Essays on Occupation-Specific Human Capital Investment and Occupational Mobility

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Abstract

My thesis focuses on occupation-specific human capital investment and occupational mobility. The first chapter of my thesis investigates gender disparities in early-career wage returns to firm tenure, occupational tenure, industry tenure, and general labor market experience. I show that the relative importance of various types of tenure differs across genders: occupational tenure matters more than industry tenure in men's wages, while industry tenure matters more than occupational tenure for women. Averaging across all occupations, early-career wage growth associated with occupational tenure is substantially higher for men than women. I then explore the underlying reasons for gender disparities in wage growth with occupational tenure. I show that gender differences in hours of work and occupational choice partially explain the gender gap in tenure returns, but I find no evidence that gender differences in human capital investment in education prior to labor market entry contribute to the gap. Given the evidence that occupational changes tend to improve occupational match quality, the observed higher occupational mobility of men relative to women may also explain the gender gap in wage growth with occupational tenure. The second chapter examines whether negative housing equity affects homeowners' occupational mobility. Homeowners with negative equity face stricter constraints and relatively higher occupational mobility cost than renters and homeowners who are not "underwater" which might potentially limit their ability to change occupations. I don't find any strong evidence that negative equity affects homeowners' occupational mobility in recourse or non-recourse states. The third chapter examines the extent to which shifts in occupational structure explain the upward trend in occupational mobility during the period of 1968-1997. I find that shifts in occupational composition can partially explain the rising occupational mobility trend for less educated young workers and more educated workers. An approximate 10-20% reduction in the estimated mobility trend when occupation is controlled for implies that occupational composition generally shifted to less stable occupations. In addition, when negative occupational employment shocks are controlled for, workers in most age-education subgroups exhibit higher increases in occupational mobility.

Keywords: Occupation-Specific Human Capital; Occupational Mobility; Occupational Structure; Gender Gap in Wage Growth; Negative Housing Equity

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Chapter 1

The Gender Gap in Early-Career Wage Growth: Occupational Tenure Matters

1.1 Introduction

It is well documented that there are significant gender differences in wage growth in the twentieth century workforce. A recent literature has tried to identify the sources of the gender disparities in earnings dynamics. Munasinghe, Reif and Henriques (2008) argue that firm-specific tenure explains the gender gap in wage growth, and show that women experience lower wage returns to firm tenure than men. Their study is based on the view of firm specificity of human capital. However, this view has been challenged by recent studies on human capital specificity. Neal (1995) and Parent (2000) present evidence that industry-specific human capital matters more than firm-specific human capital in wage determination. The more recent studies of Kambourov and Manovskii (2009a), Sullivan (2010) and Zangelidis (2008) argue, by contrast, that occupation-specific human capital is a more important determinant of men's wage growth than firm-specific human capital. It remains an open question, however, whether gender differences in firm-, occupation-, or industry-specific human capital explain the gender gap in wage growth. In this paper I investigate gender differences in early-career wage growth in the context of the occupational and industry specificity of human capital. Specifically, I decompose wage returns into firm-specific, occupation-specific, industry-specific, and general labor market experience components. This decomposition enables me to further track the potential drivers of gender disparities in earnings dynamics.

My analysis is based on a sample of young women and men in the first two decades of their careers from the 1979 Cohort of the National Longitudinal Survey of Youth (NLSY79). A wage decomposition shows that general experience dominates firm, occupational, and industry tenures in explaining wage growth for both genders. The relative importance of various types of tenure in wage determination is not the same across genders: occupational tenure is a more important determinant of male wage growth than industry tenure, while industry tenure matters more than occupational tenure for women. It is also found that, averaging across all occupations, early-career wage growth with occupational tenure is substantially higher for men than for women.

Based on human capital theory, I then explore the underlying reasons for gender disparities in wage growth with occupational tenure. Over the career life cycle, workers make decisions on the investment in different types of human capital – firm-specific, occupation-specific, industry-specific, and general experience. These investments in human capital are potentially determined by expected labor market attachment. Women in their twenties and thirties experience life cycle events such as marriage, childbirth, and family care responsibilities that make them more prone to employment interruptions and gaps. Weaker ties to the labor market potentially influence women's investment in occupation-specific human capital through three channels. First of all, according to Becker (1985), given the traditional division of labor by gender within households, women anticipate shorter and more discontinuous work lives, thus having less incentives to invest in market-oriented formal education. Meanwhile, self-selection models (Polachek, 1981; Anker, 1997) suggest that as life cycle events result in less labor market experience, forgone training and skill depreciation, rational women should choose occupations that incur lower penalties for gaps in employment; that is, they should choose occupations with relatively high starting wages, low depreciation rates and low returns on accumulated occupation-specific experience[1]. Gender differences in occupational choice accordingly affect women's investment in occupation-specific human capital prior to their labor market entry which may take the form of gender differences in the quantity or the type of education. Women therefore tend to choose the fields of study that do not require large investments in skills that are unique to an occupation.

Secondly, as argued by Becker (1985), the greater domestic commitments of women may disadvantage women in that they put less energy into work which translates into lower wage returns. According to the 2015 American Time Use Survey by the U.S. Bureau of Labor Statistics[2], among full-time employees, women worked fewer hours than men (7.8 hours compared with 8.4 hours). With relatively lower attachment to employment, women have less incentive to invest in the skills specific to that job, and in turn work fewer hours.

Thirdly, women's human capital investment may be potentially influenced by occupational segregation. Workers choose occupations that best match their skills and also maximize the expected lifetime returns given their personal characteristics. The dual roles of women – employee and mother – may make them put more weight on non-pecuniary features of an occupation, and thus lead them to self-select into "female jobs." Besides family considerations, women's choice of occupation may also be affected by employer discrimina-

[1] However, Loprest (1992), Light and Ureta (1995), Kunze (2005), and Fitzenberger and Kunze (2005) find that women earn less from entry into their first employment.

[2] https://www.bls.gov/news.release/pdf/atus.pdf

tion. Discrimination in hiring increases the costs of working in the occupations that are not typical for women, and also reduces the incentives for women to switch away from female dominated occupations, thus stipulating the choice of occupation. In addition, discrimination in wage-setting results in the devaluation of women's work[3] (England et al. 1988; Levanon, England and Allison 2009). It has been well documented that the percentage of female workers in an occupation has negative effect on wages. Predominantly female occupations are mostly characterized by low earnings, low training, and fewer opportunities for upward mobility. Occupational segregation between men and women affects the process of job selection (Tomaskovic-Devey and Skaggs, 2002), and the characteristics of occupations that are typical for women may affect workers' decision on the investment in specific skills.

These three channels suggest that women tend to have less investment in occupation-specific human capital due to their weaker ties to the labor market. I thus explore the gender gap in wage returns conditional on such human capital factors as fields of study, hours of work, and occupational choice. My analysis suggests that gender differences in hours of work and occupational choice can partially explain the gender gap in tenure effect, but I find no evidence that gender differences in human capital investment in education prior to labor market entry contribute to the gap.

In addition to explaining the gender pay gap by looking at gender differences in human capital accumulation, I also investigate the occupation-shopping[4] hypothesis. I find that men are more likely to switch occupations than women early in their careers. As occupational changes are related to career progression for young workers, additional occupational switches tend to improve occupational matching quality. Thus, gender gaps in occupational mobility potentially explain the higher wage return to occupational tenure for men.

My work relates to the literature on human capital specificity. Some recent studies in this area have focused on the relative importance of occupation-specific and industry-specific human capital in men's wage growth. Shaw (1984) was the first to empirically demonstrate the significance of occupational investment in wage determination. Goldsmith and Veum (2002) include all forms of prior workplace experience into the wage equation, and find that prior experience in an occupation and industry both have positive and significant effects on individuals' wages. The studies of Zangelidis (2008) and Kambourov and Manovskii (2009a) suggest that once occupational experience is taken into account, firm-specific and industry-specific skills contribute relatively little to the growth of wages over the career. In addition, Zangelidis (2008) and Sullivan (2010) examine heterogeneity in human capital wage premia

[3]The debate on whether there is a true devaluation effect remains unsettled.

[4]Occupation shopping refers to the period of experimentation with occupations and accompanying high rates of occupational mobility, which typically occurs at the beginning of the career life. This search theory assumes that workers' performance in or their liking for a particular occupation cannot be perfectly predicted without actual employment experience.

across occupations. Their findings suggest that the importance of occupation-specific skills and industry-specific skills varies widely across occupations.

By contrast, relatively little attention has been paid to the human capital specificity of women. Existing empirical studies seeking to explain the gender pay gap by gender differences in human capital accumulation focus on general skills and firm-specific skills only. For example, Munasinghe, Reif and Henriques (2008) find that women invest more in general skills rather than firm-specific skills compared to their male counterparts[5]. In my work, I assess the relative importance of occupational tenure and industry tenure in wage determination for both women and men. This paper aims to extend previous studies by investigating the gender gap in wage growth in the context of occupation-specific and industry-specific human capital investment.

I organize this paper in the following way. Section 1.2 contains a description of the data. In Section 1.3, I outline the empirical specifications and present the estimation results. In Section 1.4, I investigate the underlying reasons for the gender gap in wage returns with occupational tenure. I conclude with a summary of findings and a brief discussion in Section 1.5.

