experience	0.0377	0.0463	0.0221	0.0446
	(0.0003)**	(0.0015)**	(0.0010)**	(0.0013)**
Experience squared	-0.0004	-0.0008	-0.0002	-0.0005
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
Marital status	0.4689	0.5383	0.4367	0.1892
	(0.0058)**	(0.0287)**	(0.0128)**	(0.0264)**
Marital status *Experience	-0.0339	-0.0475	-0.023	-0.0005
	(0.0005)**	(0.0027)**	(0.0015)**	-0.0022
Marital status *Experience squared	0.0005	0.0007	0.0003	-0.0001
	(0.0000)**	(0.0001)**	(0.0000)**	(0.0000)**
Number of children	-0.0075	-0.0245	-0.0395	0.0233
	(0.0009)**	(0.0039)**	(0.0024)**	(0.0027)**
Cohort 1965-69	0.837	0.1809	0.9341	0.6635
	(0.0047)**	(0.0168)**	(0.0128)**	(0.0172)**

Cohort 1960-64	0.7887	0.0881	0.9814	0.6293
	(0.0048)**	(0.0204)**	(0.0135)**	(0.0173)**
Cohort 1950-59	0.7699	0.4007	1.097	0.7654
	(0.0043)**	(0.0207)**	(0.0136)**	(0.0162)**
Cohort before 1950	0.6859	0.4325	1.1711	0.5529
	(0.0046)**	(0.0210)**	(0.0152)**	(0.0184)**
Observations	482000	21600	58200	33700
R-squared	0.93	0.93	0.92	0.89

Standard errors in parentheses
* significant at 5%; ** significant at 1%

Table 3.4b Coefficients of Wage Regressions, Female Immigrants and Natives, Census 1980. Y=log(wagerate)

	White	Black	Asian	Mexican
		Natives		
Education	0.0678	0.0687	0.0671	0.0544
	(0.0000)**	(0.0001)**	(0.0004)**	(0.0002)**
Experience	0.0361	0.0303	0.0323	0.0286
	(0.0000)**	(0.0001)**	(0.0004)**	(0.0002)**
Experience squared	-0.0006	-0.0005	-0.0004	-0.0004
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
Marital status	0.12	0.0749	0.0691	0.0759
	(0.0004)**	(0.0016)**	(0.0049)**	(0.0028)**
Marital status *Experience	-0.0158	-0.0051	-0.0041	-0.0098
	(0.0001)**	(0.0002)**	(0.0006)**	(0.0003)**
Marital status *Experience squared	0.0003	0.0001	0	0.0002
	(0.0000)**	(0.0000)**	0	(0.0000)**
Number of children	-0.0393	-0.0155	-0.0343	-0.0135
	(0.0001)**	(0.0002)**	(0.0012)**	(0.0005)**
Observations	3.29E+07	4565900	258200	915900
R-squared	0.14	0.11	0.14	0.08
		Immigrants		
Education	0.0404	0.0477	0.0426	0.0206
	(0.0002)**	(0.0005)**	(0.0002)**	(0.0003)**
Experience	0.0236	0.0226	0.018	0.0102
	(0.0002)**	(0.0005)**	(0.0003)**	(0.0004)**
Experience squared	-0.0004	-0.0004	-0.0003	-0.0002
	(0.0000)**	(0.0000)**	(0.0000)**	(0.0000)**
Marital status	0.1116	0.234	0.0947	0.057
	(0.0031)**	(0.0086)**	(0.0038)**	(0.0058)**
Marital status *Experience	-0.011	-0.0154	-0.0039	-0.0006
	(0.0003)**	(0.0009)**	(0.0005)**	-0.0006
Marital status *Experience squared	0.0002	0.0002	0	0.0001
	(0.0000)**	(0.0000)**	0	(0.0000)**
Number of children	-0.033	-0.0065	-0.0049	-0.0051
	(0.0005)**	(0.0013)**	(0.0007)**	(0.0007)**
Cohort 1975-79	1.3691	1.027	1.3061	1.6791
	(0.0038)**	(0.0138)**	(0.0052)**	(0.0067)**
Cohort 1970-74	1.4936	1.1123	1.4416	1.7482
	(0.0038)**	(0.0139)**	(0.0054)**	(0.0068)**
Cohort 1965-69	1.4825	1.2255	1.498	1.7533

	(0.0037)**	(0.0144)**	(0.0057)**	(0.0072)**
Cohort 1960-64	1.4666	1.2656	1.4858	1.8075
	(0.0037)**	(0.0146)**	(0.0060)**	(0.0073)**
Cohort 1950-59	1.4724	1.3026	1.4918	1.8811
	(0.0038)**	(0.0146)**	(0.0062)**	(0.0078)**
Cohort before 1950	1.4768	1.071	1.7081	1.8898
	(0.0041)**	(0.0145)**	(0.0080)**	(0.0087)**
Observations	1130600	184600	538200	349000
R-squared	0.94	0.92	0.94	0.92

Standard errors in parentheses
* significant at 5%; ** significant at 1%

Table 3.5 Differences in Predicted Log Wages across Cohorts

Table 3.5a Differences in Predicted Log Wages across Cohorts, from Census 1970 to 1980.

	Cohorts	Immigrants		Natives		Immigrants-Natives	
White	1965-69 to 1975-79	-0.389	(0.004)	-0.259	(0.000)	-0.130	(0.004)
	1960-64 to 1970-74	-0.222	(0.004)	-0.245	(0.000)	0.023	(0.004)
	1950-59 to 1960-69	-0.251	(0.002)	-0.247	(0.000)	-0.004	(0.002)
Black	1965-69 to 1975-79	-0.219	(0.01)	-0.078	(0.001)	-0.141	(0.01)
	1960-64 to 1970-74	-0.077	(0.015)	-0.087	(0.001)	0.010	(0.015)
	1950-59 to 1960-69	-0.272	(0.015)	-0.031	(0.001)	-0.241	(0.015)
Asian	1965-69 to 1975-79	-0.265	(0.006)	-0.283	(0.005)	0.018	(0.008)
	1960-64 to 1970-74	-0.177	(0.008)	-0.243	(0.004)	0.066	(0.009)
	1950-59 to 1960-69	-0.242	(0.007)	-0.220	(0.005)	-0.022	(0.009)
Mexican	1965-69 to 1975-79	-0.064	(0.013)	-0.147	(0.003)	0.083	(0.013)
	1960-64 to 1970-74	-0.034	(0.012)	-0.124	(0.003)	0.090	(0.012)
	1950-59 to 1960-69	-0.186	(0.009)	-0.118	(0.003)	-0.068	(0.01)

Table 3.5b Differences in Predicted Log Wages across Cohorts, from Census 1980 to 1990.

	Cohorts	Immigrants		Natives		Immigrants-Natives	
White	1975-79 to 1985-89	0.047	(0.003)	0.047	(0.000)	0.000	(0.003)
	1970-74 to 1980-84	0.010	(0.003)	0.037	(0.000)	-0.027	(0.003)
	1965-69 to 1975-79	0.096	(0.003)	0.033	(0.000)	0.063	(0.003)
Black	1975-79 to 1985-89	0.090	(0.005)	-0.038	(0.001)	0.128	(0.005)
	1970-74 to 1980-84	0.078	(0.004)	-0.030	(0.001)	0.108	(0.004)
	1965-69 to 1975-79	0.106	(0.004)	-0.009	(0.001)	0.115	(0.004)
Asian	1975-79 to 1985-89	-0.021	(0.002)	0.064	(0.002)	-0.085	(0.003)
	1970-74 to 1980-84	-0.019	(0.002)	0.070	(0.002)	-0.089	(0.003)
	1965-69 to 1975-79	0.049	(0.003)	0.071	(0.002)	-0.022	(0.003)
Mexican	1975-79 to 1985-89	-0.130	(0.003)	-0.097	(0.002)	-0.034	(0.004)
	1970-74 to 1980-84	-0.144	(0.003)	-0.094	(0.001)	-0.050	(0.003)
	1965-69 to 1975-79	-0.076	(0.004)	-0.084	(0.001)	0.007	(0.004)

Table 3.5c Differences in Predicted Log Wages across Cohorts, from Census 1990 to 2000.

	Cohorts	Immigrants		Natives		Immigrants-Natives	
White	1985-89 to 1995-99	0.095	(0.002)	0.101	(0.000)	-0.005	(0.002)
	1980-84 to 1990-94	0.104	(0.002)	0.111	(0.000)	-0.007	(0.002)
	1975-79 to 1985-89	0.077	(0.003)	0.112	(0.000)	-0.035	(0.003)
Black	1985-89 to 1995-99	0.004	(0.003)	0.059	(0.000)	-0.054	(0.003)
	1980-84 to 1990-94	0.035	(0.003)	0.056	(0.000)	-0.021	(0.003)
	1975-79 to 1985-89	-0.029	(0.003)	0.053	(0.000)	-0.081	(0.003)
Asian	1985-89 to 1995-99	0.151	(0.002)	0.099	(0.002)	0.051	(0.003)
	1980-84 to 1990-94	0.091	(0.002)	0.105	(0.002)	-0.014	(0.002)
	1975-79 to 1985-89	0.063	(0.002)	0.108	(0.002)	-0.045	(0.002)
Mexican	1985-89 to 1995-99	0.098	(0.002)	0.071	(0.001)	0.026	(0.003)
	1980-84 to 1990-94	0.063	(0.002)	0.071	(0.001)	-0.008	(0.003)
	1975-79 to 1985-89	0.040	(0.002)	0.074	(0.001)	-0.034	(0.003)

Note: (1) Source.-Tables A3.4 and 3.4.

(2) Standard errors in parentheses. Standard errors are calculated by extending the two sample t-test formula to four samples. The standard error of (y1-y2)-(y3-y4)=sqrt(se1^2+se2^2+se3^2+se4^2).

(3) Natives' predicted log wages are calculated across Census years, using the same X means as used for corresponding immigrant cohorts. For example, the first row for natives in Table 3.5a is the difference in predicted wages between Census 1970 and 1980, using average X means of cohort 1965-69 and cohort 1975-79.

Table A3.1 Coefficients of Wage Regressions, Male Immigrants and Natives: Dependent Variable = Log(wage rate/10) (Male 1970-80)

	Whites		Blacks		Asians		Mexicans	
Variable	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
1980 natives:								
EDUC	0.06	(0.002)	0.05	(0.003)	0.05	(0.002)	0.05	(0.002)
EXPER	0.04	(0.003)	0.01	(0.004)	0.03	(0.003)	0.02	(0.003)
EXPER2	0.00	(0)	0.00	(0)	0.00	(0)	0.00	(0)
MAR	0.16	(0.016)	0.16	(0.02)	0.21	(0.015)	0.17	(0.018)
HLTH	-0.14	(0.027)	-0.11	(0.041)	-0.17	(0.035)	-0.13	(0.033)
SMSA	0.16	(0.013)	0.27	(0.025)	0.19	(0.019)	0.14	(0.017)
CONST.	-2.39	(0.047)	-2.33	(0.068)	-2.28	(0.05)	-2.18	(0.05)
1980 immigrants:								
EDUC	0.05	(0.001)	0.04	(0.003)	0.06	(0.001)	0.03	(0.002)
EXPER	0.03	(0.001)	0.01	(0.004)	0.02	(0.002)	0.01	(0.003)
EXPER2	0.00	(0)	0.00	(0)	0.00	(0)	0.00	(0)
MAR	0.18	(0.008)	0.09	(0.022)	0.13	(0.012)	0.17	(0.014)
HLTH	-0.18	(0.017)	-0.02	(0.062)	-0.11	(0.032)	-0.09	(0.032)
SMSA	0.12	(0.01)	0.22	(0.051)	0.00	(0.019)	0.15	(0.017)
D75	-2.21	(0.024)	-2.32	(0.083)	-2.29	(0.035)	-2.22	(0.048)
D70	-2.19	(0.024)	-2.14	(0.084)	-2.13	(0.036)	-2.06	(0.048)
D65	-2.10	(0.024)	-2.06	(0.088)	-2.02	(0.037)	-1.97	(0.05)
D60	-2.06	(0.025)	-2.06	(0.094)	-1.96	(0.04)	-1.92	(0.052)
D50	-2.06	(0.024)	-2.04	(0.093)	-1.96	(0.04)	-1.84	(0.053)
D40	-2.07	(0.025)	-2.12	(0.089)	-1.91	(0.043)	-1.86	(0.056)
1970 natives:								
EDUC	0.07	(0.001)	0.06	(0.002)	0.06	(0.007)	0.07	(0.003)
EXPER	0.04	(0.001)	0.03	(0.002)	0.04	(0.006)	0.04	(0.003)
EXPER2	0.00	(0)	0.00	(0)	0.00	(0)	0.00	(0)
MAR	0.19	(0.01)	0.17	(0.011)	0.21	(0.041)	0.22	(0.024)
HLTH	-0.12	(0.015)	-0.04	(0.019)	-0.21	(0.081)	-0.07	(0.039)
SMSA	0.19	(0.008)	0.29	(0.011)	0.02	(0.075)	0.20	(0.021)
CONST.	-2.49	(0.021)	-2.64	(0.024)	-2.31	(0.118)	-2.71	(0.046)
1970 immigrants:								
EDUC	0.05	(0.002)	0.07	(0.011)	0.07	(0.005)	0.03	(0.005)
EXPER	0.04	(0.002)	0.03	(0.014)	0.03	(0.006)	0.03	(0.006)
EXPER2	0.00	(0)	0.00	(0)	0.00	(0)	0.00	(0)
MAR	0.14	(0.018)	0.01	(0.089)	0.14	(0.042)	0.18	(0.037)
HLTH	-0.12	(0.031)	-0.14	(0.176)	-0.28	(0.086)	0.05	(0.061)
SMSA	0.12	(0.019)	0.26	(0.15)	0.03	(0.052)	0.32	(0.04)
D65	-2.18	(0.039)	-2.75	(0.236)	-2.50	(0.102)	-2.53	(0.08)
D60	-2.07	(0.041)	-2.63	(0.249)	-2.33	(0.107)	-2.38	(0.086)
D50	-2.06	(0.039)	-2.67	(0.25)	-2.31	(0.108)	-2.32	(0.088)
D40	-2.04	(0.042)	-2.86	(0.27)	-2.27	(0.118)	-2.25	(0.099)

Table A3.2 Means of Independent Variables in 1980 (Male)