1.2 Data

In this paper, I explore gender differences in the trajectories of early-career wage growth in the context of the occupational and industry specificity of human capital. My work is intended to complement the existing literature on human capital specificity and gender gap in wage growth in the U.S. in the last two decades of the twentieth century. Given these purposes, the right dataset for this study should have consistent information on labor market outcomes of young men and young women over a long period of time, especially including repeated observations on workers' job, occupation, and industry. The NLSY79 for the 1979-2000 period[6] provides the optimal data for my study, and enables me to compare my findings with those reported previously.

The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14 to 22 years of age when first surveyed in 1979. These NLSY79 youth were re-interviewed annually through 1994 and biennially thereafter[7]. In 2000, the last year in my

[5]Munasinghe, Reif and Henriques (2008) also point out that human capital hypothesis based on firm specificity of capital can explain less than 50% of the gender pay gap.

[6]Before 2000, occupations and industries in the NLSY79 survey are consistently coded with the 1970 Census codes. For the 2002, 2004 and 2006 surveys, occupations and industries are coded with the 2000 Census codes and its two revisions, respectively. To avoid the problem related to inconsistencies in codes, I restrict my analysis to the years of 1979-2000 of the NLSY79.

[7]The NLSY79 longitudinal file is constructed using information provided in the yearly interviews. The change in interview schedule has no impact on the availability of variables used in this study, but may affect

sample, the NLSY79 cohort were 35 to 43 years old. My sample is restricted to white males and females who are 18 years or older and from the nationally representative core sample. To closely follow the sample restrictions imposed in the related literature (Parent (2000) and Sullivan (2010)), I eliminate all observations that at the time of the interview were self-employed, worked less than 20 hours per week[8], employed in the government[9] or agricultural sectors, or were serving in the military. Although the NLSY79 records information about multiple jobs, only the Current Population Survey (CPS) designated job is considered in my sample because it is the main or more recent job. The wage measure in this study is hourly wage deflated by the consumer price index[10] with 1987 as the base year. To exclude erroneous wage information, I drop the observations if reported hourly wages are less than \$1 or in excess of \$100.

The NLSY employment history file contains weekly records of each respondent's labor force activities. The data provide detailed job information including the start and end date of work with a specific employer as well as employment breaks. This information allows me to construct the cumulative experience and tenure series by keeping a running tally of actual weeks worked instead of using a proxy for potential experience[11]. Tenure and overall experience are measured in years, so they are computed by dividing total actual weeks worked by 52. Although employment status is recorded at the weekly level which means that I have as many as 52 observations on tenure and experience each year, wages are observed only once per year. Given this feature of the data, only tenure and experience variables in the weeks that wages are observed are used in wage regressions. It means that

the quality of the data due to the longer recall period. See Dugoni et al. (1997) for a discussion of the effect of the switch to biennial interviews on the quality of the NLSY data.

[8]To construct tenure and experience variables, Parent (2000) and Sullivan (2010) consider only employment that the weekly hours worked are at least 20. In my study, I follow their choice of 20 hours per week as a cut off point. As a result, 4311 person-year observations (7.6% of total observations) are dropped.

[9]Kambourov and Manovskii (2008) find that occupational mobility for government workers is two times lower than the mobility of private-sector workers, and has declined substantially over the 1968-1997 period, while private-sector workers exhibit an upward trend in mobility. They explain that the observed mobility trend for government workers may be due to the changes of government regulation such as contracting out of many government-provided services which results in a change in the occupational mix employed by the government. In addition, according to survey on public sector employment statistics conducted by International Labour Organization (ILO) in 1998, in the U.S., women were more represented in the public sector (55.5%) as compared to the whole economy where women's employment as a share of total employment reached only 48.4%. In my study, in order to investigate factors causing gender differences in wage growth other than the effect of unequal representation of women in public sector employment, I follow related literature (e.g., Munasinghe, Reif and Henriques, 2008;, Kambourov and Manovskii, 2008, 2009a; Parent, 2000) to exclude the observations with government employment from the sample. For those who subsequently worked in a government job, only observations before government job are included.

[10]CPI data is from U.S. Bureau of Labor Statistics.

[11]The potential experience proxy is subject to some well-known limitations. See Kidd and Shannon (1997) for a discussion.

I have one record per worker per year, and the measure of tenure and experience for that record is the accumulated tenure and experience as of the survey week that wage is observed.

Occupational and industry affiliation data is also available for each job in the NLSY79. The 3-digit 1970 census classifications (U.S. Census Bureau 1971) are used to code occupations and industries for the 1979-2000 period. I use these codes to construct occupation and industry tenure series. Occupation (industry) tenure is simply the total amount of experience that a worker has accumulated in the current occupation (industry). To identify occupation and industry switches, I follow the common approach that an occupation or industry switch is considered to be genuine whenever a switch on the original NLSY79 data coincides with a switch of employer[12] [13]. This approach rules out within-firm mobility between occupations[14].

Table 1.1 presents summary statistics of the sample used in the estimation. There are 2,229 men and 2,253 women in the sample who contribute 23,017 and 20,879 observations respectively. The reported statistics are based on the pooled sample. As shown in this table, average age is very similar across men and women. The averages of some standard human capital measures such as completed years of schooling and AFQT scores are also similar across these two groups. Given the similar educational background, the gender difference in real hourly wage is striking. The average real hourly wages for men is $9.57 while it is only $7.45 for women. It implies that there exists an almost 30% wage premium for men. In addition, men on average accumulate more overall labor market experience as well as firm-specific, occupation-specific, and industry-specific experiences, and are more likely to work in a unionized workplace. Compared to the gender wage discrepancy, the gender differences in tenures and experience are relatively modest. On marital status and parental status, women in the sample are more likely to be married and have children than are men.

[12]This approach was proposed by Neal (1999) when he noticed that in the NLSY79 coding errors and missing data may result in a change in industry affiliation within a continuous employment spell associated with a single firm. He argues that transitions between industries within a typical firm are almost impossible because a typical firm only operates in one industry. Parent (2000) adopts the same strategy in the NLSY79 to construct industry experience variables to identify the industry specificity of human capital. Some studies exploring occupational experience identify occupation switches in the same way as they identify industry switches. Kambourov and Manovskii (2009a), for example, adopt this approach in the Panel Survey of Income Dynamics (PSID) on identifying both occupation and industry switches in the preferred specification of their wage equation.

[13]Mellow and Sider (1983) examine the extent of response errors in occupation and industry classifications by matching occupation and industry reported by employees with employer reports of their employee's occupation and industry. They find agreement rates for occupation codes are 58% and 81% at the three and one digit level. The corresponding figures for industry codes are 84% and 92%

[14]It is reasonable to think that there is considerable scope for an occupational change to occur in a typical firm. For instance, someone who starts as a tradesperson and then gradually transitions to a managerial role within a firm experiences an occupation change at some point without switching employers. Sicherman and Galor (1990) and Biddle and Roberts (1994) develop models of within-firm occupational mobility.

In the next section I present the econometric model used to explore the reasons behind the gender wage discrepancy.

1.3 Regression Specifications and Results

1.3.1 Earnings Function Estimation

In order to assess the relationship between wages and firm, occupational, and industry tenures, as well as overall labor market experience, I estimate the following standard human capital model of wage determination:

$$y_{ijmnt} = \beta_1 Exp_{it} + \beta_2 Firm\_Ten_{ijt} + \beta_3 Occ\_Ten_{imt} + \beta_4 Ind\_Ten_{int} + \beta_5 Old\_Firm_{ijt} + \gamma X_{it} + \varepsilon_{ijmnt} \quad (1.1)$$

where y_{ijmnt} is the log of the real hourly wage of individual i employed at firm j in occupation m and industry n in time period t. Exp_{it} represents overall labor market experience as of time t measured in years, $Firm\_Ten_{ijt}$ represents the firm tenure of individual i with employer j at time t, and Occ_Ten_{imt} and Ind_Ten_{int} measure tenures in the current occupation and industry, respectively. To account for nonlinear relationships between wages and the various forms of experience, the squared term of firm tenure, and the squared and cubic terms of occupation and industry tenure and overall work experience are also contained in the model. Old_Firm_{ijt} is a dummy variable that equals one if the individual is not in the first year working at the current firm, i.e. if $firm\_Ten_{ijt} > 1$, and equals zero otherwise. This dummy variable is included so that the wage response to the first year of tenure with the current firm is not restricted by the quadratic specification of the tenure profiles[15]. X_{it} is a vector of standard controls including an intercept term, education dummies[16], AFQT score, a marital status dummy, a parental status dummy, a union dummy, one-digit occupation and industry dummies, year dummies, and region dummies. In order to capture the wage effects of industry specific shocks, an interaction term between year and broad one-digit industry categories is also included in wage regressions.

In addition to the above-mentioned observed variables, unobserved individual-specific characteristics and match values on firm, occupation or industry may also affect wage outcomes. Individuals with the same overall level of experience and education would receive different wages if they differ in certain unobserved individual characteristics such as innate

[15] Altonji and Shakotko (1987), for example, finds large first year experience effects.

[16] By education, workers are categorized into four groups: those who have less than 12 years of education, those who are high school graduates, those who has some college, and those who have 16 years of education or more.

ability, drive and industriousness. Similarly, rational workers self select into firms, occupations or industries that their innate ability best matches, and individuals who have formed better matches with their employers, occupations or industries will receive higher wages than others with the same observable characteristics. Thus, the error term ε_{ijmnt} is decomposed as:

$$\varepsilon_{ijmnt} = \lambda_i + \eta_{ij} + \phi_{im} + \omega_{in} + \nu_{ijmnt} \tag{1.2}$$

where λ_i is a fixed individual effect, η_{ij} is a job match component, ϕ_{im} is the occupation match component, ω_{in} is the industry match component, and ν_{ijmnt} is the transitory component. The unobserved individual effect and match variables are assumed to be time invariant.

I start by pooling the data and estimating the econometric model (1) by using OLS. As was recognized as far back as Altonji & Shakotko (1987), wage regressions that include tenure variables are potentially affected by an endogeneity problem that the unobserved personal characteristics and match-specific components are likely to be correlated with the tenures. For example, workers with high levels of innate ability, λ_i, are expected to have more continuity of employment, accordingly accumulate more general working experience and receive higher wages. In addition, a worker in a better employer match is more likely to stay with the same employer longer and have higher wage. Similarly, a worker who has made a good occupation/industry match is expected to have higher tenure in that occupation/industry and have a higher wage. Various hypothetical correlations between these error components and the key independent variables – firm/occupation/industry tenures and overall experience – will bias the estimated wage returns to tenures and experience in a standard OLS regression. To address these potential biases resulting from match heterogeneity and individual heterogeneity, I employ the instrumental variable approach which is proposed by Altonji & Shakotko (1987). The instruments for the tenure variables are the deviations of the tenure variables around their means on a given job/occupational/industry match. For instance, let $\overline{Firm\_Ten_{ij}}$ be the average tenure of individual i during the current job spell with employer j. The instrument for individual i's firm tenure with employer j at time t, $Firm\_Ten_{ijt}$, is constructed as $\widetilde{Firm\_Ten_{ijt}} = Firm\_Ten_{ijt} - \overline{Firm\_Ten_{ij}}$[17]. Obviously, the tenure variables and their instruments are linearly dependent. And by construction, $\widetilde{Firm\_Ten_{ijt}}$ sums to zero over the years during which individual i is with employer j, it is thus orthogonal to the unobserved job match component of the error term, η_{ij}. Similarly, the squared firm tenure and the dummy variable denoting whether the individual is in the first year of a job spell are instrumented with $\widetilde{Firm\_Ten^2_{ijt}} = Firm\_Ten^2_{ijt} - \overline{Firm\_Ten^2_{ij}}$,

[17]For example, if a worker has been in a job for five years, his firm tenure with this specific employer over five years are 1, 2, 3, 4, 5, respectively, then the average $\overline{Firm\_Ten_{ij}}$=3, and the corresponding instruments $\widetilde{Firm\_Ten_{ijt}}$ over the sample years are thus -2, -1, 0, 1, 2, respectively.

and $\widetilde{Old\_Firm}_{ijt} = Old\_Firm_{ijt} - \overline{Old\_Firm}_{ij}$, respectively. The same approach are applied to the other experience variables - occupational tenure, industry tenure, and general experience - that is, these variables are instrumented with their deviations from the spell-specific averages. The objective of this instrumental variable approach is to provide tenure and experience coefficients that are more reflective of the true wage returns to tenures and experience.

As discussed in a long list of studies such as Altonji and Shakotko (1987), Topel (1991), and Altonji and Williams (2005), the instrumental variable approach outlined above does not control for all potential endogeneity biases. In specificity, this approach does not correct for possible correlations between the various tenure variables and the unobserved non-own match-specific components. There are 7 potential non-own correlations in the model[18]. General experience may be correlated with job match component η_{ij}, occupation match component ϕ_{im}, and industry match component ω_{in}. Occupational tenure may be correlated with η_{ij} and ω_{in}. Industry tenure may be correlated with η_{ij} and ϕ_{im}[19]. These correlations would cause bias in the estimation of returns to tenure and experience.

There may be positive correlations between overall experience and the unobserved job-, occupation-, or industry-specific matches. These correlations might result from job, occupation or industry shopping over the course of a career. The more general experience a worker has, the more time he shops around for the firm, occupation or industry that his innate ability best matches, the higher match values he would form when he makes an employment choice. And match values determine his wage. Failure to control for these correlations would result in an upward bias in the return to general experience and an offsetting downward bias in the returns to firm, occupation or industry tenures. A similar argument applies to the potential correlations between occupation or industry tenure and unobserved job match quality component. If higher experience in an occupation or industry is a prerequisite for a better job match, that is, high-paying employers hire workers only after they have accumulated enough human capital in that occupation or industry, then the observed wage increase should be largely attributable to higher occupation or industry tenure. However, this case cannot unveil all the reasons behind the positive correlation between occupation/industry tenure and job match quality. Shopping around within occupation or industry spells, for example, may be one factor that explains the correlation. If these correlations are failed to be controlled for, the coefficients on occupation and industry tenures would be overestimated and the coefficient on firm tenure would be underestimated. In addition, occupational shop-

[18]By construction, the instruments for various tenures are uncorrelated with the individual-specific term λ_i. I assume that workers do not switch occupations or industries within job spells, thus firm tenure is uncorrelated with occupation match component ϕ_{im} and industry match component ω_{in} in this model.

[19]Parent (2000) argues that industry tenure is unlikely to be correlated with the quality of employer matches, η_{ij}.

ping within industry spells or industry shopping within occupation spells potentially result in biased estimation of the returns to occupational and industry tenures. Currently, there is no literature providing a satisfactory approach to deal with this issue.

As I am using panel data and following the same individuals over time, the error terms within an individual would be serially correlated due to the presence of the fixed individual effect and various match components. Consequently, standard errors in the instrumented model are adjusted for clustering at the individual level.

1.3.2 Wage Returns to Tenure and Experience

Table 1.2 presents estimates of wage growth associated with various types of tenure and experience. In this study, I only report the estimated coefficients on the tenure and experience variables and some key background variables that are of direct interest. Table 1.4 reports the estimated cumulative wage returns to two, five or eight years of firm-specific, occupation-specific, or industry-specific tenures, or overall experience. I calculate these cumulative wage returns by using the coefficient estimates of the model discussed earlier including the effects of higher order terms of tenure and experience.

To explore how the inclusion of occupation and industry tenures in the analysis will influence Munasinghe, Reif and Henriques (2008)'s conclusion, I firstly run the regression in the absence of occupation and industry tenure variables, and its IV estimates are presented in column 1-2 of Table 1.2. The result implies that the effect of firm tenure on wage growth is significant for both men and women. Then, I incorporate occupational and industry tenures in the regression. The OLS estimates (column 3-4) and the IV estimates (column 5-6) of the wage parameters show that the inclusion of occupational and industry tenure drives related firm tenure variables to be insignificant for both men and women, and occupational and/or industry tenure variables are the ones that have a significant positive effect on wages. The implication is that when occupational and industry tenure are left out of the analysis, their effects on wages are erroneously attributed to firm tenure as well as overall labor market experience. This result is consistent with the literature that argues for the occupational and industry specificity of human capital[20].

The performance of the IV estimation on correcting for bias in OLS estimation depends upon the instruments' explanatory power. One common concern with an IV approach is the possible use of weak instruments, which tends to bias IV estimates towards OLS estimates. Table 1.3 reports the F-statistics based on the test of whether the instruments all

[20]Pavan (2011) uses structural estimates of a search model to empirically distinguish between the relative importance of firm tenure and career tenure for generating wage growth, where career is empirically identified as a combination of occupation and industry. Contrary to existing estimates in the literature (e.g., parent, 2000; Kambourov and Manovskii, 2009a) that wage returns for firm tenure are either negligible or negative, he finds positive wage effect of firm tenure. He argues that this is because the endogeneity problems that are not solved by the standard IV techniques employed in the literature underestimates the importance of firm-specific matches for wage growth.

have zero coefficients in the first stage equations predicting the endogenous variables. The test statistics of all twelve first stage equations for each gender are well above the critical values for weak instruments as reported by Stock and Yogo (2005). This implies that the instruments in this study are strong in the IV regressions for both men and women.

Another requirement for a valid instrumental variable is that the instrument is independent of the unobservable error process. In this study, the instruments are orthogonal by construction to individual characteristics and their own match effects. To further test for the exogeneity of these instruments, I increase the number of the excluded instruments by adding the cube of the initial instruments into the regressions, and then perform the Sargan-Hansen J test of overidentifying restrictions. The test results (Table 1.3) suggest that, in both regressions for men and women, the instruments are exogenous. Thus, the instruments in this study are valid.