	Year of Migration					
	1975-1979	1970-1974	1965-69	1960-64	1950-59	<1950
White:						
EDUC	13.79	11.57	11.73	12.33	12.53	12.72
EXPER	18.59	22.23	24.69	25.57	27.01	33.52
EXPER2	455.10	621.11	726.50	760.28	868.54	1237.47
MAR	0.77	0.82	0.84	0.83	0.83	0.84
HLTH	0.02	0.02	0.02	0.03	0.03	0.06
SMSA	0.91	0.91	0.90	0.90	0.90	0.87
N	4940	4423	6034	5852	15423	10635
Black:						
EDUC	11.67	12.22	12.52	13.14	12.41	10.74
EXPER	19.59	20.28	22.56	23.48	27.48	32.40
EXPER2	491.04	524.74	611.34	643.71	899.32	1180.73
MAR	0.65	0.72	0.74	0.74	0.67	0.68
HLTH	0.02	0.02	0.01	0.03	0.04	0.07
SMSA	0.96	0.98	0.98	0.98	0.95	0.84
N	1183	1790	1513	563	524	586
Asian:						
EDUC	13.94	15.25	15.59	15.67	15.02	12.45
EXPER	17.66	16.46	18.29	20.14	22.89	33.77
EXPER2	426.53	366.52	429.95	489.62	626.58	1252.17
MAR	0.75	0.81	0.86	0.85	0.82	0.86
HLTH	0.02	0.02	0.01	0.01	0.03	0.04
SMSA	0.94	0.95	0.94	0.93	0.93	0.91
N	7286	5689	3777	1727	1936	985
Mexican:						
EDUC	6.17	6.51	6.93	7.14	8.25	7.95
EXPER	24.27	23.25	23.90	28.12	30.24	36.13
EXPER2	687.41	624.31	659.35	906.96	1067.49	1446.21
MAR	0.61	0.81	0.84	0.85	0.85	0.85
HLTH	0.02	0.03	0.03	0.04	0.04	0.06
SMSA	0.87	0.90	0.89	0.85	0.86	0.83
N	3496	4762	3323	2479	3261	1613

Table A3.3 Decomposition of Cross-section Growth in Immigrant/Native Relative Wages (Male)

	Cross-Section Growth		Within-Cohort Growth		Across-Cohort Growth	
White						
1965-69	0.114	(0.008)	0.095	(0.012)	0.019	(0.015)
1960-64	0.129	(0.003)	0.027	(-0.075)	0.101	(0.005)
1950-59	0.021	(0.001)	0.033	(-0.008)	-0.012	(-0.001)
Black						
1965-69	0.259	(0.007)	-0.062	(-0.084)	0.320	(0.026)
1960-64	0.081	(0.007)	-0.200	(0.068)	0.281	(0.04)
1950-59	0.023	(0.015)	-0.174	(0.047)	0.197	(0.045)
Asian						
1965-69	0.275	(0.004)	0.119	(0.009)	0.155	(0.01)
1960-64	0.174	(0.005)	-0.006	(-0.003)	0.180	(0.016)
1950-59	0.024	(0.006)	-0.051	(0.038)	0.075	(0.024)
Mexican						
1965-69	0.253	(0.004)	0.142	(0.016)	0.111	(0.009)
1960-64	0.139	(0.005)	0.050	(-0.015)	0.090	(0.007)
1950-59	0.106	(0.004)	0.101	(-0.084)	0.005	(0)

Source.-Tables A3.1 and A3.2.
Note.- Standard errors are given in parentheses.

Table A3.4 Means of Independent Variables of Female Immigrants Aged 18-64, by Census Year and by Ethnic Group

	Census 1970, White			
	1965-69	1960-64	1950-59	<1950
educ	10.59	10.63	11.00	10.71
exper	15.91	19.23	21.75	34.65
exper2	403.66	532.19	657.55	1334.00
mar	0.62	0.65	0.66	0.65
hlth	0.05	0.05	0.05	0.06
smsa	0.80	0.84	0.84	0.81
marexper	10.72	12.91	16.14	21.90
marexper2	267.17	338.90	481.86	811.66
nchild	0.79	1.02	1.16	0.90
N	553	526	1423	2187
	Census 1970, Black			
	1965-69	1960-64	1950-59	<1950
educ	9.91	11.08	10.80	11.51
exper	17.94	21.10	26.35	31.52
exper2	449.54	626.99	832.94	1101.11
mar	0.37	0.36	0.47	0.61
hlth	0.08	0.07	0.03	0.06
smsa	0.92	1.00	0.97	1.00
marexper	6.21	6.23	9.81	18.84
marexper2	142.17	127.61	263.09	636.54
nchild	0.52	1.18	0.75	0.92
N	106	28	32	36
	Census 1980, Asian			
	1965-69	1960-64	1950-59	<1950
educ	13.23	11.71	12.39	11.55
exper	11.17	17.07	18.79	27.83
exper2	260.91	485.57	503.91	935.08
mar	0.53	0.61	0.66	0.72
hlth	0.05	0.05	0.04	0.06
smsa	0.88	0.83	0.83	0.86
marexper	7.19	11.01	14.76	20.50
marexper2	166.17	294.66	399.93	668.25
nchild	0.75	1.13	1.56	1.43
N	206	113	156	10
	Census 1980, Mexican			
	1965-69	1960-64	1950-59	<1950
educ	6.72	5.82	7.03	7.52
exper	18.24	23.05	21.72	34.39
exper2	479.62	681.06	631.90	1387.04
mar	0.39	0.56	0.53	0.61

hlth	0.08	0.08	0.08	0.09	
smsa	0.84	0.88	0.82	0.83	
marexper	8.03	12.64	11.91	18.41	
marexper2	195.61	353.80	319.21	662.29	
nchild	1.41	1.84	2.06	1.19	
N	51	64	111	102	

Census 1980, White

	1975-79	1970-74	1965-69	1960-64	1950-59
educ	12.56	11.19	11.37	12.16	12.29
exper	13.56	17.62	19.46	18.94	24.30
exper2	323.93	461.98	546.04	522.09	755.69
mar	0.67	0.69	0.67	0.63	0.67
hlth	0.02	0.02	0.03	0.03	0.03
smsa	0.93	0.91	0.91	0.90	0.91
marexper	9.86	13.33	14.29	14.09	17.02
marexper2	235.75	353.48	395.72	395.24	527.63
nchild	0.74	1.09	1.09	1.10	1.05
N	1176	1076	1611	1798	3557

Census 1980, Black

	1975-79	1970-74	1965-69	1960-64	1950-59
educ	11.55	12.00	12.21	12.11	12.23
exper	14.72	15.56	20.83	20.07	18.13
exper2	356.54	378.07	568.60	579.98	520.07
mar	0.38	0.42	0.48	0.44	0.39
hlth	0.01	0.02	0.03	0.05	0.05
smsa	0.99	1.00	1.00	0.96	0.95
marexper	6.08	7.01	10.24	9.26	7.09
marexper2	148.02	151.94	272.11	246.50	194.77
nchild	0.94	1.24	1.54	1.36	1.04
N	421	533	505	153	147

Census 1980, Asian

	1975-79	1970-74	1965-69	1960-64	1950-59
educ	12.85	13.63	13.90	13.08	12.95
exper	12.54	14.72	17.26	19.44	24.01
exper2	278.07	329.53	419.19	541.29	733.65
mar	0.63	0.70	0.72	0.71	0.68
hlth	0.02	0.01	0.03	0.02	0.04
smsa	0.94	0.95	0.94	0.93	0.94
marexper	9.02	10.94	13.27	15.48	17.32
marexper2	201.93	236.19	313.06	430.45	531.56
nchild	1.02	1.26	1.42	1.24	1.06
N	1912	1569	897	431	490

Census 1980, Mexican

	1975-79	1970-74	1965-69	1960-64	1950-59

educ	7.12	7.17	8.17	9.21	9.12
exper	14.53	17.03	19.16	18.07	24.44
exper2	316.77	392.05	520.91	504.41	760.77
mar	0.55	0.64	0.64	0.57	0.67
hlth	0.03	0.02	0.02	0.05	0.02
smsa	0.94	0.95	0.91	0.89	0.89
marexper	8.43	11.41	12.88	11.09	16.78
marexper2	179.51	258.10	339.23	300.80	508.23
nchild	1.28	1.84	1.84	1.74	2.02
N	789	998	606	437	508

Census 1990, White

	1985-89	1980-84	1975-79	1970-74	1965-69
educ	14.11	13.96	13.54	12.92	13.27
exper	12.26	15.46	17.02	16.74	19.00
exper2	263.36	352.83	436.34	456.69	534.84
mar	0.59	0.65	0.62	0.56	0.62
hlth	0.01	0.03	0.03	0.02	0.03
smsa	0.92	0.92	0.91	0.89	0.89
marexper	8.17	11.13	12.07	11.89	13.75
marexper2	173.29	248.74	309.44	323.56	398.74
nchild	0.54	0.84	0.94	0.89	0.89
N	1275	1012	1097	1438	1879

Census 1990, Black

	1985-89	1980-84	1975-79	1970-74	1965-69
educ	12.30	12.55	13.32	13.61	13.70
exper	13.53	15.12	16.30	17.06	22.55
exper2	281.88	345.61	397.32	425.67	658.17
mar	0.37	0.40	0.44	0.39	0.45
hlth	0.03	0.02	0.02	0.04	0.03
smsa	0.99	0.99	0.99	0.98	0.99
marexper	5.66	6.64	7.90	7.44	10.32
marexper2	116.22	148.51	186.67	177.95	293.49
nchild	0.87	1.21	1.26	1.36	1.18
N	548	709	543	554	389

Census 1990, Asian

	1985-89	1980-84	1975-79	1970-74	1965-69
educ	13.73	13.63	13.98	14.24	14.76
exper	13.00	14.82	15.99	17.95	19.34
exper2	298.61	348.83	380.78	463.37	535.95
mar	0.56	0.61	0.66	0.65	0.66
hlth	0.02	0.02	0.02	0.02	0.03
smsa	0.95	0.96	0.95	0.93	0.92
marexper	8.23	10.50	11.89	13.71	14.32
marexper2	190.67	249.83	280.17	350.91	395.73

nchild	0.75	1.09	1.22	1.19	1.04
N	2449	2712	2476	1862	987

Census 1990, Mexican

	1985-89	1980-84	1975-79	1970-74	1965-69
educ	8.63	8.16	8.11	8.92	9.48
exper	13.37	15.88	18.46	19.00	21.97
exper2	286.03	363.22	475.77	521.71	650.20
mar	0.45	0.54	0.61	0.62	0.58
hlth	0.02	0.02	0.03	0.03	0.03
smsa	0.93	0.92	0.94	0.92	0.93
marexper	6.48	9.28	12.26	13.26	13.16
marexper2	138.41	208.03	303.59	360.31	380.75
nchild	0.93	1.50	1.91	1.95	1.79
N	1394	1539	1620	1408	764

Census 2000, White

	1995-99	1990-94	1985-89	1980-84	1975-79
educ	14.84	15.02	14.58	14.45	14.31
exper	12.66	15.26	16.86	16.75	18.64
exper2	268.06	348.23	393.60	424.50	511.39
mar	0.57	0.62	0.61	0.55	0.59
hlth	0.10	0.11	0.11	0.11	0.09
smsa	0.81	0.84	0.82	0.74	0.77
marexper	8.22	10.75	11.56	11.23	13.05
marexper2	172.57	245.04	267.31	290.32	367.44
nchild	0.70	0.85	0.95	0.91	0.81
N	2273	2019	1316	1266	1270

Census 2000, Black

	1995-99	1990-94	1985-89	1980-84	1975-79
educ	12.94	13.15	13.61	13.52	14.05
exper	13.19	15.15	16.85	19.50	21.25
exper2	292.29	349.88	402.02	506.80	567.96
mar	0.34	0.40	0.41	0.44	0.46
hlth	0.21	0.18	0.20	0.22	0.19
smsa	0.92	0.92	0.93	0.94	0.92
marexper	5.34	6.96	7.58	9.41	10.54
marexper2	115.28	155.22	171.84	236.82	282.07
nchild	0.77	1.12	1.25	1.49	1.40
N	816	831	982	979	584

Census 2000, Asian

	1995-99	1990-94	1985-89	1980-84	1975-79
educ	14.78	14.42	14.25	14.21	14.77
exper	12.36	15.63	17.25	17.84	20.18
exper2	285.77	371.80	427.19	457.34	549.32
mar	0.57	0.62	0.65	0.61	0.64

hlth	0.14	0.16	0.15	0.15	0.12
smsa	0.85	0.88	0.87	0.89	0.87
marexper	8.20	10.85	12.55	12.77	14.24
marexper2	190.82	260.56	307.15	328.71	386.02
nchild	0.67	1.03	1.18	1.19	1.10
N	2966	3575	3462	3551	2882
			Census 2000, Mexican		
	1995-99	1990-94	1985-89	1980-84	1975-79
educ	9.36	9.26	9.51	9.37	9.46
exper	13.67	15.70	18.00	20.09	23.06
exper2	300.68	356.03	434.82	525.14	673.93
mar	0.50	0.58	0.62	0.59	0.62
hlth	0.18	0.19	0.20	0.21	0.19
smsa	0.76	0.79	0.78	0.79	0.80
marexper	7.69	10.07	12.06	12.63	15.11
marexper2	176.91	231.82	286.78	327.18	440.35
nchild	0.94	1.50	1.80	1.98	1.97
N	2883	2918	2912	2303	2072

Figure 2.1 Employment Annual Changes, Maryland vs. the U.S.

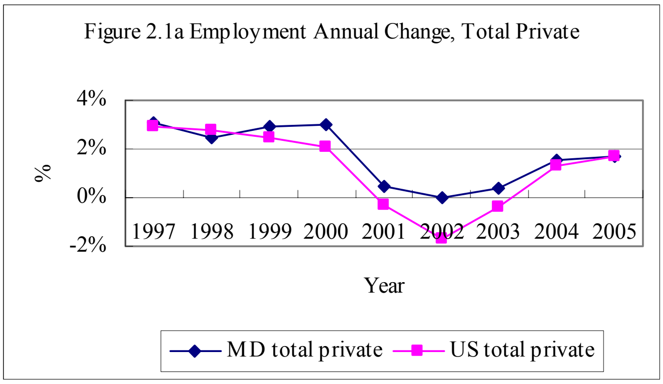


Figure 2.1a Employment Annual Change, Total Private

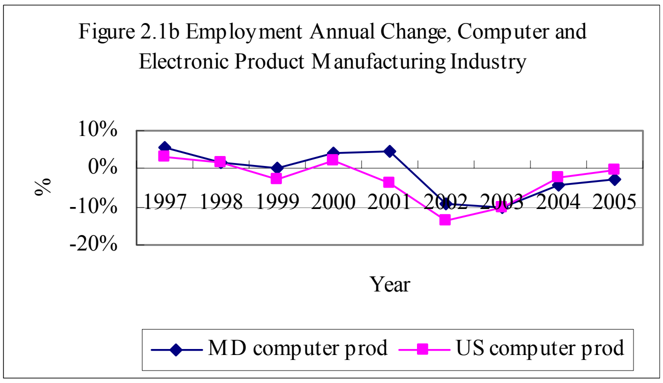


Figure 2.1b Employment Annual Change, Computer and Electronic Product Manufacturing Industry

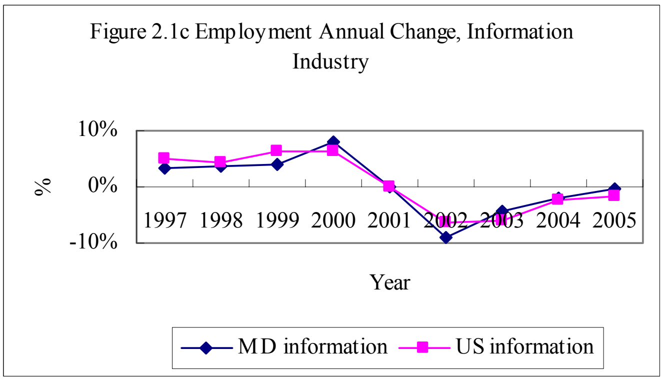


Figure 2.1c Employment Annual Change, Information Industry

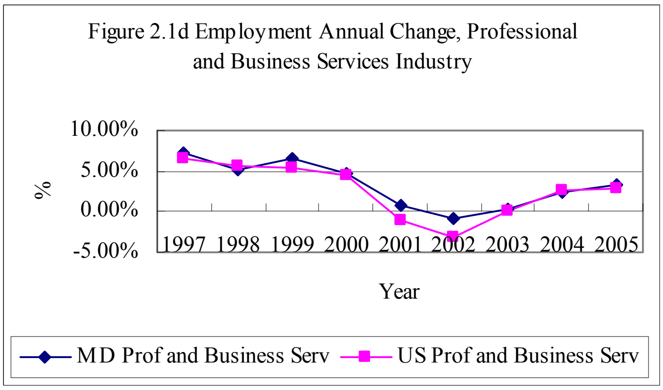
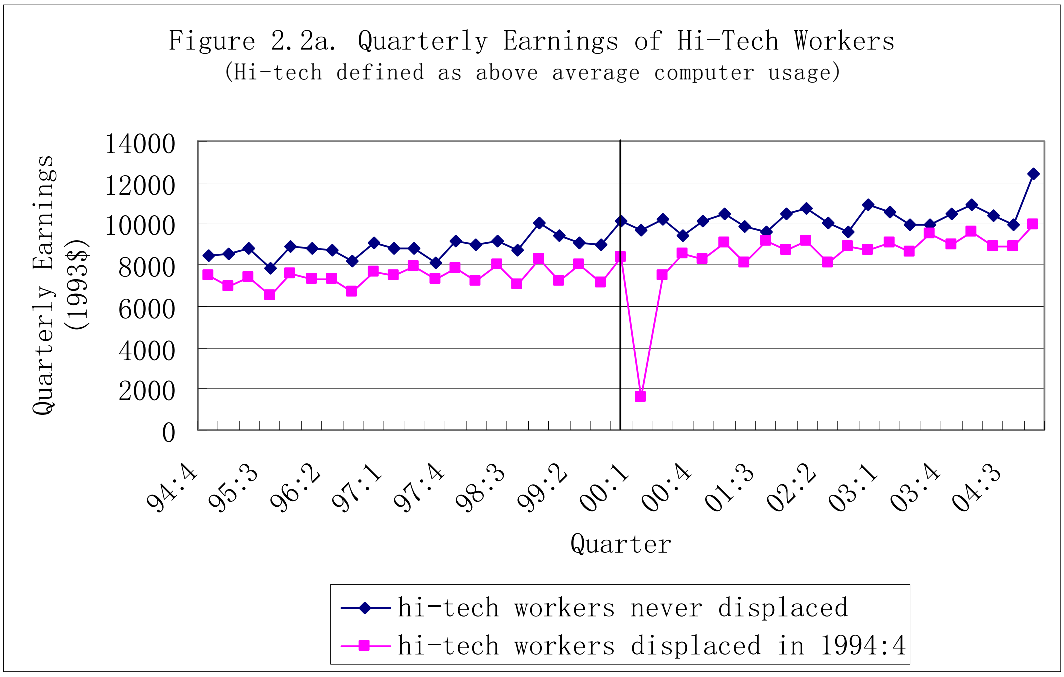


Figure 2.1d Employment Annual Change, Professional and Business Services Industry

Source: Author's calculation from the BLS.

Figure 2.2 Quarter Earnings, Hi-tech Workers and Low-tech Workers



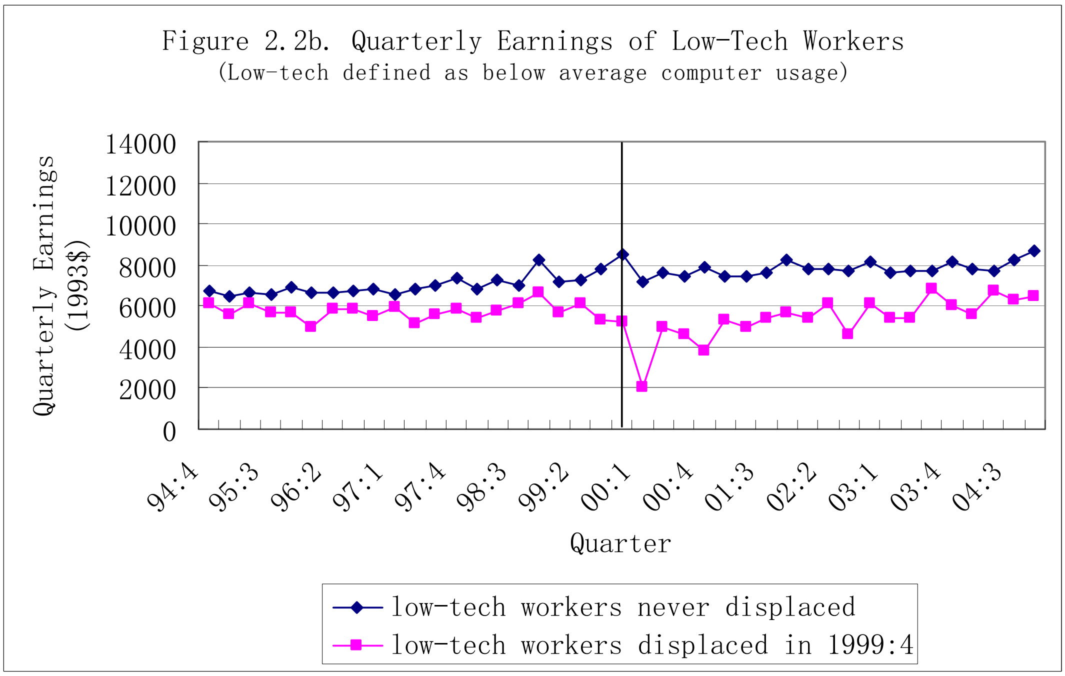
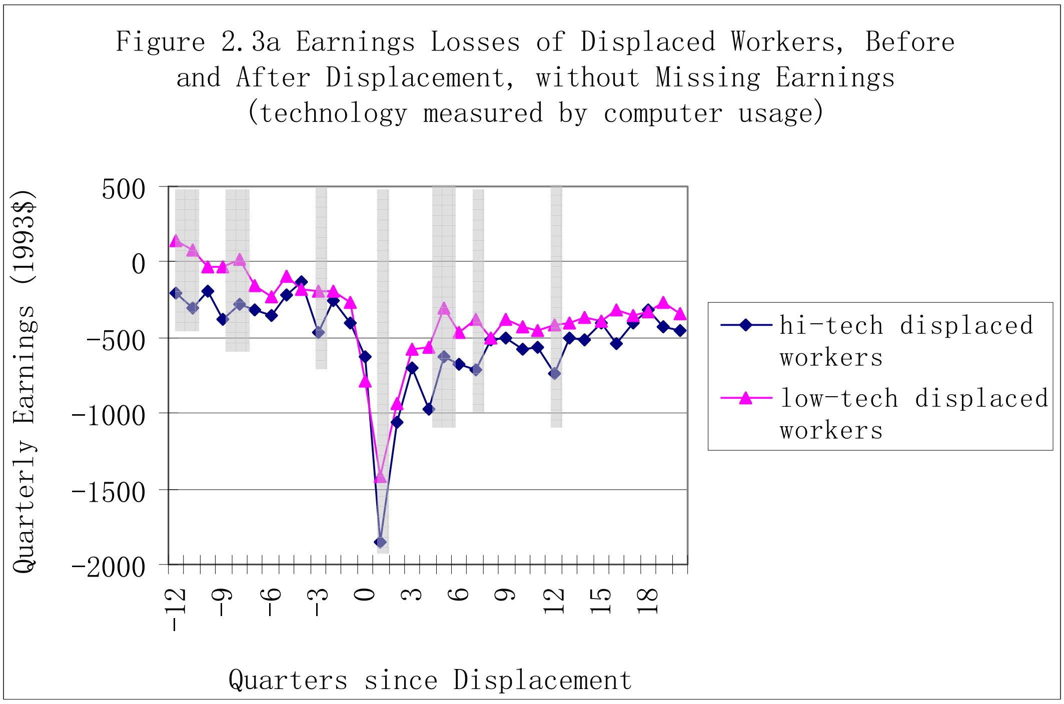


Figure 2.3 Earnings Losses of Displaced Workers, before and after Displacement, without Missing Earnings



Note: Lines labeled "hi-tech displaced workers" depict the predicted quarterly earnings of a typical hi-tech displaced worker, by applying the estimated coefficients from equation (2) to the median technology level of all hi-tech workers. Lines labeled "low-tech displaced workers" depict the predicted quarterly earnings of a typical low-tech displaced worker, by applying the estimated coefficients from equation (2) to the median technology level of all low-tech workers. Technology is measured by fraction of workers using computers at work. Shaded areas indicate that the associated coefficients are statistically significant from zero at the 5% level.

This Note applies to Figures 3b through 3d, except that different technology measures are used in each of the following figures.

Figure 2.3b Earnings Losses of Displaced Workers, Before and After Displacement, without Missing Earnings (technology measured by hi-tech investment)

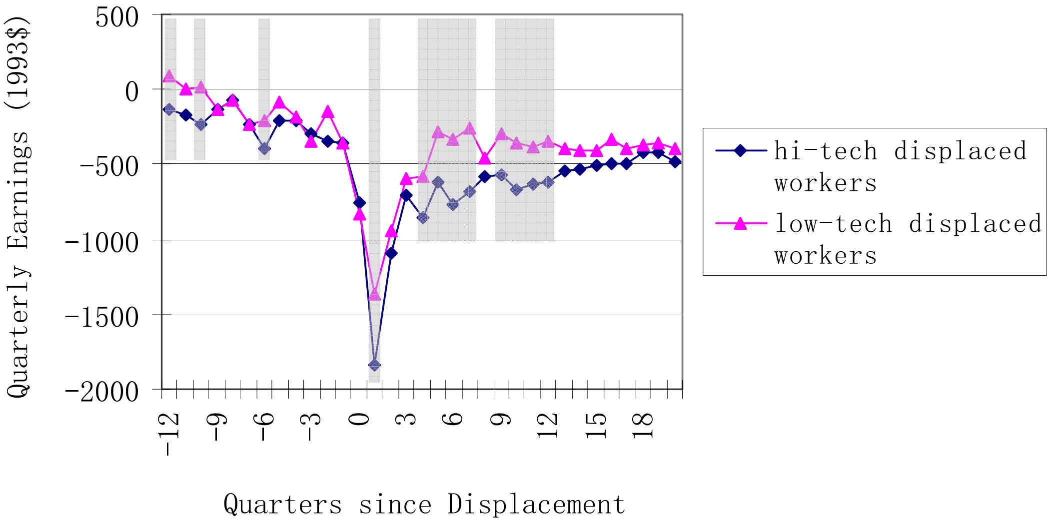


Figure 2.3c Earnings Losses of Displaced Workers, Before and After Displacement, without Missing Earnings (technology measured by R&D expenditures)

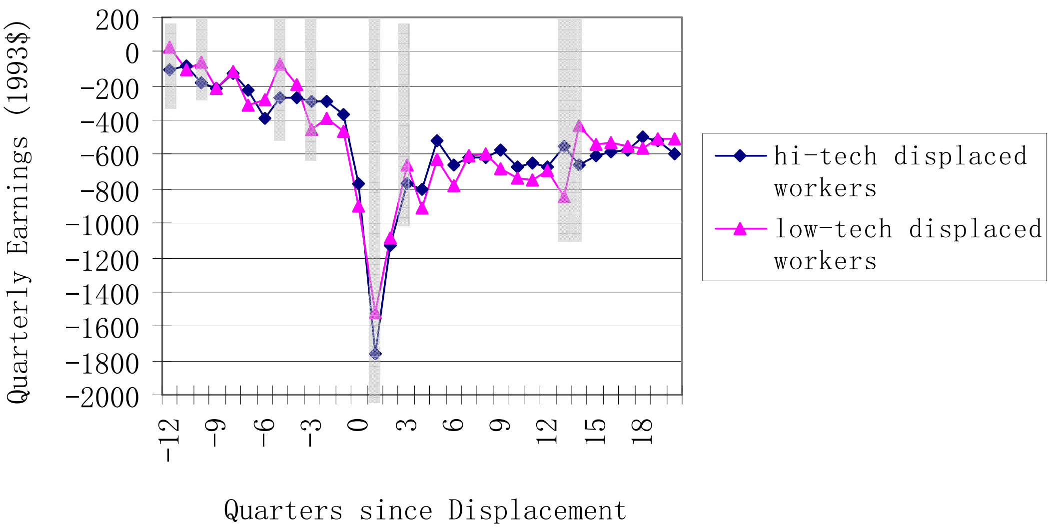


Figure 2.3d Earnings Losses of Displaced Workers, Before and After Displacement, without Missing Earnings (technology measured by fraction of scientists and engineers)