As shown in Table 1.4, for men, the finding of occupational specificity of human capital is robust across both OLS and IV specifications, and robust across different periods of human capital accumulation[21]. The OLS estimates imply that the accumulation of the first five years of occupational tenure results in a wage growth of 24.3% , five years of overall experience results in a wage growth of 13.9%, while wage growth with firm tenure or industry tenure is negligible. In general, the finding that occupational tenure and general experience are the two most important factors in wage determination for men is supported by the IV estimates. However, the IV estimates indicate a substantially flatter occupational tenure slope and greater overall experience profile. The corresponding figure based upon the IV estimates is a wage growth of 12.8% for five years of occupational tenure and 27.4% for five years of overall experience. The IV estimate of the contribution of five years of occupational tenure is only half of the corresponding OLS estimate. These results indicate that the strong correlation between wages and occupational tenure observed in the OLS estimation is partially due to heterogeneity bias, especially the bias caused by the correlation between the permanent individual component of wages and the length of tenure in an occupation. In summary, the IV results indicate that the contribution of occupational tenure to wage growth is modest, while overall experience is the most important determinant of wage growth[22]. My estimates of the returns to occupational tenure for men are similar to those reported by Kambourov and Manovskii (2009a). Applying the instrumental variable methodology proposed by Altonji and Shakotko (1987) on data from the PSID, their study shows that five years of occupational experience increase wages by 11.97%. However, they don't estimate wage returns for women.

[21]The contribution of occupational tenure on wages are also examined for longer period than what is shown in Table 1.4 , e.g., ten years and twenty years of occupational tenure. The finding still holds for longer period of tenures in occupations.

[22]Using NLSY data, Schonberg (2007) also finds that general human capital plays the most important role in determining wage growth.

In my study of women, the OLS and IV estimates tell different stories about human capital specificity. The OLS estimation results reveal that both occupation and industry tenure are significant, and wage returns to industry tenure are substantially smaller than that to occupational tenure. Based on the OLS estimates, five years of occupational tenure for women are associated with a 24.3% growth in wage, while five years of industry tenure are associated with a 9.4% wage growth. However, based on the IV estimates, women's tenure with an occupation has a very weak and quantitatively low relationship with the wage. The IV estimates imply that five years of occupation experience increase women's wages by 2.7%, while five years of industry experience increase their wages by 6.2%. The IV results suggest that industry-specific human capital is relatively more important in wage determination for women than occupation-specific human capital. In addition, similar to the study of men, accompanying the smaller IV estimates of the occupational and industry tenure slope is an increase in the overall experience profile. Five years of total labor market experience raises women's wages by 30.2% in the IV estimation, while the corresponding figure in the OLS estimation is 16.4%. In the IV estimation, just like wage decomposition for men, general labor market experience is the most important determinant of the wage growth of women.

A comparison of the OLS estimates with the IV estimates shows that the proposed heterogeneity correction in the IV specification decreases the estimated wage growth associated with occupational tenure for women (for example, from 24.3% to 2.7% for five years of occupational tenure) substantially more than it does for men (24.3% to 12.8%). These findings imply that the extent of correlation between occupational tenure and individual heterogeneity as well as occupation match quality component is stronger for women, and hence heterogeneity correction increases the gender gap in wage growth associated with occupational tenure. In contrast, the changes in the industry tenure slope due to heterogeneity correction are not as substantially different across genders as that of occupational tenure. The estimated wage growth associated with five years of industry tenure for women are reduced from 9.4% in the OLS estimation to 6.2% in the IV estimation. The corresponding figures for men are 5.4% and 1.3%, respectively.

In summary, general experience dominates other types of experience in explaining wage growth for both genders. However, the relative importance of occupational and industry tenure in wage determination is not the same between men and women. In general, for men, wage growth associated with occupational tenure is higher than that with industry tenure, but *vice versa* for women. Based on the estimated five-year accumulative returns in the IV specification, in magnitude, wage growth with occupational tenure is lower for women than men, wage growth with industry tenure is higher for women than men, while wage growth with general experience is similar across genders. In particular, the estimated returns to five years of occupational tenure are about four times greater for men (12.8%) than they are for women (2.7%), and the estimated returns to five years of industry tenure are about four times greater for women (6.2%) than they are for men (1.3%). The key inference question is whether the observed gender disparities in wage growth are statistically significant. The bottom panel of Table 1.4 reports the results of the tests on gender gap in wage growth. It shows that, in the IV specification, wage growth with occupational tenure is significantly higher for men than women, while wage growth with industry tenure is not significantly higher for women than men. In addition, there is no evidence that wage growth with general experience is significantly different between men and women. This conclusion is reached under the assumption that the estimates of wage returns to tenure and experience are unbiased. However, as I discussed in Section 1.3.1, the instrumental variable approach fails to correct for all possible correlations between various tenure variables and the unobserved non-own match-specific components. Thus, this conclusion is subject to the presence of potential endogeneity biases.

1.3.3 Heterogeneity in Gender Disparities in Wage Returns across Occupations

Following the related literature, the specification of the preceding regression imposes the restriction that the wage returns to various types of tenure and experience are constant across occupations. By including the dummy variables for one-digit occupations in the wage growth equation (1), I assume that occupation only affects the wage level, not the lifecycle profile of wage growth. However, there is no reason to believe that the monetary returns to tenure and experience are the same across occupations. This is mainly because the extent to which skills required for jobs are occupation-specific, industry-specific, firm-specific, or completely general in nature varies across occupations. For instance, a doctor may be highly rewarded for his occupation-specific knowledge on medical diagnosis and treatment, while a laundry service worker probably doesn't acquire any skills that are occupation-specific. By estimating the wage equations separately for each one-digit occupation for men, Sullivan (2010) empirically demonstrates that the relative importance of tenure and experience in wage determination varies widely across occupations[23]. For example, according to his estimates, general experience is approximately twice as valuable for operatives compared to craftsmen, while occupational experience has a statistically significant effect on wages for craftsman, but not for operatives. Restricting the effects of human capital variables to be constant across occupations potentially obscures gender disparities in the specificity of skills in different occupations. At this point, it is useful to check if heterogeneity in wage returns across occupations exists for women as well, and how it affects gender disparities in tenure effects.

[23]In his regressions, within-firm occupation switches are allowed. His study shows that the estimates of occupation and industry experience effects are sensitive to the treatment of within-firm occupational mobility. When within-firm occupation switches are ruled out, human capital is primarily occupation-specific. When within-firm occupation switches are allowed, human capital is both occupation and industry-specific.

Table 1.5 shows the five-year cumulative wage returns to tenure and experience by estimating the wage equations in the IV specification separately for eight occupation classifications. Variation in wage growth with tenures and experience across occupations is found for both genders. For example, men in professional occupations realize a 21.4% wage increase after five years of general experience, which is the smallest general experience effect accruing to workers in any occupation. In contrast to professionals, salesmen experience the largest wage gains from general experience among all workers, which is 55.6% wage increase after five years of experience. This finding is consistent with those reported by Sullivan (2010). For women, substantial differences across occupations in the roles played by various types of skills are also found. These findings suggest that heterogeneity in the returns to human capital is an important feature of the wage determination process for both men and women. It also implies that the conclusion reached in Section 1.3.2 that occupational (industry) tenure is more important than industry (occupational) tenure in wage growth for men (women) doesn't hold when the specificity of human capital is not restricted to be the same across occupations.

A comparison of wage returns between men and women shows that, for each broad occupation grouping, wage growth for men associated with occupational tenure is generally higher in magnitude than that for women. However, the null hypothesis that occupational experience effects are the same across genders is not rejected at the 5% level for all occupation groupings except sales. A similar conclusion holds also for industry experience. For sales, industry-specific skill is of significantly greater importance in wage growth determination for women than it is for men. However for other occupations, there is no evidence that industry experience effects are different across genders. In summary, gender disparities in wage returns are statistically significant for sales workers, but not significant in other occupations.

1.3.4 Sensitivity of the Empirical Results to the Assumption about Within-Firm Occupational Mobility

In the model presented in Section 1.3.2, all within-firm occupation switches are treated as false transactions created by misclassification of occupations. Using NLSY79 data, Sullivan (2010) provides evidence against this strong assumption and shows that within-firm occupation switches are primarily true occupational transactions. He also finds that the relative importance of occupational tenure and industry tenure in wage determination is quite sensitive to the assumption about within-firm occupational mobility. When within-firm occupation switches are ruled out, occupation-specific capital is a far more important determinant of men's wages than industry-specific capital. However when within-firm occupational switches are allowed, occupation- and industry-specific human capital are of approximately equal importance in determining wages. In this section, I examine whether or not the empirical results derived in Section 1.3.2 is robust when the assumption about within-firm occupational mobility is relaxed.

Table 1.6 shows the estimates of cumulative wage returns to various types of tenure and experience when within-firm occupation switches are allowed. Allowing within-firm occupational mobility results in shorter occupational tenure for both genders. The estimates for specifications of the model that allow within-firm occupational switches indicate that general experience is still the most important factor in wage determination. However, for men, the relative importance of occupational tenure and industry tenure in wage determination changes. Consistent with the findings of Sullivan (2010), men's wage returns to occupational tenure get smaller and wage returns to industry tenure get bigger compared to the case that rules out mobility between occupations within a firm. For women, the empirical results that industry tenure matters more than occupational tenure in wage growth still hold when within-firm occupation switches are allowed. Hypothesis tests regarding equality of wage returns across genders show that early-career wage growth associated with five-year or eight-year occupational tenure is still substantially higher for men than for women at the 10% or 5% level respectively. It suggests that relaxing the assumption about within-firm occupation switches does not change my finding of gender disparities in human capital investment.