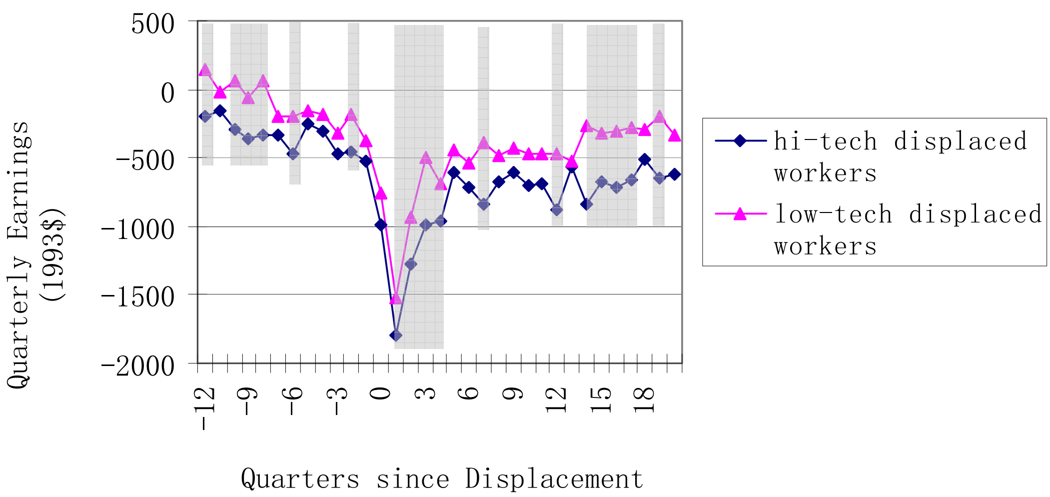
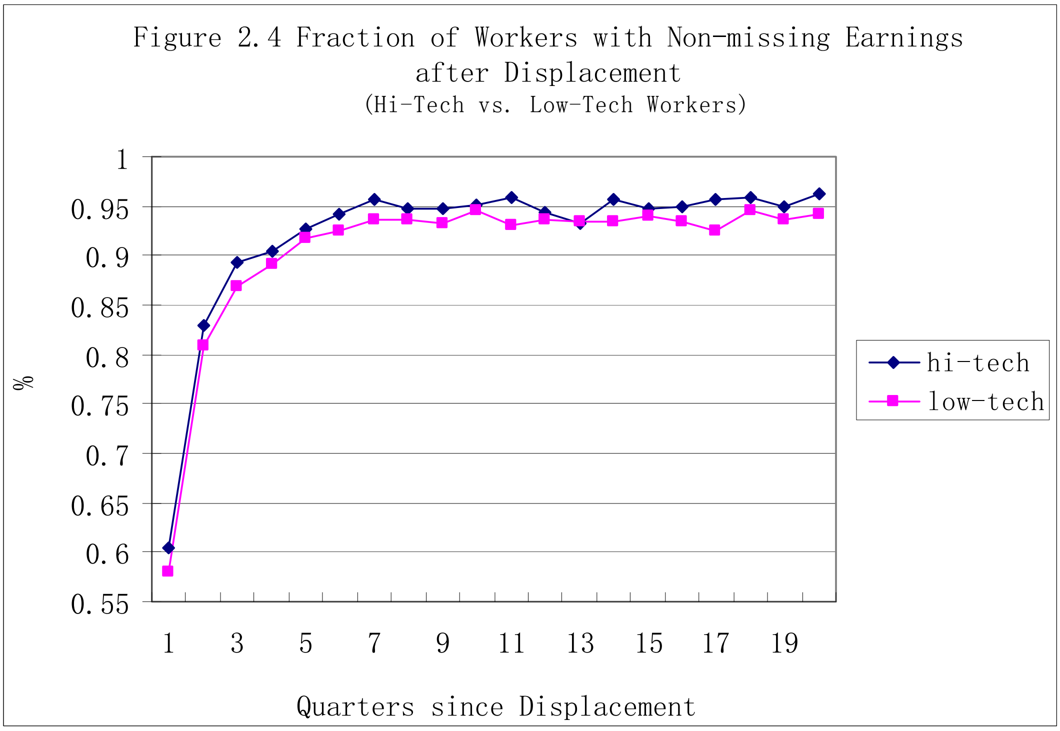
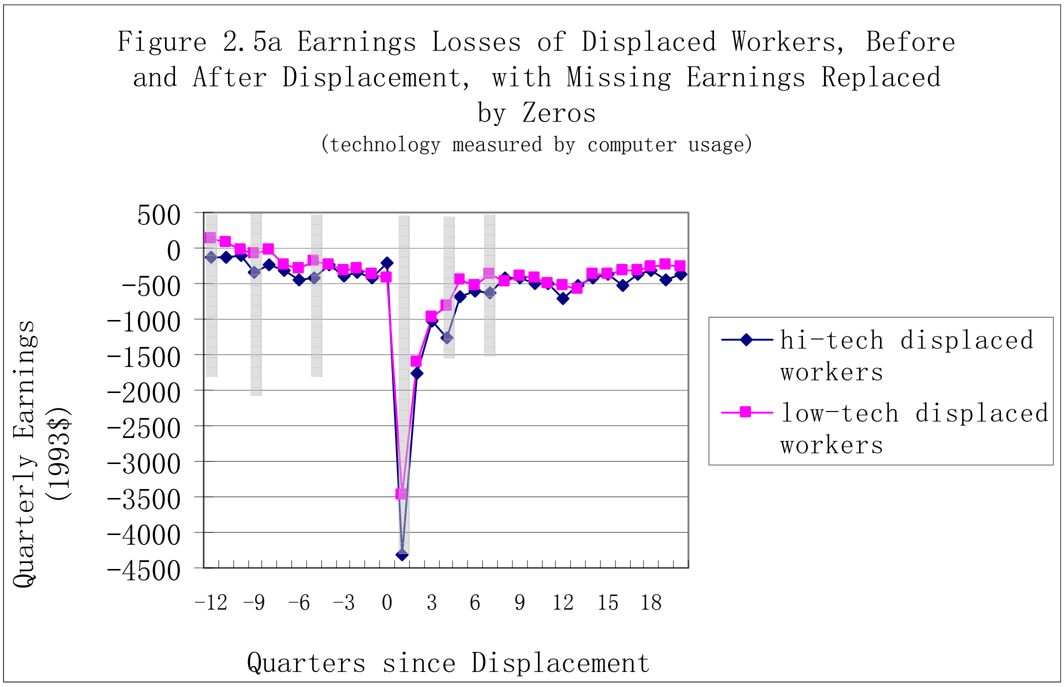


Figure 2.4 Fraction of Working with Non-missing Earnings after Displacement



Note: The differences are statistically significant between hi-tech and low-tech workers in all quarters.

Figure 2.5 Earnings Losses of Displaced Workers, before and after Displacement, with Missing Earnings Replaced by Zeros



The same notes for Figures 2.3a-2.3d can be applied to Figures 2.5a-2.5d, except that Figures 2.5a-2.5d are based on a sample including missing earnings, which are coded as zero earnings in wage regressions.

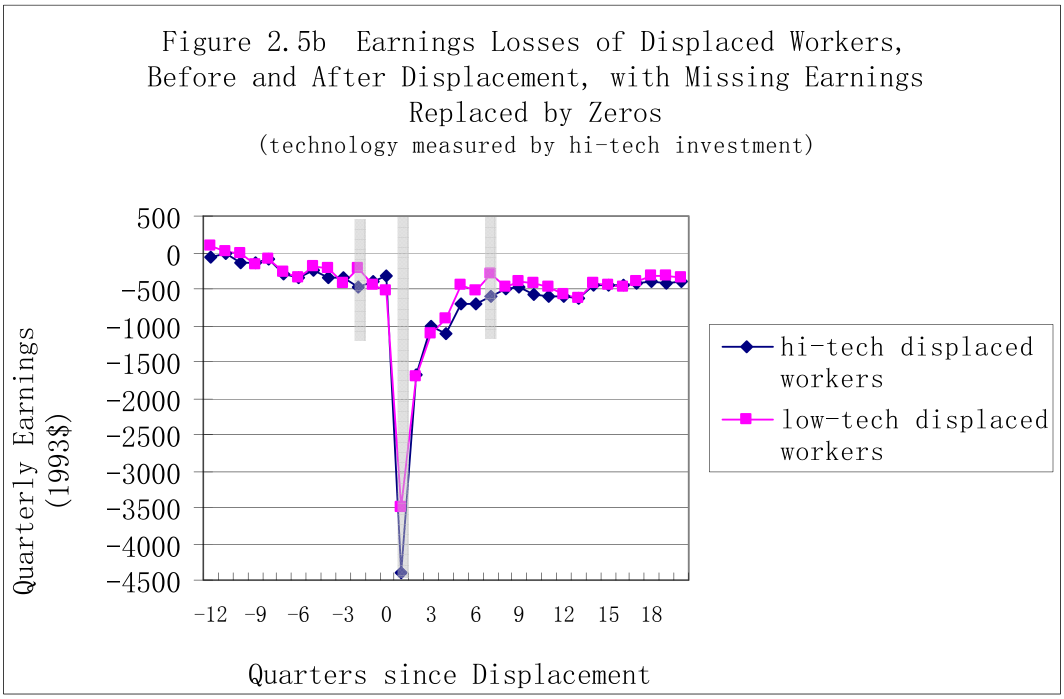


Figure 2.5c Earnings Losses of Displaced Workers, Before and After Displacement, with Missing Earnings Replaced by Zeros
(technology measured by R&D expenditure)

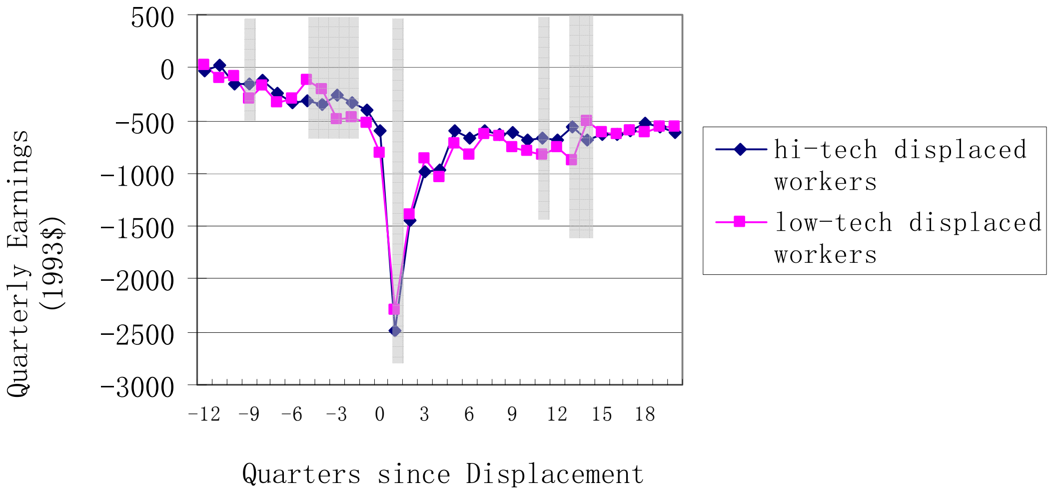


Figure 2.5d Earnings Losses of Displaced Workers, Before and After Displacement, with Missing Earnings Replaced by Zeros
(technology measured by fraction of scientists and engineers)

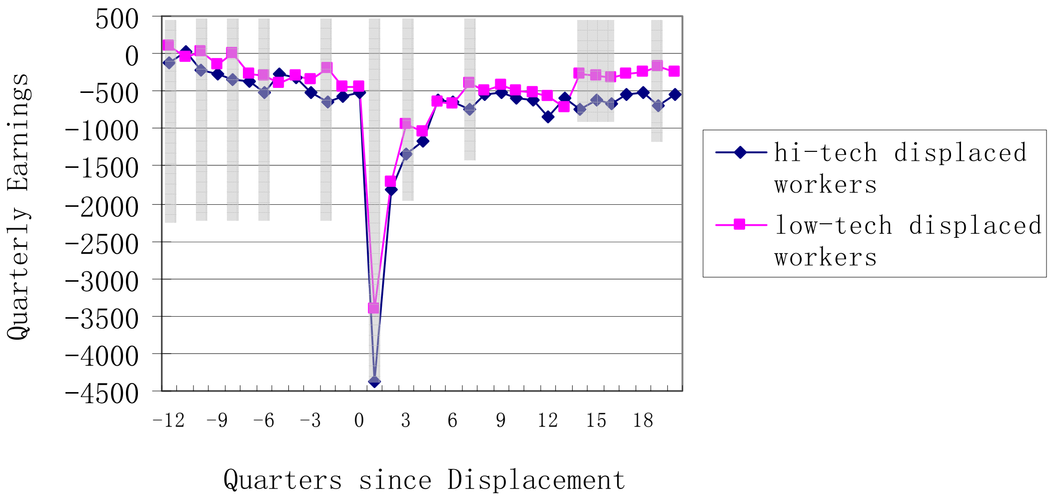
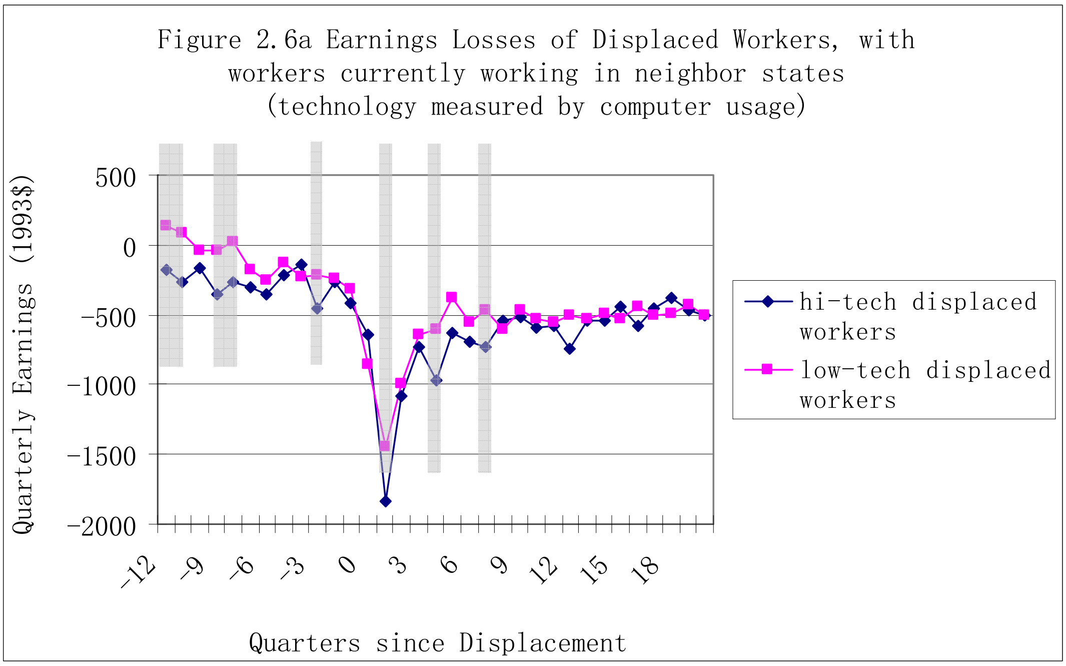
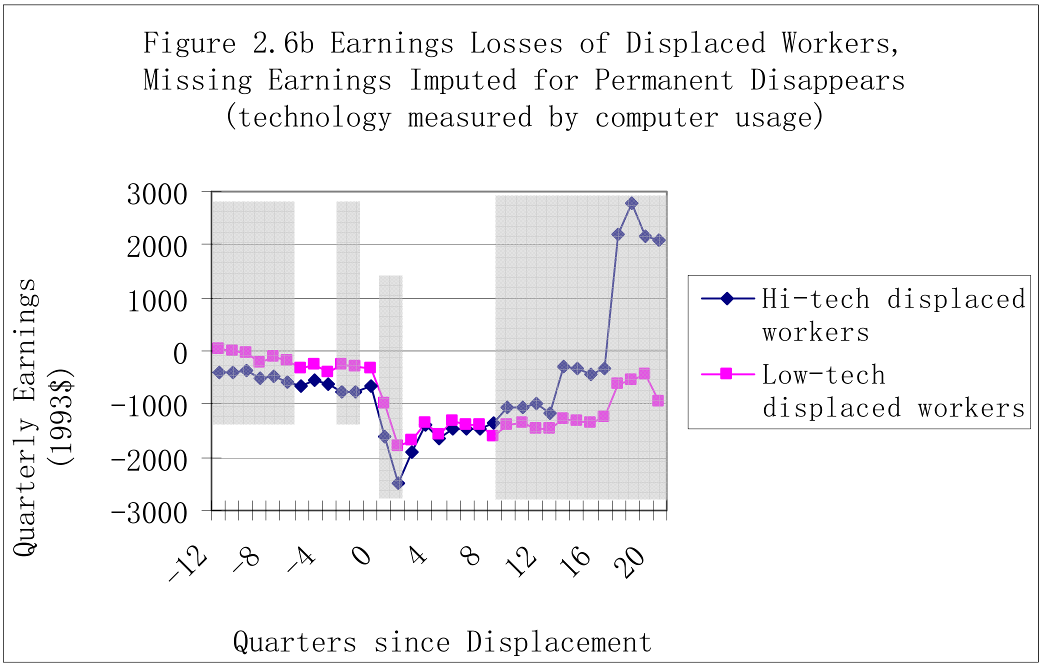


Figure 2.6 Earnings Losses of Displaced Workers, before and after Displacement, after Controlling for Sample Attritions



The same notes for Figures 2.3a can be applied to Figures 2.6a-2.6c, except that Figures 2.6a-2.6c are based on samples including some workers who drop out from the MD data. Approaches imputing the missing earnings of these "disappearers" are discussed in the text.



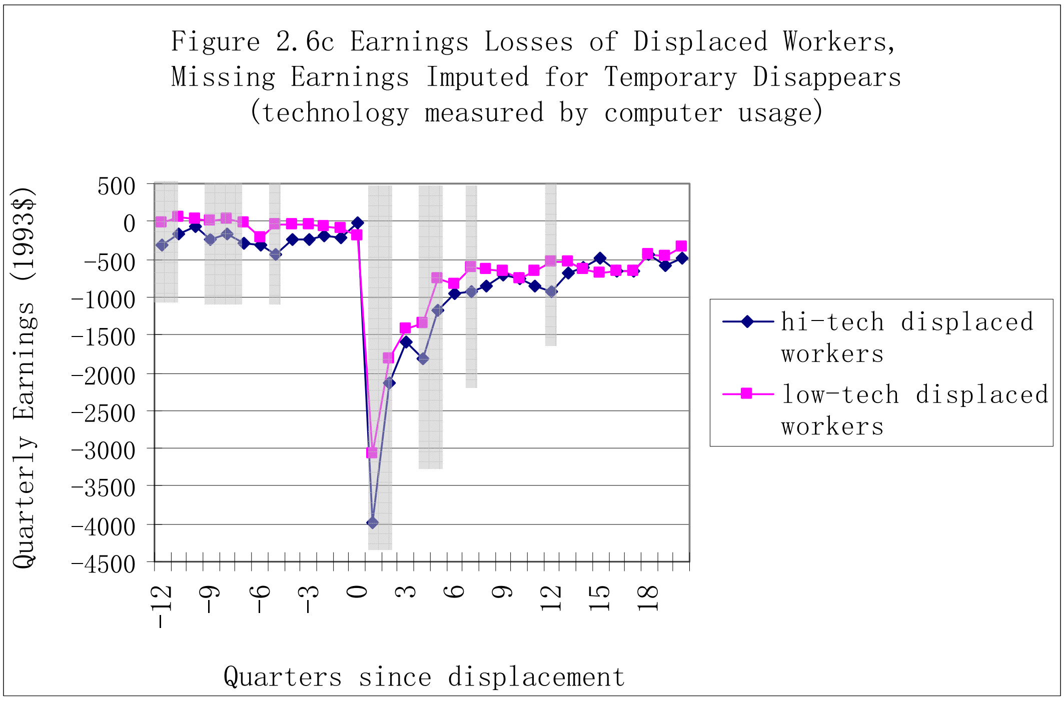
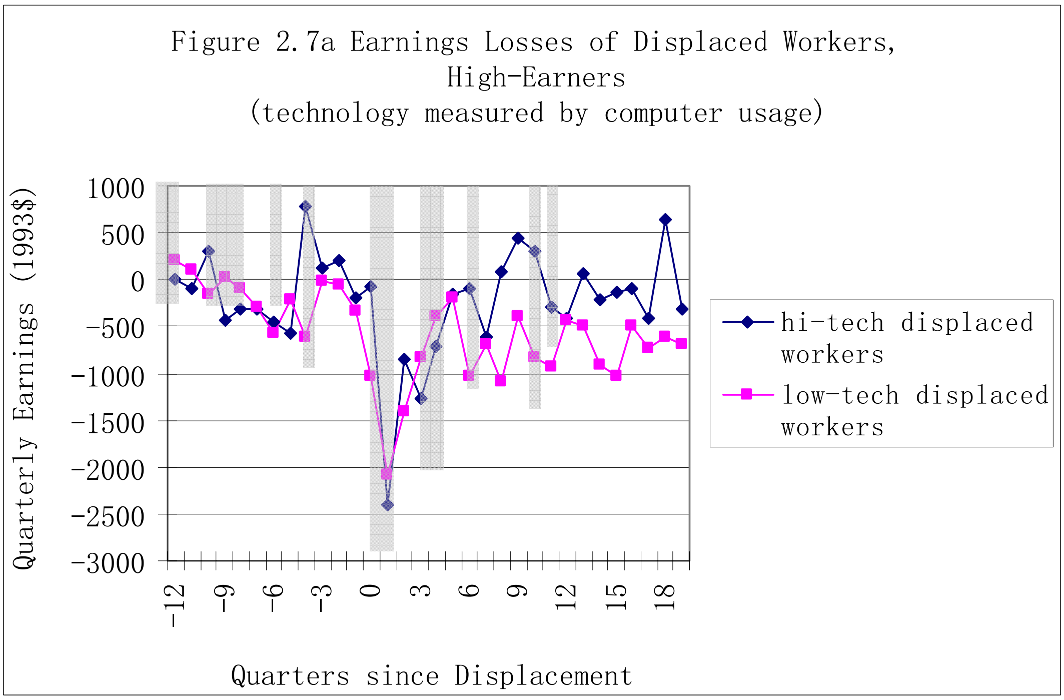


Figure 2.6c Earnings Losses of Displaced Workers,
Missing Earnings Imputed for Temporary Disappears
(technology measured by computer usage)
Quarterly Earnings (1993$)
500
0
-500
-1000
-1500
-2000
-2500
-3000
-3500
-4000
-4500
-12
-9
-6
-3
0
3
6
9
12
15
18
Quarters since displacement
hi-tech displaced workers
low-tech displaced workers

Figure 2.7 Earnings Losses of Displaced Workers, before and after Displacement, by Earnings Rank



The same notes for Figures 2.3a can be applied to Figures 2.7a-2.7c, except that Figures 2.7a-2.7c are based on three different samples defined by workers' earnings ranks.

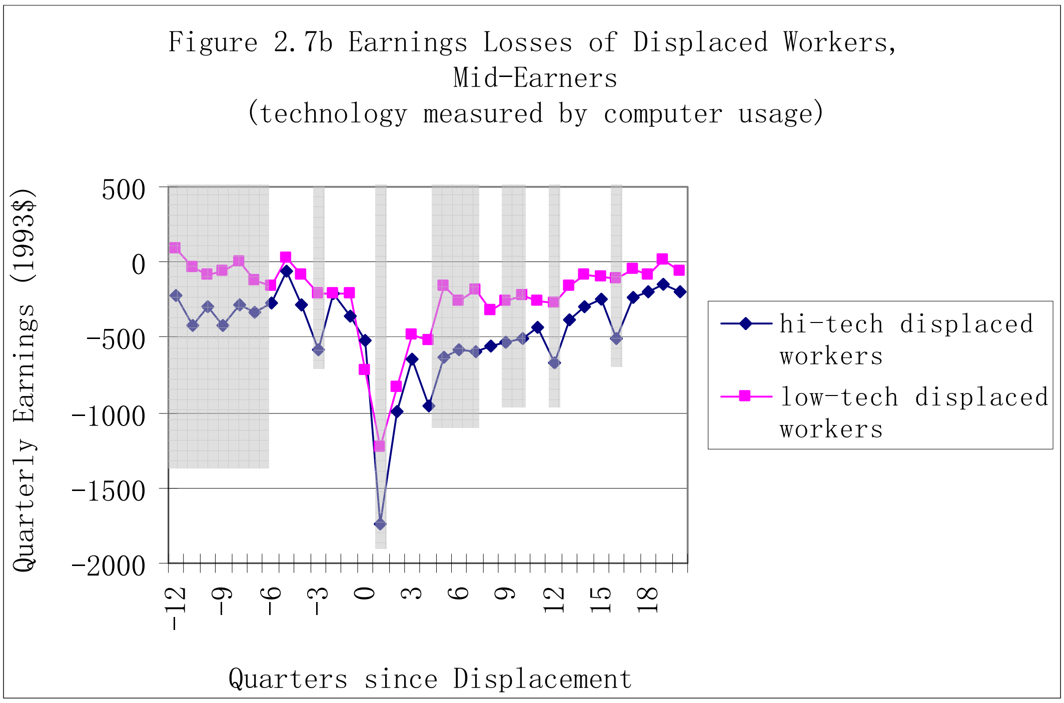


Figure 2.7c Earnings Losses of Displaced Workers,
Low-Earners
(technology measured by computer usage)

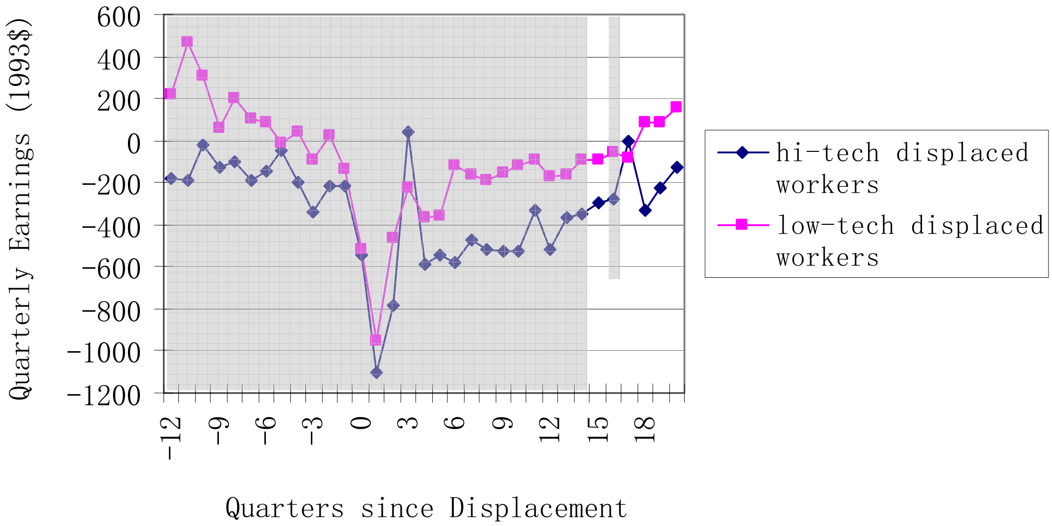
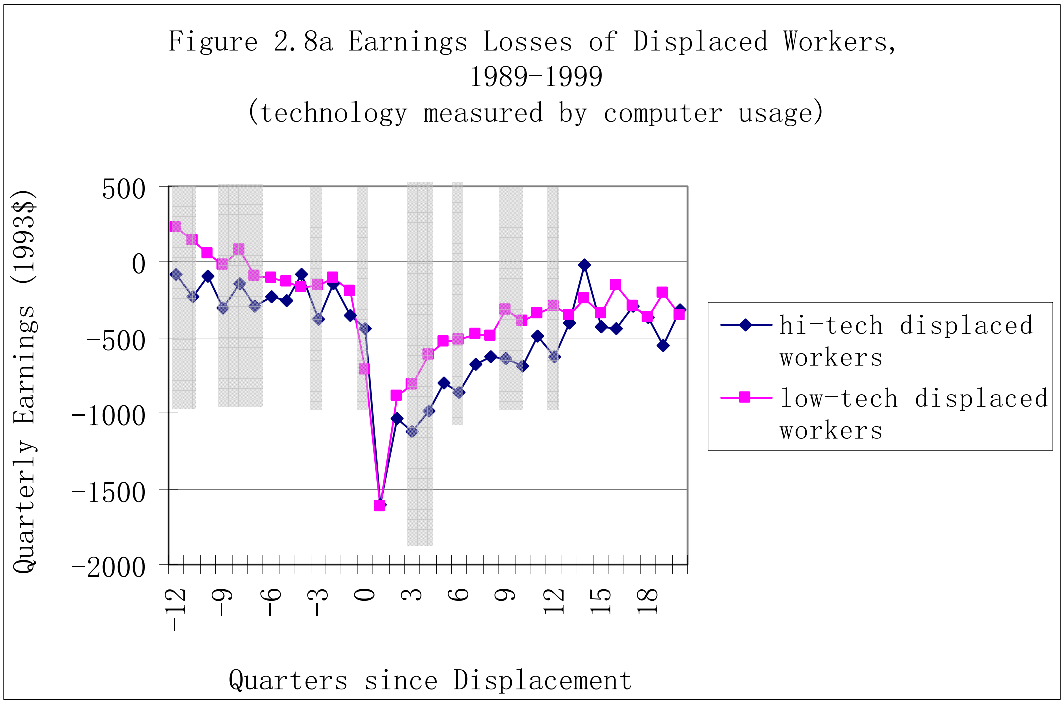


Figure 2.8 Earnings Losses of Displaced Workers, before and after Displacement, by Sample Period



The same notes for Figures 2.3a can be applied to Figures 2.8a and 2.8b, except that Figures 2.8a and 2.8b are based on two samples of different time periods.