1.4 Gender Differences in Wage Growth with Occupational Tenure

In this section, I investigate why the specificity of human capital is different between men and women. In particular, I explore the underlying reasons why wage growth with occupational tenure is higher for men than women. This study focuses on two theories of wage growth - the human capital model, and job/occupation/industry shopping theory.

1.4.1 Gender Differences in Human Capital Accumulation

The most common approach to explaining the gender wage gap is based on the human capital model developed by Becker (1993) and Mincer (1974). The human capital model implies that the differences in wages between men and women might be derived from gender differences in human capital accumulation. There are several dimensions in which gender differences in human capital accumulation affect the gender gap in early-career wage growth with occupational tenure. First, there are differences between men and women in the investment in education prior to labor market entry. Compared to men, women are more likely to choose the fields of study that do not require large investments in skills that are unique to an occupation. Secondly, women put less effort into work that translates into lower productivity and wages. Thirdly, occupational sex segregation lock women in low pay occupations. I discuss each of these in turn below.

Gender Differences in Initial Occupational Choice

Let's first consider gender differences in human capital investment prior to labor market entry. As discussed before, due to expected lower labor market attachment, women have less incentives to invest in market-oriented formal education (Becker, 1985; Polachek, 1981; Anker 1997). For example, women are more likely to enter occupations such as clerical and service work that do not require large investments in skills that are unique to an occupation. In contrast, men tend to concentrate in career-oriented fields of study such as engineering, law, and medicine. Brown and Corcoran (1997) and Black et al. (2008) document gender differences in subject of degree for college graduates in the US, and argue that occupational segregation is related to gender differences in schooling content.

To capture gender differences in human capital investment prior to labor market entry, I examine if there exist gender differences in the quantity or the type of education. In terms of the quantity of education, the observed gender differences in years of schooling (shown in Table 1.1) do not favor men. For the type of education, I follow relevant literature (e.g., Manning and Swaffield, 2008) to use the occupation of the first job as a proxy for a worker's field of study. The indexes of occupational investment intensity quoted from Shaw (1987) and the distribution of initial occupation by gender are shown in Table 1.7. The information on initial occupation distributions reveals sizeable gender differences in which 35.29% of women first enter clerical occupations compared to 9.12% of men and 24.05% of women first enter service occupations compared to 10.98% of men. The common jobs men first do are craft, operatives and labor work. 17.99% of men choose to be craft workers as their first jobs compared to only 1.92% of women, 21.05% of men enter the occupation of operatives compared to 9.31% of women, and 14.85% of men start their careers by doing labor work compared to 2.36% of women. According to the indexes of the intensity of occupational investment, the common jobs men first do (craft and operatives) require larger investment in occupation-specific skills than do the common jobs women first do (clerical and service work). These observations are consistent with the arguments of Becker (1985) and self-selection models.

The evidence of Fitzenberger and Kunze (2005) shows that women are more likely to be locked in their initial low-pay occupations as they exhibit less occupational mobility than men. This finding implies that the influence of gender differences in initial occupational choice tends to be persistent over experience, and thus potentially results in a gender gap in career choices. To examine if the gender gap in wage growth with occupational tenure is partially attributed to gender differences in initial human capital investment, I estimate wage growth with controls for the occupation in the first job. Specifically, based on the intensity index in Table 1.7, initial occupations are classified into two categories: initial occupations with high intensity occupational investment, which include professionals, managers and craft, and initial occupations with low intensity occupational investment, which include sales, clerical, operatives, labor and service. I firstly estimate the model separately for each category of initial occupation. The estimated five-year cumulative wage growth is shown in Table 1.8. Similar to the results for the whole sample, five-year occupational tenure increases men's wages significantly in each initial occupation subgroup, while wage growth with occupational tenure for women is not significantly different from zero. The results of the hypothesis tests on the equality of wage growth across genders suggest that wage growth with occupational tenure is significantly higher for men than for women at a 10% level even after controlling for initial occupation. The gender differences in wage growth with occupational tenure for both initial occupation subgroups are not quite different from the one observed for the whole sample. Gender differences in initial occupation do not seem to be able to explain much of the gender gap in early career wage growth associated with occupational tenure.

However, the evidence shown in Table 1.8 does not take into account the gender differences in the distribution of initial occupation. Assuming that initial occupation affects not only wage level but also wage growth with tenures, I include a dummy variable for each category of initial occupation and its interaction with various tenure variables in the wage growth regression for the whole sample. The results are summarized in Table 1.9. The coefficients on initial occupation and its interactions with tenure variables are jointly significantly different from zero. When it comes to explaining gender differences in wage growth with occupational tenure, initial occupation has little explanatory power. Associated with five-year occupational tenure, the predicted gender gap in wage growth only falls from 10.1% to 9.4% after controlling for initial occupation. The results of statistical significance tests show that the gender gap in wage growth with occupational tenure still exists, and does not shrink significantly with controls for initial occupation. This result suggests that gender differences in type of education and associated initial occupational choice do not contribute to the gender gap in wage growth with occupational tenure. This conclusion is consistent with the findings of Manning and Swaffield (2008) and Machin and Puhani (2003) that field of study can explain a sizeable part of the gender wage gap in the UK but has little explanatory power on the gender gap in wage growth.

Gender Differences in Hours of Work

It is also suggested by Becker (1985) that the greater domestic commitments of women may disadvantage women in that they put less effort into work that translates into lower productivity and wages. As shown in Table 1.10, men work more hours per week than women. This substantial gender differential still holds even when controlling for marriage status, parental status, or schooling. To take a closer look, I divide workers into two groups: those who work part time (i.e. less than 35 hours per week) and those who work full time (more than 35 hours per week). My data show that women are more likely to work part time than men: 21% of women work part time compared to 8% of men. Among part-time workers, average working hours of women is not significantly different from that of men. Among full-time workers, men work more hours than women. These statistics suggest that gender differences in hours of work are not only due to women's greater likelihood of working part time, but also due to the fact that, among full-time workers, men work longer than women[24].

To examine if gender differences in hours of work are able to explain the gender gap in early-career wage growth, I firstly estimate the model separately for part-time and full-time employees. The predicted wage growth with tenures and experience are shown in Table 1.11. For both men and women who work part time, overall experience is still the most important determinant of wage growth, but the contribution of occupational tenure to wage growth is not significant. There is no evidence that wage growth with occupational tenure is higher for male part-time workers than for their female counterparts. In contrast, for full-time workers, occupational tenure can explain a significant part of wage growth for men, and there exists a gender gap in wage growth associated with five-year occupational experience. When I further divide full-time workers into those who work 35-45 hours per week and those who work more than 45 hours per week, and estimate the model for each group, the implied gender gap in wage return with occupational tenure shrinks and becomes insignificant. Thus, it seems that gender differences in hours of work can partially explain the gender gap in wage returns.

To further illustrate the contribution of hours of work on the gender gap in wage growth, I include controls for hours of work and their interactions with all tenure terms in the regression for the whole sample. I take two approaches to controlling for hours of work. Firstly, I use a categorized measure of hours of work. Based on hours of work, workers are classified into three groups: those who work less than 35 hours per week, those who work 35-45 hours per week, and whose who work more than 45 hours per week. Secondly, I use a continuous measure of hours of work. The estimation results are presented in Table 1.12. The implied gender gap in wage growth with occupational tenure significantly shrinks and becomes statistically insignificant after controlling for hours of work in either approach. It suggests that the observed gender gap in wage growth can be partially attributed to gender differences in hours of work.

[24]Note that my sample is restricted to those who worked at least 20 hours per week. Due to this restriction, 1349 observations for male workers (4.6% of the sample for men) and 2962 observations for female workers (10.8% of the sample for women) are dropped. The greater gender differential in hours of work is observed when this restriction is removed. As it turns out, average weekly hours of work for those who work no more than 20 hours per week are 11.31 hours for men versus 11.40 hours for women, average weekly hours of work for those who work part time (i.e. work no more than 35 hours per week) are 20.47 hours for men versus 20.68 hours for women, and average weekly hours of work for the whole sample are 42.37 hours for men versus 35.27 hours for women.

Occupational Sex Segregation

As men invest more in human capital than women and are more attached to the labor market, they are selected into occupations with higher specific training and higher wage growth, resulting in occupational segregation (Barron et al., 1993; Kuhn, 1993; Royalty, 1996). Over decades, even though women have made continuous progress in occupational integration through the dramatic increase in labor force participation, catch up in educational attainment, battles against discrimination in hiring and wage setting, and so on, the marked difference in the occupational distribution of men and women continues to characterize the labor market. U.S. Bureau of Labor Statistics 2013 shows that three in four workers in education and health services are women, nine in ten workers in the construction industry and seven in ten workers in manufacturing are men. In the literature on gender inequality, occupational sex segregation has received much attention[25]. "Female jobs" are normally characterized by low earnings, low training, and fewer opportunities for upward mobility. The inverse relationship between earnings and the proportion of females employed in an occupation has been well documented (Blau and Beller, 1988; Groshen, 1991; Kilbourne et al., 1994; MacPherson and Hirsch, 1995; Sorenson, 1990). It is also found that both men and women suffer a wage penalty in predominantly female occupations (Hegewisch and Harmann, 2014).