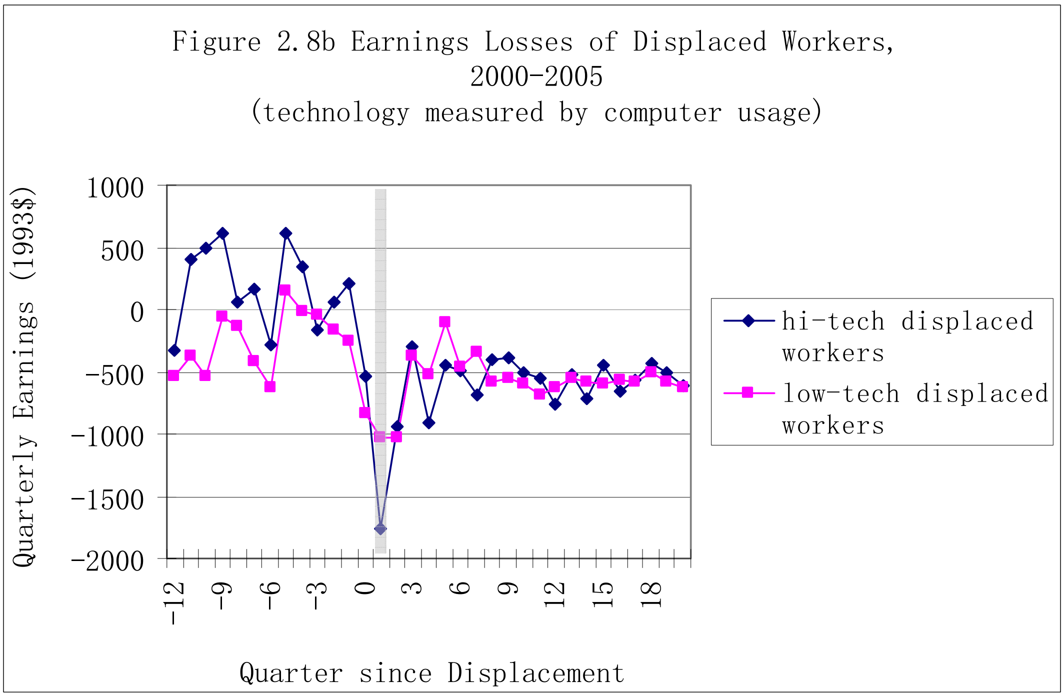
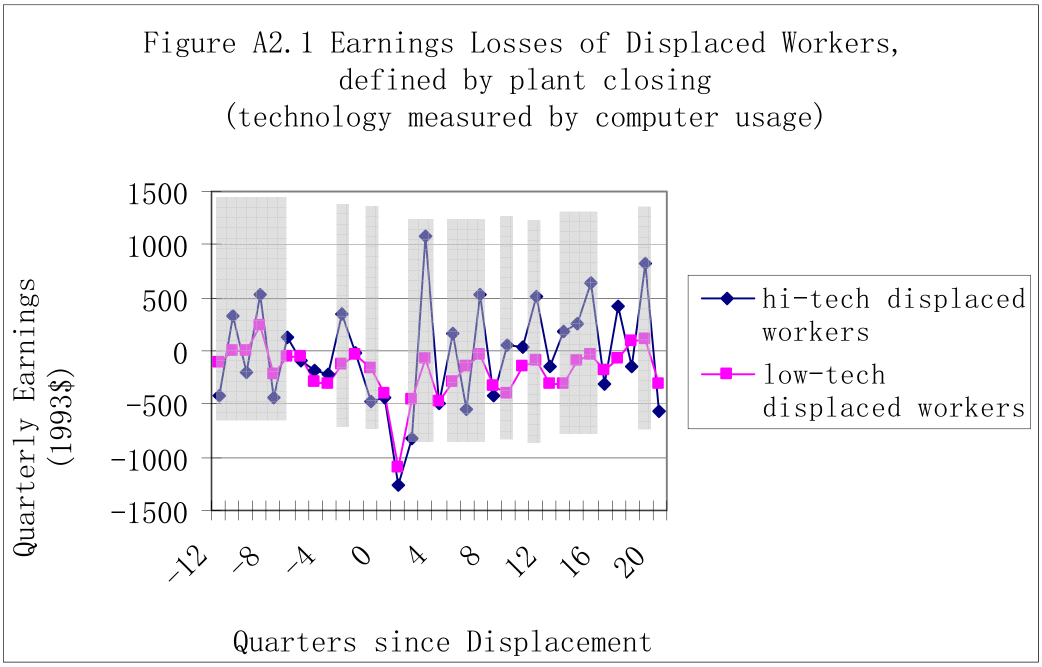
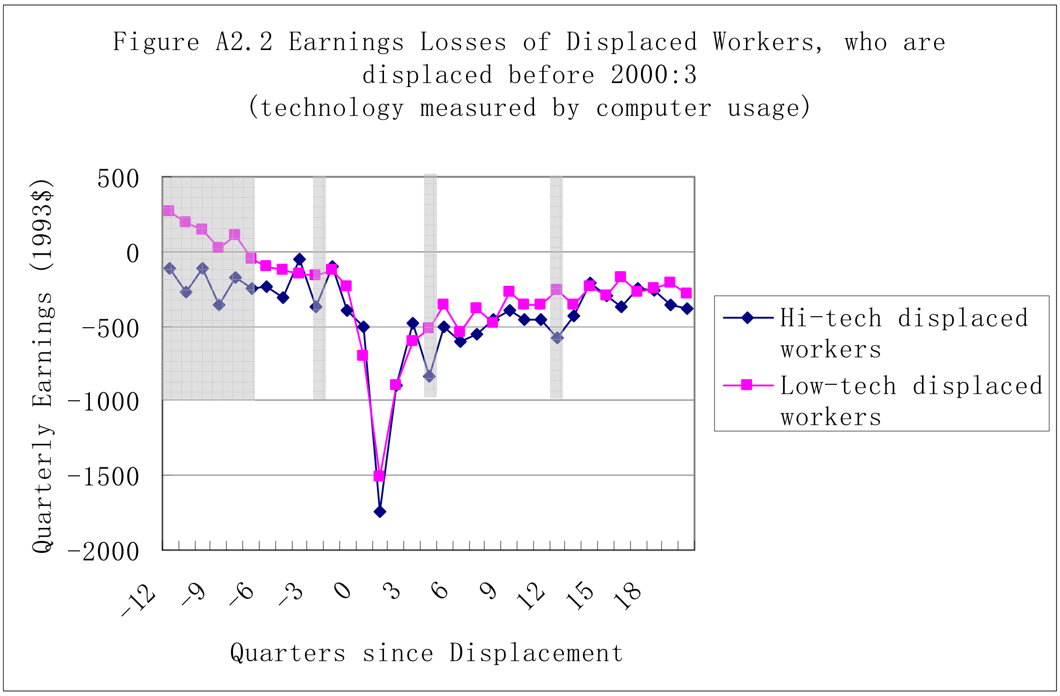


Figure A2.1 Earnings Losses of Displaced Workers, before and after Displacement, Defined by Plant Closing



Note: (1) Displaced workers are defined as workers who lose jobs as part of a plant closing. Mergers and splits are ruled out using the same criteria as those used in the definition of displacement based on mass layoff. (2)Lines labeled "hi-tech displaced workers" depict the predicted quarterly earnings of a typical hi-tech displaced worker, by applying the estimated coefficients from equation (2) to the median level computer usage of all hi-tech workers. Lines labeled "low-tech" depict the predicted quarterly earnings, assuming computer usage is equal to the median level of all low-tech workers. Shaded areas indicate that the associated coefficients are statistically significant from zero at the 5% level.

Figure A2.2 Earnings Losses of Displaced Workers, before and after Displacement, Who are Displaced before 2000:3



Note: (1) Displaced workers included in this figure are constrained to those who lose jobs before 2000:3. For these workers, all the twenty quarters post displacement can be observed in the data set. (2)Lines labeled "hi-tech displaced workers" depict the predicted quarterly earnings of a typical hi-tech displaced worker, by applying the estimated coefficients from equation (2) to the median level computer usage of all hi-tech workers. Lines labeled "low-tech" depict the predicted quarterly earnings, assuming computer usage is equal to the median level of all low-tech workers. Shaded areas indicate that the associated coefficients are statistically significant from zero at the 5% level.

Figure 3.1 Fraction of Female Immigrants Speaking only English or Speaking English very well

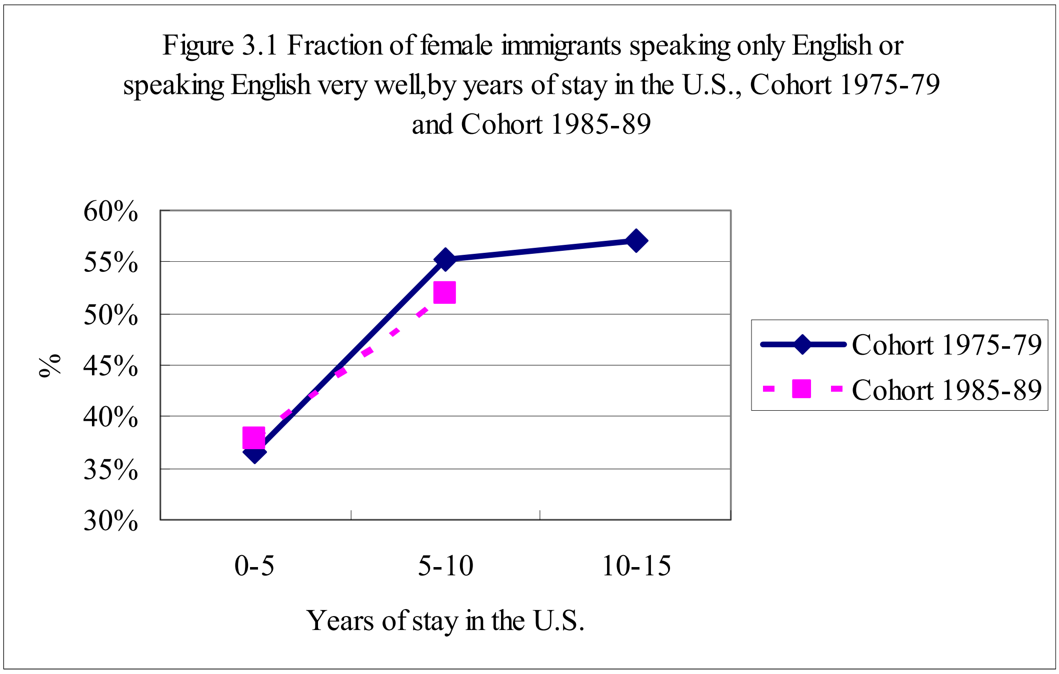


Figure 3.2 Fraction of High School Dropouts

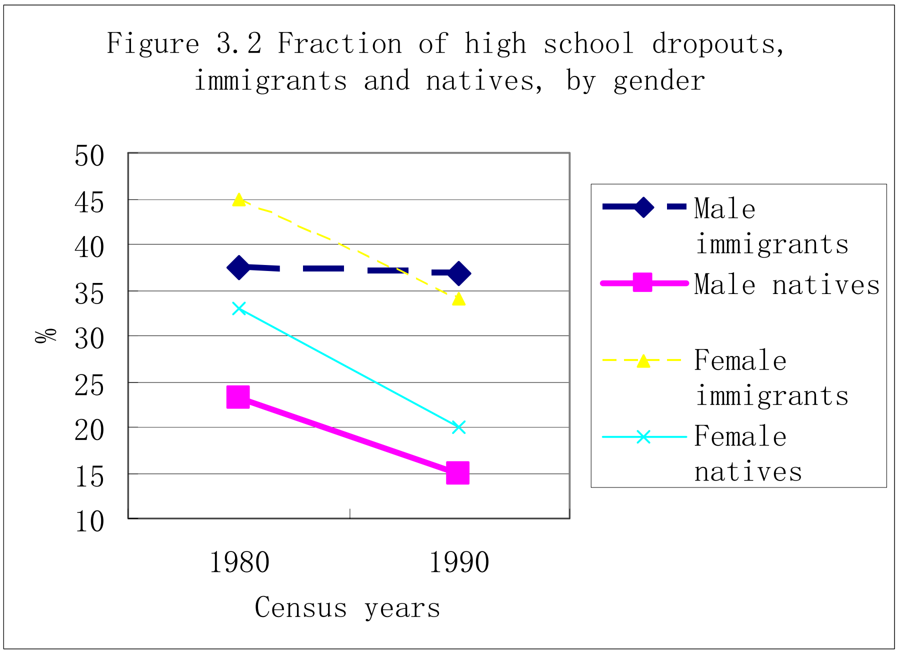
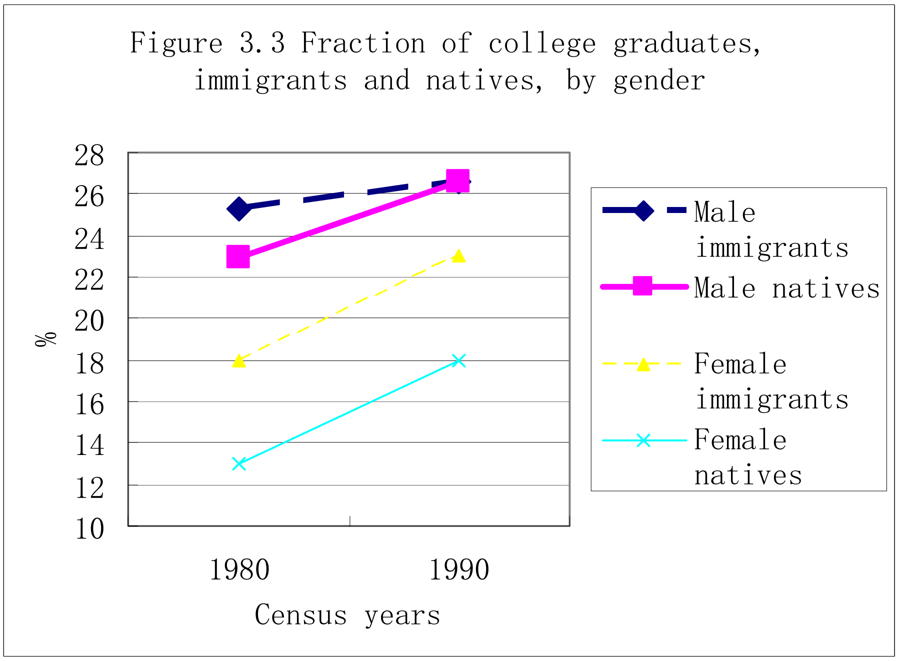


Figure 3.3 Fraction of College Graduates



Data source: Female: Table 3.2 in this paper; Male: Table 2 in Borjas (1995).