As men and women are not equally distributed across occupations, and the specificity of skills varies widely across occupations, I then examine if the observed gender differences in tenure effects are attributed to occupational sex segregation. Following Rose and Hartmann (2004) and Hegewisch et al. (2010), I divide occupations into three different categories based on the gender composition of three-digit occupations[26] – "female dominated occupations", where women are at least 75% of workers; "sex integrated occupations", where women are fewer than 75% but more than 25% of workers; "male dominated occupations", where women are fewer than 25% of workers. My sample (Table 1.13) shows that female dominated occupations employ 46.6% of all women, but only around one in twenty men (5.3%) work in the female dominated occupations. The similar imbalance holds for male dominated occupations. Only 5.6% of all women but 47.6% of all men work in these "male jobs". The remaining workers have work experience in mixed-gender occupations. Table 1.13 also shows some sample occupations based on occupational sex segregation. Among the professional occupations, occupations such as nurses and elementary and secondary school

[25] For example, the 1963 report of the President's commission on the Status of Women states:"The difference in occupational distribution of men and women is largely responsible for the fact that in 1961, the earnings of women working full time averaged only about 60% of those of men working full time."

[26] The gender composition of each occupation for the period 1979-1984, 1985-1994, and 1996-2000 is measured by using IPUMS 1980, 1990, and 2000, respectively. The crosswalk used in this study is based on the crosswalks constructed by the Census Bureau (https://usa.ipums.org/usa/volii/occ_ind.shtml).

teachers are female dominated, while occupations such as engineers and science technicians are male dominated. The occupation of craftsmen are mainly male dominated. Among the occupations of clerical and service workers, occupations are either female dominated (e.g., secretaries, waiters) or sex-integrated (e.g., storekeepers, cooks).

Table 1.14 summarizes the cumulative returns to five years of occupation-, industry-, and firm-specific experience, and general experience in each occupation category. Allowing wage effects to vary across occupation categories enables me to investigate whether the features that characterize female dominated occupations discourage women from having similar investment in occupation-specific skills as men. The estimates show that general experience is most valued for both genders in each occupation category. In sex integrated occupations, human capital accumulates primarily at the level of occupations for men, but at the level of industry for women. However, this pattern of human capital specificity is not observed in other occupation categories. In female dominated or male dominated occupations, neither occupational tenure nor industry tenure has a statistically significant effect on wage growth. The middle section of Table 1.14 presents the results of hypothesis tests on the equality of wage growth across genders conditional on occupational feminization. In sex integrated occupations, wage growth with occupational tenure is significantly higher for men than it is for women. But there is no evidence that a gender gap in wage returns exists in female dominated or male dominated occupations. This result is consistent with the prediction of theories of women's self-selection into "female jobs".

I also test if tenure effects differ across occupation categories. The null hypothesis that wage growth with occupational tenure is equal across female dominated occupations and sex integrated occupations is rejected at the 5% level for men. This test result suggests that occupational sex segregation can explain, at least partially, the observed gender differences in wage returns to occupational tenure.

In summary, the evidence presented in this section suggests that gender differences in hours of work and occupational choice can partially explain the gender gap in early career wage growth with occupational tenure. But I find no evidence that gender differences in human capital investment in education prior to labor market entry play a role in explaining the gap.

1.4.2 Occupational Mobility, Occupational Match Quality

Occupation switching is one of the defining characteristics of the careers of young workers. Workers possess a set of differentiated skills, and occupations are production units that make use of different combinations of these skills. The task of choosing an occupation is to match with an occupation that best utilizes a worker's skills. However, due to information incompleteness, occupation match quality is an experience-good and not known ex ante. By trying different occupations, workers gradually learn through their labor market experience what type of occupations best suit them. Occupational change thus plays an important role in the process of occupational matching, especially for young workers (Fitzenberger and Spitz, 2004). As shown by Guvenen et al. (2015), occupational match quality[27] raises both the level and the growth rate of the wage of a worker, and conditioning on the initial match quality, additional occupation switches tend to improve the match.

I therefore argue that, given that additional occupation switches tend to improve occupational match quality, if the occupational mobility rate for men is higher than for women in their early careers, this might partially explain why we observe lower wage growth with occupational tenure for women. Table 1.15 shows annual average occupational mobility rates for my NLSY sample for years 1979-1993[28]. Preliminary data analysis shows that for those who are single or those who don't have kids, women are less likely to switch occupations than their male counterparts. To further examine if there exist gender differences in occupational mobility, I run a probit regression to check the effects on occupational mobility of a set of explanatory variables including gender dummy, marital status and its interaction with gender, parental status and its interaction with gender, education and its interaction with gender, age, age squared, overall working experience, occupational tenure, year/region dummies, and one-digit occupation/industry dummies. The probit estimates for the full sample are shown in column (1) of Table 1.16. The significant coefficient of the female indicator variable confirms that the occupational mobility rate of single childless women is lower than their male counterparts. In addition, the regression result shows that the gender disparity in occupational mobility also exists for those who have kids. However, the changes in occupational mobility rates due to marriage are not the same between men and women. Married women are not less mobile than men.

Note that career progression is not the only reason for occupational change. Some occupational changes are more closely related to family considerations such as marriage and fertility decisions. Greater domestic commitment of women (specially married women with dependent children) leads them put more weight on non-pecuniary features when they choose occupations. Using data for Portugal, Crespo et al (2014) find that women have a lower probability of upward mobility and a higher probability of downward mobility than men. As some occupational changes are not in pursuit of career advancement, they may not result in higher occupational matching quality.

My data do not provide direct information on the reasons which lead to an occupational change. However, there are other ways to help to reduce the proportion of occupational changes potentially related to family considerations. First, I restrict the sample to workers who are at most 25 years old. The exclusion of relatively older workers ensures that not many

[27]Guvenen et al. (2015) measures occupational match quality as the distance between a worker's strengths and those required by his occupation.

[28]Since 1994, the respondents of NLSY79 were interviewed every two years. Observations starting from 1994 are thus excluded from the calculation of annual occupational mobility rate.

workers have stepped into their marriage and/or prime child-bearing years. The estimation results for this subsample are shown in column (2) of Table 1.16. Second, my data collected information on the reasons why the workers left their last jobs. This helps me to identify if workers left their jobs for family related reasons such as getting married, having children, rather than establishing themselves in a career. As within-firm occupation switches are not allowed in my model, I thus exclude those who switch occupations accompanying with a job change for family reasons. The regression result for this subsample is listed in column (3) of Table 1.16. In both regressions, the coefficient of the female indicator variable is still negative and significant, and the coefficient of the interaction term between parental status and female indicator become insignificant. These results suggest that men indeed switch occupations in search of career advancement more frequently than women during their early careers no matter if they are married or have kids. My finding is consistent with the results of studies on gender differences in occupational mobility rates. Maltseva (2005), for example, shows that women have lower occupational mobility rates than men. By using a West-German sample of young workers, Fitzenberger and Kunze (2005) also find that occupational mobility at the 2-digit level is lower for women than for men during the first ten years of working experience.

Note that the incidence of occupational switching related to career progression is not the only element determining occupational matching quality. It is likely that search effort for new occupations is systematically different between men and women. Moreover, due to greater domestic commitment, women may value other non-pecuniary dimensions of occupations more than men, then even the same levels of search effort are unlikely to generate comparable occupational matching across women and men given their specific skills. One implication of lower levels of occupation search effort and placing relatively more weight on non-pecuniary characteristics of occupations is that wage gains due to occupational changes should be smaller for women than for men. Using a West-German sample of young workers with apprenticeship training, Fitzenbergery and Kunze (2005) provide supportive evidence that wage gains due to occupational changes are higher for men than for women. Reshid (2016) also find significant lower wage growth effects of upward occupational mobility for young women in Sweden. All of these findings support my argument that the observed higher occupational mobility of men relative to women may contribute to the gender gap in wage growth with occupational tenure.

1.5 Conclusions

Previous research on gender gap in wage returns is based on the view of firm specificity of human capital. However, this view has been challenged by recent studies on the human capital accumulation process showing that, when occupational and industry experience is taken into account, the wage effect of firm tenure becomes negligible. In this paper, I examined gender differences in wage growth in the context of occupational and industry specificity of human capital. Specifically, I presented an empirical analysis of gender differences in wage returns to firm tenure, occupational tenure, industry tenure, and overall labor market experience.

My data are derived from NLSY79, covering the period between 1979 and 2000. In order to control for unobserved individual heterogeneity and match heterogeneity, I employed the instrumental variable approach proposed by Altonji and Shakotko (1987). A wage decomposition analysis shows that general experience dominates other types of tenure in explaining wage growth for both genders. The relative importance of various types of tenure in wage determination differs across genders: occupational tenure matters more than industry tenure in men's wages, while industry tenure matters more than occupational tenure for women's wages. It is also found that, averaging across all occupations, early-career wage growth with occupational tenure is substantially higher for men than it is for women.