Figure 3.4 Raw Log Wages

Figure 3.4a Raw log wages, white immigrants and natives

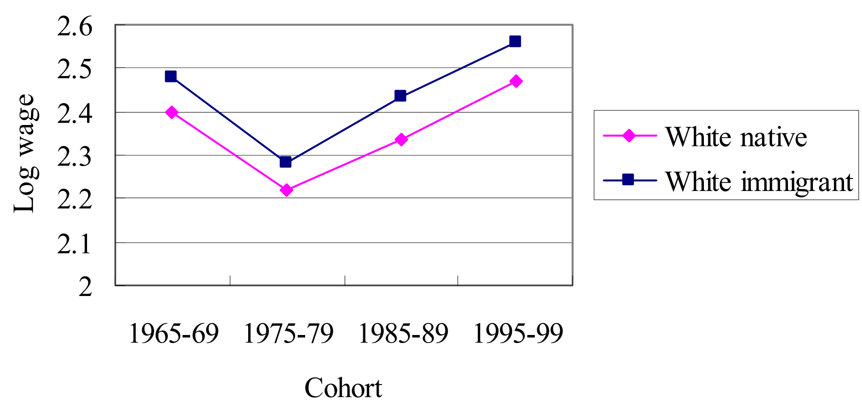


Figure 3.4b Raw log wages, black immigrants and natives

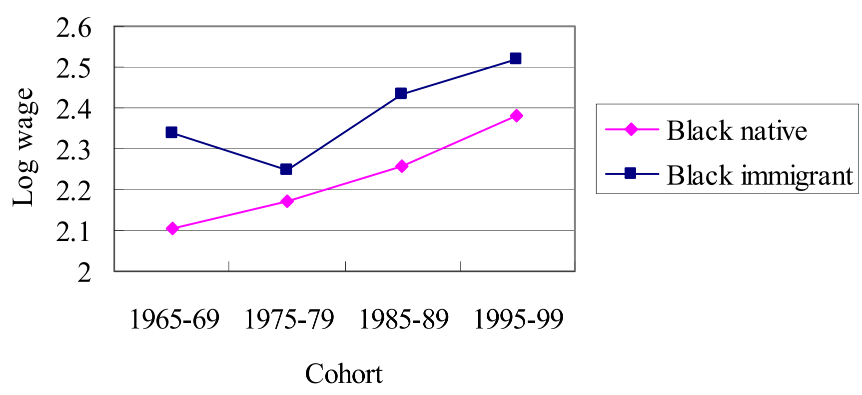


Figure 3.4c Raw log wages, Asian immigrants and natives

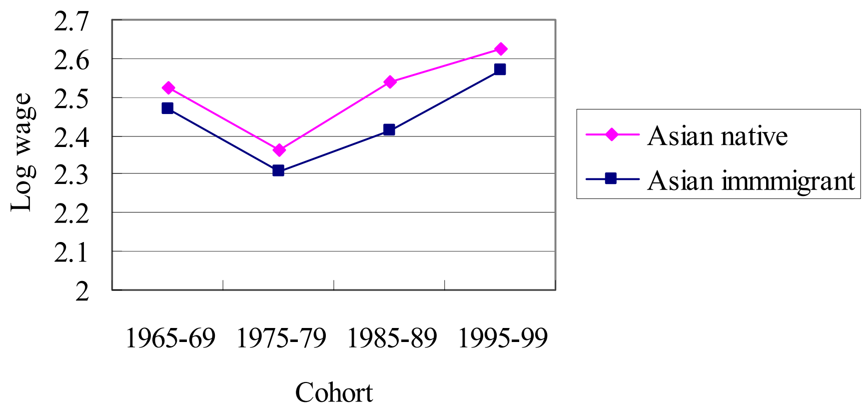
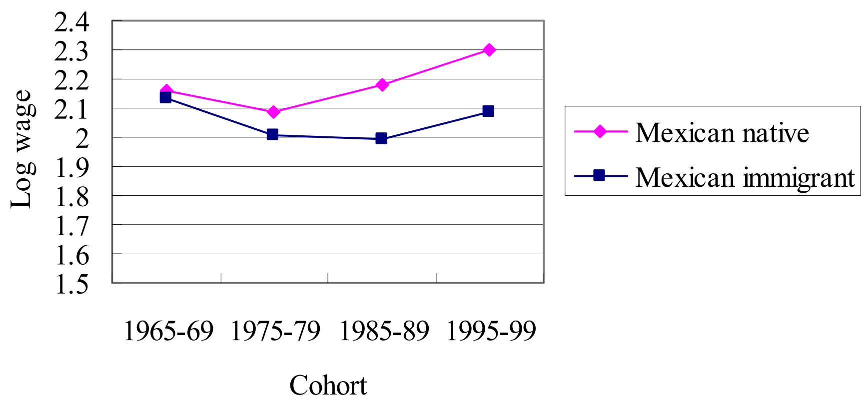


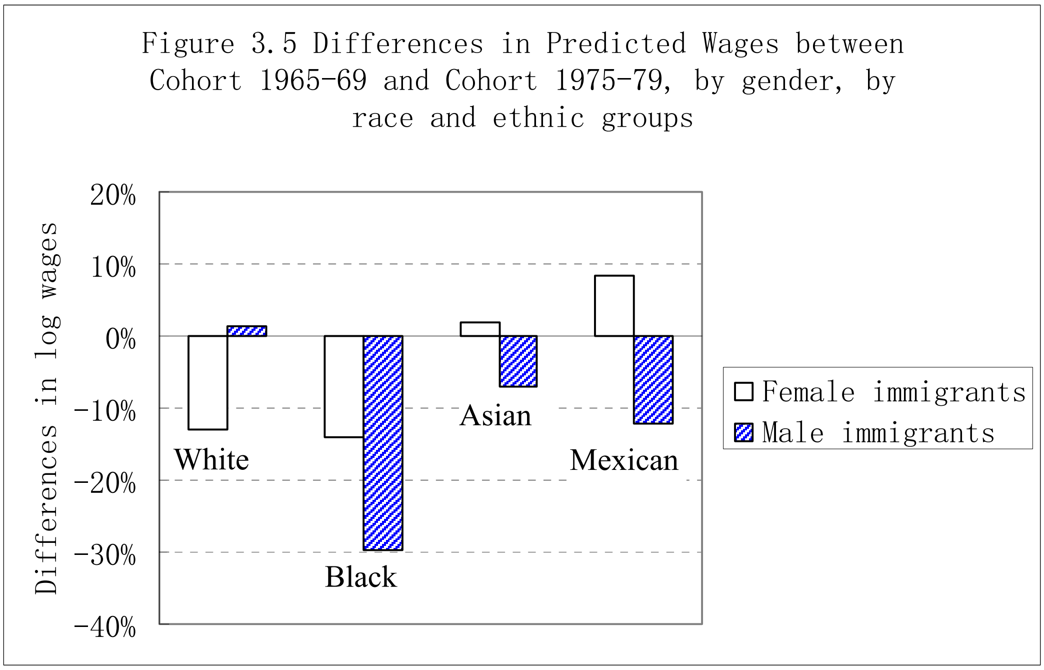
Figure 3.4d Raw log wages, Mexican immigrants and natives



Note: (1) Immigrants' average raw log wages are measured within five years of stay in the U.S. for each cohort. For example, average log wage of cohort 1965-69 is measured in Census 1970.

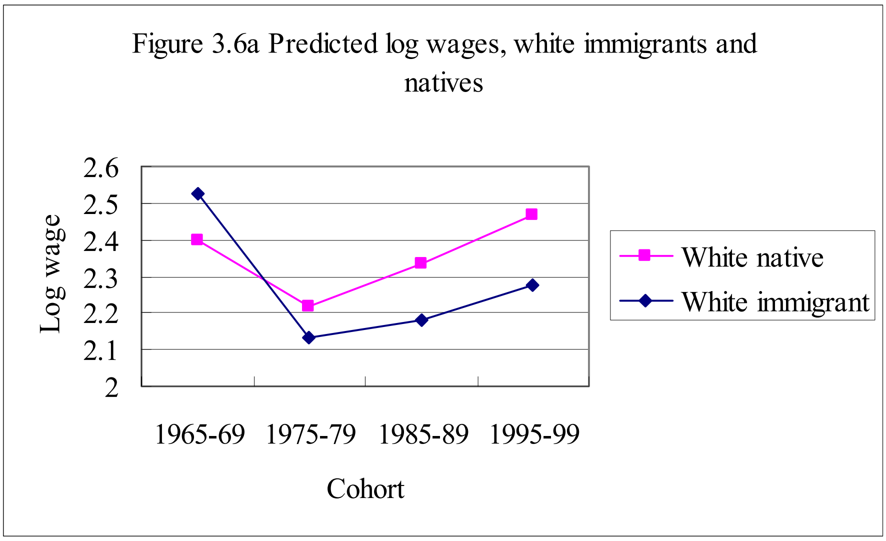
(2) Natives' average raw log wages are measured in corresponding Census years to each immigrant cohort. For example, average log wage in Census 1970 is drawn for natives side by side with immigrant cohort 1965-69.

Figure 3.5 Differences in Predicted Wages between Cohort 1965-69 and Cohort 1975-79



Note: (1) Data source: Table 3.5a for female immigrants; Table 5 in Borjas (1985) for male immigrants;
(2) Each bar represents the predicted wage of cohort 1975-79 minus that of cohort 1965-69. Predicted wages are calculated within five years after the cohort arrives in the U.S.

Figure 3.6 Predicted Log Wages



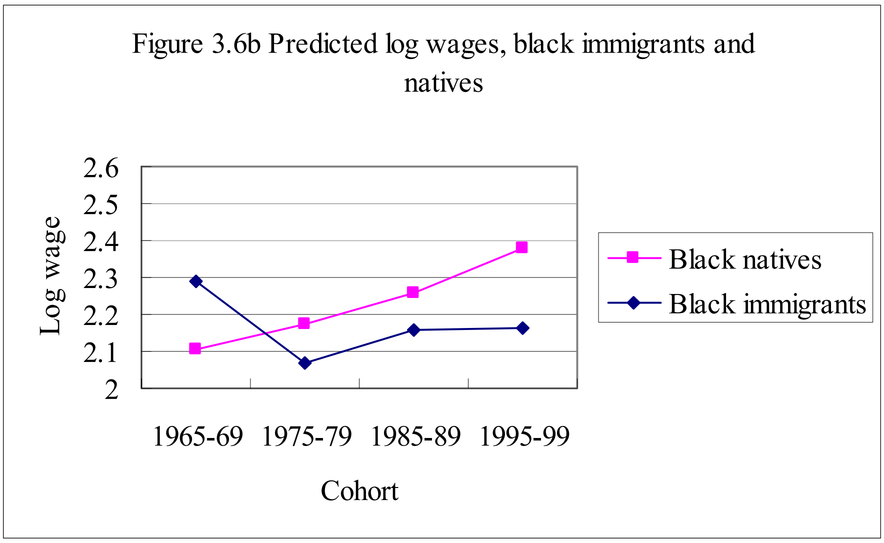


Figure 3.6c Predicted log wages, Asian immigrants and natives

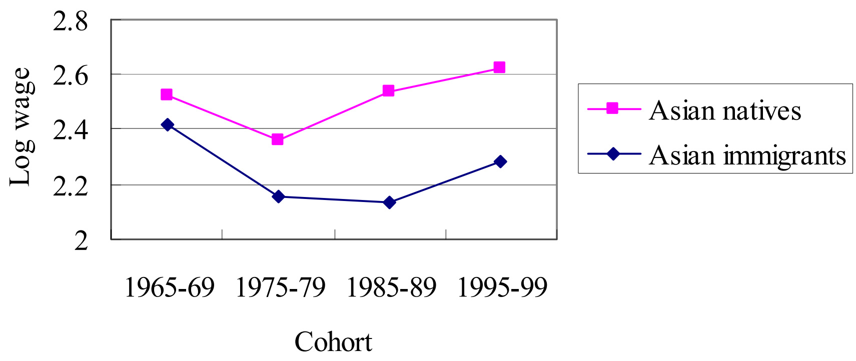
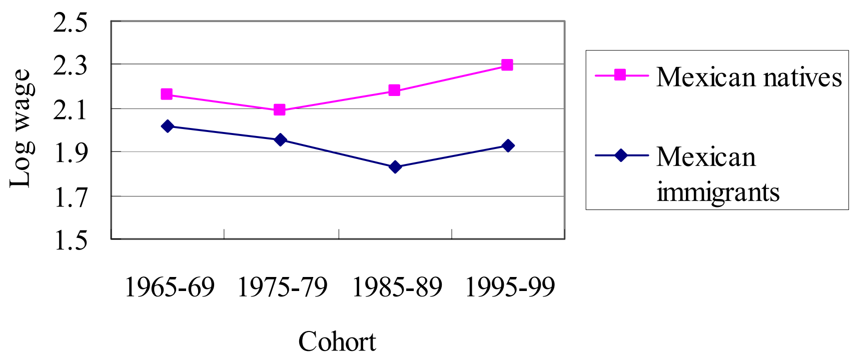


Figure 3.6d Predicted log wages, Mexican immigrants and natives



Note: (1) Immigrants' predicted log wages are measured within five years of stay in the U.S. for each cohort. For example, predicted log wage of cohort 1965-69 is measured in Census 1970.