I then explore the underlying reasons for gender disparities in wage growth with occupational tenure. My analysis shows that gender differences in hours of work and occupational choice can partially explain the gender gap in tenure effect, but I find no evidence that gender differences in human capital investment in education prior to labor market entry contribute to the gap. Given the evidence that additional occupation switches tend to improve occupational match quality, I argued that the observed higher occupational mobility for men compared to their female counterparts can also potentially explain the gender gap in early-career wage growth with occupational tenure.

As discussed in the previous section, the IV approach fails to control all possible correlations between various types of tenure and experience and non-own match-specific components. Extensive research on controlling for heterogeneity biases is imperative to facilitate the study in this field. In addition, my empirical analysis could be extended by exploring gender disparities in wage gains upon occupation switching, or by introducing instruments for women's expected commitment to labor market. For example, women's expectation on occupational duration, future labor market participation, and the timing of marriage and childbearing can be utilized to refine my study. A better understanding of women's work expectations will help further track the drivers of gender disparities in earnings dynamics.

In the U.S., educational, employment, and family building circumstances has significantly changed in the past several decades. Current population survey time trend data show that in 1990, when the NLSY79 cohort were ages 25-33, 23.7% of men and 22.8% of women who were 25 years or older had completed high school or college. While in 2009, when the NLSY97 cohort were ages 25-29, the corresponding number for men was 26.6% and the corresponding number for women had substantially increased to 34.8%. Over the same period, labor force participation among women increased while labor force participation among men decreased. Significant progress on gender equality in occupation and industry has also been observed during the past decades. For example, in recent years, women outnumbered men in U.S. law schools and medical schools. The continuous progress women have made on education and employment together with the changing living arrangements would change their wage trajectories over time. Therefore, the findings of this paper are specific to the 1980s and 1990s and might no longer be relevant today. To explore gender gap in wage growth in recent cohorts, it would be desirable to reexamine the wage trajectories of men and women by using more recent data, e.g., the NLSY97.

Table 1.1: Key Variables and Descriptive Statistics.

	Male	Female
Real Hourly Wage	$9.57	$7.45
	(5.88)	(4.40)
Overall Experience	6.85	6.26
	(5.31)	(4.81)
Firm Tenure	3.26	2.99
	(3.69)	(3.50)
Occupational Tenure	3.43	3.14
	(3.75)	(3.56)
Industry Tenure	3.43	3.17
	(3.77)	(3.59)
Age	27.30	27.22
	(5.67)	(5.72)
Years of Education	13.48	13.68
	(2.48)	(2.28)
AFQT score	56445.81	55965.40
	(27716.86)	(25713.74)
Percent Married	0.45	0.50
	(0.50)	(0.50)
Percent Have Children	0.38	0.43
	(0.49)	(0.49)
Percent Unionized	0.15	0.08
	(0.36)	(0.28)
number of Individuals	2229	2253
number of Observations	23017	20879

Notes: The data come from the NLSY79 for the period between 1979 and 2000. The sample is restricted to white males and females from the nationally representative core sample, aged 18 and older. Only the CPS designated job is considered. Those who report being self-employed, being in the military, or being employed in government or agricultural sector are excluded. I also eliminate all observations if reported hourly wages are less than $1 or in excess of $100. Standard deviations are in parentheses.

Table 1.2: Earnings Functions Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	IV		OLS		IV	
	Male	Female	Male	Female	Male	Female
Overall experience	0.062***	0.062***	0.028***	0.030***	0.058***	0.058***
	(0.007)	(0.006)	(0.003)	(0.005)	(0.007)	(0.006)
Overall exp.^{2}/100	-0.188***	-0.194***	-0.058***	-0.050	-0.172***	-0.162***
	(0.027)	(0.035)	(0.010)	(0.038)	(0.027)	(0.040)
Overall exp.^{3}/10000	0.140***	0.252***	0.023***	0.011	0.126***	0.175*
	(0.027)	(0.066)	(0.005)	(0.078)	(0.026)	(0.081)
Firm tenure	0.005	0.007	-0.009	-0.027***	-0.010	-0.009
	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.006)
Firm ten.^{2} /100	-0.072**	-0.076***	0.054	0.090*	-0.001	-0.015
	(0.026)	(0.022)	(0.050)	(0.043)	(0.044)	(0.034)
Old firm	0.017*	0.014*	0.010	0.022**	-0.004	0.006
	(0.008)	(0.007)	(0.009)	(0.008)	(0.010)	(0.007)
Occupational tenure			0.074***	0.055***	0.041***	0.004
			(0.010)	(0.008)	(0.010)	(0.008)
Occ. ten.^{2} /100			-0.732***	-0.256**	-0.417**	0.021
			(0.135)	(0.089)	(0.135)	(0.073)
Occ. ten.^{3} /10000			2.255***	0.162	1.385*	-0.189
			(0.523)	(0.223)	(0.551)	(0.178)
Industry tenure			0.013	0.034***	0.000	0.024**
			(0.010)	(0.009)	(0.011)	(0.008)
Ind. ten.^{2} /100			-0.034	-0.322***	0.034	-0.231**
			(0.133)	(0.092)	(0.128)	(0.076)
Ind. ten.^{3} /10000			-0.288	0.948***	-0.332	0.696***
			(0.485)	(0.244)	(0.472)	(0.198)
Marital status	0.101***	0.036***	0.087***	0.032***	0.099***	0.036***
	(0.012)	(0.010)	(0.011)	(0.009)	(0.012)	(0.010)
Parental status	0.021	-0.090***	0.028*	-0.088***	0.023	-0.089***
	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)
Constant	1.838***	1.550***	1.809***	1.711***	1.836***	1.592***
	(0.058)	(0.089)	(0.055)	(0.113)	(0.057)	(0.098)
Observations	23017	20879	23017	20879	23017	20879
Individuals	2229	2253	2229	2253	2229	2253
adj. R^2	0.276	0.430	0.454	0.448	0.316	0.434

Notes: Control variables include marital status, parental status, education dummies, AFQT score, union status, occupational tenure, industry tenure, firm tenure, general experience, region dummies, year dummies, one-digit occupation/industry dummies, and interactions between year and one-digit industry dummies. The model is estimated separately for men and women. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.3: Specification Test for the Validity of Instrumental Variables

	Male	Female
Testing for Weak Instruments:		
(F-statistics in the First Stage Regressions)		
Overall experience	138.20 (0.000)	494.33 (0.000)
Overall experience^2	1100.50 (0.000)	2573.06 (0.000)
Overall experience^3	2914.57 (0.000)	14016.30 (0.000)
Firm tenure	970.70 (0.000)	1181.92 (0.000)
Firm tenure^2	1011.88 (0.000)	1277.07 (0.000)
Old firm	10746.48 (0.000)	11582.86 (0.000)
Occupational tenure	1000.33 (0.000)	1432.39 (0.000)
Occupational tenure^2	1133.73 (0.000)	2729.48 (0.000)
Occupational tenure^3	964.49 (0.000)	16174.71 (0.000)
Industry tenure	1013.33 (0.000)	1268.03 (0.000)
Industry tenure^2	1089.20 (0.000)	1568.59 (0.000)
Industry tenure^3	931.84 (0.000)	3113.69 (0.000)
Sargan-Hansen J Test:		
χ^2 (p-value)	2.962 (0.0853)	0.248 (0.6184)

Notes: Degree of freedom of first stage F-test is 12. P-values are in parentheses. The null hypothesis of Sargan-Hansen J test is that the overidentifying restrictions are valid, i.e., all instruments are uncorrelated with the error term.

Table 1.4: Cumulative Wage Returns to Tenure and Experience.

Cumulative wage returns:	2 years		5 years		8 years	
	Male	Female	Male	Female	Male	Female
A) OLS						
Overall experience	0.057***	0.069***	0.139***	0.164***	0.216***	0.249***
Firm tenure	-0.007	-0.028*	-0.028	-0.083**	-0.038	-0.121***
Occupational tenure	0.130***	0.106***	0.243***	0.243***	0.272***	0.339***
Industry tenure	0.024	0.052**	0.054	0.094**	0.074	0.102*
Total returns	0.213***	0.210***	0.450***	0.452***	0.597***	0.621***
B) IV						
Overall experience	0.111***	0.125***	0.274***	0.302***	0.426***	0.460***
Firm tenure	-0.027*	-0.010	-0.062**	-0.035	-0.095**	-0.063*
Occupational tenure	0.070***	0.010	0.128***	0.027	0.142***	0.042
Industry tenure	0.004	0.035*	0.013	0.062*	0.020	0.067
Total returns	0.162***	0.163***	0.366***	0.369***	0.503***	0.521***

Hypothesis tests:
H_0: returns to various types of experience equal across genders.