(2) Natives' predicted log wages are measured in corresponding Census years to each immigrant cohort. For example, predicted log wage in Census 1970 is drawn for natives side by side with immigrant cohort 1965-69.

Bibliography

Addison, John T., Fox, Douglas A., Ruhm, Christopher J., “Technology, trade sensitivity, and labor displacement,” *Southern Economic Journal*. Jan 2000, 66, (3), 682 - 699.

Addison, John T. and Portugal, Pedro “Job Displacement, Relative Wage Changes, and Duration of Unemployment,” *Journal of Labor Economics*, Vol. 7, No. 3, 281-302, Jul.1989

Aghion, Philippe, Howitt, Peter and Violante, Gianluca “General Purpose Technology and Wage Inequality,” *Journal of Economic Growth*, Vol. 7(4), December 2002, 315-345

Ahituv, Avner and Zeira, Joseph “Technical Progress and Early Retirement,” Working Paper 2002

Allen, Steven G., “Technology and the Wage Structure,” *Journal of Labor Economics*, Apr. 2001, Vol. 19, No. 2, 440-483

Anderson, P. 1982 “Self-Esteem in the Foreign Language: A Preliminary Investigation,” *Foreign Language Annals* 15: 109-114.

Autor, David H.; Frank Levy and Richard J. Murnane. “The Skill Content of Recent Technological Change: An Empirical Exploration,” *The Quarterly Journal of Economics*, 118(4), November 2003, 1279-1333.

Baker, Michael and Benjamin, Dwayne, “The Role of the Family in Immigrants' Labor-Market Activity: An Evaluation of Alternative Explanations,” *The American Economic Review*, Vol. 87, No. 4. (Sep., 1997), 705-727.

Baker, Michael, Benjamin, Dwayne, Cegep, Andree Desaulniers and Grant, Mary, “The Distribution of the Male/Female Earnings Differential, 1970-1990,” *The Canadian Journal of Economics*, Vol. 28, No.3. (Aug., 1995), 479-501.

Bartel, Ann P., and Sicherman, Nachum, “Technological Change and Retirement Decisions of Older Workers,” *Journal of Labor Economics*, 1993, Vol. 11, 162-183

Bartel, Ann P., and Sicherman, Nachum, “Technological Change and Wages: An Interindustry Analysis,” *Journal of Political Economy*, April 1999, Vol. 107, No. 2, 285-325

Bednarzik, Robert, “Restructuring Information Technology: Is Offshoring a Concern?” *Monthly Labor Review*, August 2005, 11-21

Berman, Eli, Lang, Kevin and Siniver, Erez, “Language-Skill Complementarity: Returns to Immigrant Language Acquisition,” *NBER Working Papers 7737*, 2000

Blau, Francine D. and Beller, Andrea H., "Black-White Earnings Over the 1970s and 1980s: Gender Differences in Trends," *The Review of Economics and Statistics*, Vol. 74, No.2. (May, 1992), 276-286.

Blinder, Alan S., "Wage Discrimination: Reduced Form and Structural Estimates," *The Journal of Human Resources*, Vol. 8, No.4 (Autumn, 1973), 436-455.

Bohn, Sarah, "Immigration and the U.S. Labor Market," *Dissertation*, University of Maryland, 2007

Borjas, George and Rachel Friedberg, "The Immigrant Earnings Turnaround of the 1990s," *NBER Summer Institute, Labor Series Workshop,* 2006

Borjas, George J. and Bratsberg, Bernt, "Who Leaves? The Outmigration of the Foreign-Born," *The Review of Economics and Statistics*, Vol. 78, No. 1. (Feb., 1996), 165-176.

Borjas, George J. "Assimilation and Changes in Cohort Quality Revisited: What Happened to Immigrant Earnings in the 1980s?" *Journal of Labor Economics*, Vol. 13, No. 2. (Apr., 1995), 201-245.

Borjas, George J. "The Economics of Immigration," *Journal of Economic Literature*, Vol. 32, No. 4. (Dec., 1994), 1667-1717.

Borjas, George J. "National Origin and the Skills of Immigrants in the Postwar Period," *Immigration and the work force: Economic consequences for the United States and source areas*. Borjas, George J. and Freeman, Richard B., eds. University of Chicago Press, 1992.

Borjas, George J. "Self-Selection and the Earnings of Immigrants," *The American Economic Review*, Vol. 77, No. 4. (Sep., 1987), 531-553.

Borjas, George J. "Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants," *Journal of Labor Economics*, Vol. 3, No. 4. (Oct., 1985), 463-489

Bresnahan, Timothy and Trajtenberg, Manuel, "General Purpose Technologies:. Engines of Growth?" *Journal of Econometrics*, January 1995, 65(1), 83-108

Carliner, Geoffery 1996. "The Wages and Language Skills of U.S. Immigrants," National Bureau of Economic Research (NBER), Working Paper Number 5763, September.

Carliner, Geoffery, "The Language Ability of US Immigrants: Assimilation and Cohort Effects," International Migration Review, 2000, 34:158-182

Carrington, William J., and Zaman Asad, "Interindustry Variation in the Costs of Job Displacement," *Journal of Labor Economics*, 1994, Vol. 12, No.2, 243-275

Chiswick, Barry R., Yew Liang Lee and Paul W. Miller. 2006. "Immigrants' Language Skills and Visa Category," *International Migration Review*, Volume 40, Number 2, pages 419- 450.

Chiswick, B.R. and Paul W. Miller. 1995. "The Endogeneity between Language and Earnings: International Analyses," *Journal of Labor Economics*, Volume 13, Number 21.

Chiswick, Barry R. "Is the New Immigration Less Skilled Than the Old?" *Journal of Labor Economics*, Vol. 4, No. 2. (Apr., 1986), 168-192.

Chiswick, Barry R. "The Effect of Americanization on the Earnings of Foreign-born Men," *The Journal of Political Economy*, Vol. 86, No. 5. (Oct., 1978), 897-921.

Cooke, Sandra D., "Information Technology Workers in The Digital Economy," *Digital Economy*, 2003, 19-34

Dardia, Michael, Grose Tracey, Roghmann, and O'Brien-Strain, Peggy "The High-Tech Downturn in Silicon Valley: What Happened to All Those Skilled Workers?" Final Report, The SPHERE Institute, Apr. 2005

Duleep, Harriet Orcutt and Dowhan, Daniel J. "Has the Lab or Market Quality of U.S. Immigrants Fallen? Evidence from Longitudinal Data," Working paper

Duleep, Harriet Orcutt and Regets, Mark C. "Measuring Immigrant Wage Growth using Matched CPS Files," *Demography*, Vol. 34, Issue 2 (May, 1997), 239-249

Duleep, Harriet Orcutt and Sanders, Seth, "The Decision to Work by Married Immigrant Women" *Industrial and Labor Relations Review*, Vol. 46, No. 4. (Jul., 1993), 677-690.

Dustmann, Christian, 1994. "Speaking Fluency, Writing Fluency and Earnings of Migrants," *Journal of Population Economics*, Springer, vol. 7(2), pages 133-56.

Fallick, Bruce C., "A Review of the Recent Empirical Literature on Displaced Workers," *Industrial and Labor Relations Review*, 1996, Vol. 50, No. 1, 5-16

Farber, Henry S., "What Do We Know About Job Loss in the United States? Evidence from the Displaced Workers Survey, 1984-2004," *Working Paper* 2005

Farber, Henry, Haltiwanger, John, and Abraham, G. Katharine "The Changing Face of Job Loss in the United States, 1981-1995," *Brookings Papers on Economic Activity. Microeconomics,* Vol. 1997. (1997), pp. 55-142

Funkhouser Edward and Trejo, Stephen J. "The Labor Market Skills of Recent Male Immigrants: Evidence from the Current Population Survey," *Industrial and Labor Relations Review*, Vol. 48, No. 4. (Jul., 1995), pp.792-811

Funkhouser Edward and Trejo, Stephen J. "Labor Market Outcomes of Female Immigrants in the United States," *The Immigrant Debate: Studies on the Economics, Demographic, and Fiscal Effects of Immigrants* (1998) pp. 239-288

Gibbons, Robert, and Katz, Lawrence F. "Layoffs and Lemons", *Journal of Labor Economics*, Vol. 9, No. 4, 351-380, Oct. 1991

Groshen, Erica L. and Potter, Simon "Has Structural Change Contributed to a Jobless Recovery?" *Current Issues in Economics and Finance*, Federal Reserve Bank of New York, Vol. 9, August 2003

Hamermesh, Daniel "What Do We Know About Worker Displacement in the U.S.?" *Industrial Relations*, Vol. 28, No. 1, winter 1989

Heckman, James J., "Sample Selection Bias as a Specification Error," *Econometrica,* Vol. 47, No.1. (Jan., 1979), 153-162.

Hotchkiss, Julie L., Pitts. Melinda M., and Robertson, John C. "Earnings on the Information Technology Rollercoaster: Insight from Matched Employer-Employee Data," *Federal Reserve Bank of Atlanta Working Paper 2005-11*, June 2005

Howland, Marie; Peterson, George E. "Labor Market Conditions and the Reemployment of Displaced Workers," *Industrial and Labor Relations Review* 42(1) 109-122

Jacobson, Louis S., Lalonde, Robert J., and Sullivan, Daniel G. "Earnings Losses of Displaced Workers," *The American Economic Review*, Vol. 83. No.4 Sep.1993, 685-709

Jasso, Guillermina, Rosenzweig, Mark R. and Smith, James P. "The changing skill of new immigrants to the United States: recent trends and their determinants," Working paper 1998

Jovanovic, Boyan and Rousseau, Peter L. "General Purpose Technologies," NBER Working Paper No. 11093, Jan. 2005

Juhn, Chinhui, Murphy, Kevin M. and Pierce, Brooks "Wage Inequality and the Rise in Returns to Skill," *The Journal of Political Economy*, Vol. 101, Issue 3, (Jun., 1993), 410-442.

Kletzer, Lori G., and Fairlie, Robert W. "The Long-Term Costs Of Job Displacement of Young Adult Workers," *Industrial and Labor Relations Review*, Vol. 56, No. 4 July 2003, 682

Kletzer, Lori G., "Job Displacement," *Journal of Economic Perspectives*, 1998, Vol. 12, No. 1, 115-136

LaLonde, Robert J. and Topel, Robert H. “Labor Market Adjustments to Increased Immigration,” in John M. Abowd and Richard B. Freeman, eds. 1991, pp. 167-99.

Lazear, Edward P., “Agency, Earnings Profiles, Productivity, and Hours Restrictions,” *American Economic Review*, September 1981, 71, 606-620

LeBlanc, R. and Painchaud, G. 1985 “Self Assessment as a Second Language Placement Instrument,” TESOL Quarterly, Volume 19, Number 4, pages 673-687.

Lengermann, Paul A., and Vilhuber, Lars, “Abandoning the Sinking Ship, The Composition of Worker Flows Prior to Displacement,” 2002, 1-39

Long, James E. “The Effect of Americanization on Earnings: Some Evidence for Women,” *The Journal of Political Economy*, Vol. 88, No. 3. (Jun., 1980), 620-629.

Lubotsky, Darren, “Chutes or Ladders? A Longitudinal Analysis of Immigrant Earnings,” Working paper, Aug.2000

MacDonald, Glenn, and Weisbach Michael S., “The Economics of Has-beens,” *Journal of Political Economy*, 2004, vol.112, 289-310

McManus, Walter, William Gould and Finis Welch. 1983. “Earnings of Hispanic Men: The Role of English Language Proficiency,” *Journal of Labor Economics*, Volume 1, Number 2, pages 101-130.

Meares, Carol Ann, “Office of Technology Policy,” *Digital Work Force*, 7-20

Mincer, Jacob and Polachek, Solomon, “Family Investments in Human Capital: Earnings of Women,” *The Journal of Political Economy*, Vol. 82, No. 2, Part 2: Marriage, Family Human Capital, and Fertility. (Mar. - Apr., 1974), S76-S108.

Neal, Derek, “Industry-Specific Human Capital: Evidence from Displaced Workers,” *Journal of Labor Economics*, 1995, vol.13, 653-677

Ong, Paul M., and Mar, Don, “Post-Layoff Earnings among Semiconductor Workers,” *Industrial and Labor Relations Reviews*, 1992, Vol. 45, 366-379

Podgursky, Michael; Swaim, Paul, “Job Displacement and Earnings Loss: Evidence from the Displaced Worker Survey,” *Industrial and Labor Relations Review*. Oct 1987, 41, (1), 17 – 29

Ruhm, Christopher J. “Are Workers Permanently Scarred by Job Displacements?” *The American Economic Review*, Vol.81, No.1 March 1991, 319

Schoeni and Dardia, “Earnings Losses of Displaced Workers in the 1990s,” RAND 1996

Shuy, R. 1981 "Conditions Affecting Language Learning and Maintenance among Hispanics in the United States," NABE Journal (National Association for Bilingual Education), Vol. 6, Number 1, pages 1-17.

Spolsky, B. 1989. "Conditions for Second language Learning," Oxford: Oxford University Press.

Stevens, Ann Huff, "Persistent Effects of Job Displacement: The Important of Multiple Job Losses," *Journal of Labor Economics*, January 1997, Vol. 15, No. 1, 165-188

Stevens, Gillian 1994 "Immigration, Emigration, Language Acquisition, and the English Language Proficiency of Immigrants in the United States," *In Immigration and Ethnicity: The Integration of America's Newest Arrivals,* Edited by Barry Edmonston and Jeffery Passel, Washington, DC: Urban Institute Press.

Swaim, Paul, and Podgursky, Michael, "The Distribution of Economic Losses among Displaced Workers: A Replication," *Journal of Human Resources*, 1991, Vol. 26, No. 4, 742-755

Topel, Robert, "Specific Capital and Unemployment: Measuring the Costs and Consequences of Job Loss," Carnegie-Rochester Conference Series on Public Policy 33, 1990, 181-214

Violante, Gianluca "Technological Acceleration, Skill Transferability and the Rise of Residual Inequality," *Quarterly Journal of Economics*, February 2002, Vol. 117(1), 297-338

Wellington, Alison J., "Changes in the Male/Female Wage Gap, 1976-85," *The Journal of Human Resources*, Vol. 28, No.2. (Spring, 1993), 383-411.

Yuengert, A.M., "Immigrant Earnings, Relative to What? The Importance of Earnings Function Specification and Comparison Points," *Journal of Applied Econometrics*, Vol. 9, No.1. (Jan. – Mar., 1994), pp.71-90