	2 years	5 years	8 years
	χ^2 statistic (p-value)	χ^2 statistic (p-value)	χ^2 statistic (p-value)
A) OLS			
Overall experience	2.23 (0.136)	2.05 (0.152)	1.70 (0.193)
Firm tenure	1.18 (0.278)	2.47 (0.116)	3.26 (0.071)
Occupational tenure	1.02 (0.313)	0.00 (0.999)	1.06 (0.304)
Industry tenure	1.64 (0.200)	0.84 (0.360)	0.25 (0.618)
Total returns	0.06 (0.805)	0.01 (0.943)	0.45 (0.503)
B) IV			
Overall experience	1.66 (0.198)	1.31 (0.253)	0.93 (0.335)
Firm tenure	0.91 (0.341)	0.67 (0.413)	0.60 (0.440)
Occupational tenure	7.97 (0.005)	6.10 (0.014)	3.69 (0.055)
Industry tenure	1.98 (0.160)	1.42 (0.234)	0.84 (0.360)
Total returns	0.01 (0.906)	0.02 (0.885)	0.27 (0.601)

Notes: The accumulative wage returns are expressed as changes in wages, and are calculated based on the coefficient estimates in pooled regressions for men and women, with all controls interacted with sex except region dummies, year dummies, one-digit occupation/industry dummies, and interactions between year and one-digit industry dummies. Hypothesis tests test the null hypothesis that wage returns to various types of specific human capital are the same across genders. For example, wage growth with five-year firm tenure are the same across genders. Standard errors are in parentheses. *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level, respectively.

Table 1.5: Five-year Cumulative Wage Returns to Tenure and Experience by One-Digit Current Occupation

		male	female
Professionals	overall experience	0.214***	0.325***
	firm tenure	-0.088	-0.123*
	occupational tenure	0.138	0.058
	industry tenure	0.036	0.089
	observations	3142	3538
Managers	overall experience	0.396***	0.458***
	firm tenure	-0.062	0.098
	occupational tenure	0.130	-0.029
	industry tenure	0.000	-0.011
	observations	3039	2407
Sales	overall experience	0.556***	0.374***
	firm tenure	0.080	0.205
	occupational tenure	0.326*	-0.195
	industry tenure	-0.301**	0.147
	observations	1444	1311
Clericals	overall experience	0.330***	0.260***
	firm tenure	-0.181	0.007
	occupational tenure	0.290	0.054
	industry tenure	0.104	0.032
	observations	1784	7109
Craft	overall experience	0.324***	0.503***
	firm tenure	-0.078	-0.003
	occupational tenure	0.065	-0.113
	industry tenure	0.103	0.214
	observations	5200	459
Operatives	overall experience	0.224***	0.193**
	firm tenure	0.016	0.008
	occupational tenure	-0.051	-0.169
	industry tenure	0.106	0.253
	observations	4380	1846
Laborers	overall experience	0.456**	0.378**
	firm tenure	0.093	-0.028
	occupational tenure	0.058	0.114
	industry tenure	-0.113	-0.057
	observations	2175	403
Service	overall experience	0.379***	0.343***
	firm tenure	-0.265*	-0.120
	occupational tenure	0.101	0.040
	industry tenure	0.097	0.032
	observations	1853	3806

Notes: The five-year accumulative wage returns are expressed as changes in wages, and calculated based on the IV estimates for each one-digit occupation category. *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level, respectively.

Table 1.6: Cumulative Wage Returns to Tenure and Experience, Under the Assumption that Within-Firm Occupation Switches are allowed.

Descriptive Statistics:

	Male	Female
Occupational tenure	1.65	1.70
	(1.82)	(2.00)

Cumulative wage returns in the IV specification:

	2 years		5 years		8 years	
	Male	Female	Male	Female	Male	Female
Overall experience	0.113***	0.125***	0.277***	0.303***	0.429***	0.462***
Firm tenure	-0.011	-0.004	-0.029	-0.021	-0.051	-0.043
Occupational tenure	0.019	-0.004	0.047*	-0.003	0.069**	-0.001
Industry tenure	0.042**	0.041**	0.075**	0.077**	0.080*	0.088**

Hypothesis tests:
H_0: returns to various types of experience equal across genders.

	2 years	5 years	8 years
	χ^2 statistic (p-value)	χ^2 statistic (p-value)	χ^2 statistic (p-value)
Overall experience	1.47 (0.225)	1.16 (0.281)	0.86 (0.355)
Firm tenure	0.14 (0.704)	0.07 (0.788)	0.05 (0.831)
Occupational tenure	1.50 (0.220)	3.80 (0.051)	4.51 (0.034)
Industry tenure	0.00 (0.947)	0.00 (0.961)	0.04 (0.851)

Notes: The accumulative wage returns are calculated based on the IV estimates in the analysis with the assumption that within-firm occupation switches are allowed. Standard errors are in parentheses. *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level, respectively.

Table 1.7: The Intensity of Investment in Occupational Skills and the Distribution of Initial Occupation

	Intensity of occupational investment			Distribution of initial occupation	
	SVP	TQ	Shaw Index	male	female
Professionals	4.38	2.64	0.49	12.43%	13.55%
Managers	4.29	2.71	0.62	7.27%	5.33%
Sales	0.57	0.81	0.52	6.31%	8.18%
Clericals	0.78	1.40	0.43	9.12%	35.29%
Craft	2.53	2.58	0.76	17.99%	1.92%
Operatives	0.98	0.66	0.47	21.05%	9.31%
Laborers	0.44	0.63	0.20	14.85%	2.36%
Service	0.70	1.10	0.24	10.98%	24.05%

Notes: The indexes of the intensity of occupational investment are quoted from Shaw (1987). The SVP is the Standard Vocational Preparation "indicating the amount of time required to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job", estimated by the Bureau of Employment Security. The TQ is the mean response to the question "on a job like yours how long would it take the average new person to become fully trained and qualified?", asked in the Panel Study of Income Dynamics survey. The Shaw Index is the proxy for occupational investment intensity estimated by Shaw (1984, 1987). Three indexes are highly correlated. Percentage distributions of workers by initial occupation are measured for each gender by using the data from the NLSY79 for the period 1979-2000.

Table 1.8: Five-year Cumulative Wage Returns to Tenure and Experience, by the Intensity of Occupational Investment

	whole sample		Initial occupations with high intensity occupational investment (professionals, managers, craft)		Initial occupations with low intensity occupational investment (sales, clerical, operatives, labor, service)	
	male	female	male	female	male	female
Overall experience	0.274***	0.302***	0.241***	0.329***	0.305***	0.330***
Firm tenure	-0.062**	-0.035	-0.103**	-0.070	-0.041	-0.022
Occupational tenure	0.128***	0.027	0.105*	-0.040	0.124**	0.029
Industry tenure	0.013	0.062*	0.094	0.140*	-0.018	0.046
Observations	23017	20879	7417	3608	15600	17271

Hypothesis tests:
H_0: Wage growth with various types of experience equal across genders.

	whole sample	High intensity	Low intensity
	χ^2 statistic (p-value)	χ^2 statistic (p-value)	χ^2 statistic (p-value)
Overall experience	1.31 (0.253)	2.23 (0.136)	0.78 (0.378)
Firm tenure	0.67 (0.413)	0.27 (0.605)	0.22 (0.637)
Occupational tenure	6.10 (0.014)	4.49 (0.034)	3.57 (0.059)
Industry tenure	1.42 (0.234)	0.33 (0.568)	1.79 (0.180)

Notes: The five-year accumulative wage returns are calculated based on the IV estimates in pooled regressions for men and women. The models are estimated for whole sample at first, and then estimated separately by the intensity of investment in occupational skills. Based on the intensity index in Table 1.7, initial occupations are classified into two categories: initial occupations with high intensity of occupational investment, which include professionals, managers and craft, and initial occupations with low intensity of occupational investment, which include sales, clerical, operatives, labor and service. Standard errors are in parentheses. *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level, respectively.

Table 1.9: Gender Differences in Five-year Cumulative Wage Returns to Tenure and Experience, With Controls for the Intensity of Occupational Investment

	No controls for the intensity of occupational investment	with controls for the intensity of occupational investment
Gender gap in wage growth (men-women) with:		
Overall experience	-0.028	-0.056*
Firm tenure	-0.027	-0.012
Occupational tenure	0.101*	0.094*
Industry tenure	-0.049	-0.060
controls for initial occupation		p-value=0.000

Hypothesis tests:
H_0: Gender gap in wage growth with various types of experience do not change after controlling for the intensity of occupational investment.

	χ^2 statistic (p-value)
Overall experience	60.33(0.000)
Firm tenure	2.99 (0.084)
Occupational tenure	1.07 (0.301)
Industry tenure	1.00 (0.316)

Notes: Gender differences in five-year accumulative wage returns are calculated based on the IV estimates in pooled regressions for men and women, with controls for the intensity of occupational investment. Standard errors are in parentheses. *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level, respectively.

Table 1.10: Hours of Work Per Week by Gender, NLSY 1979-2000

	Male	Female
overall	43.59	38.22
	(9.81)	(8.43)
Unmarried	42.05	38.62
	(10.26)	(8.85)
Married	45.45	37.81
	(8.91)	(7.97)
No Children	42.39	38.77
	(9.88)	(8.37)
Have Children	45.55	37.47
	(9.37)	(8.47)
High school or less	43.48	38.01
	(9.09)	(7.78)
More than High school	43.71	38.40
	(10.55)	(8.96)
Part time (hours of work < 35)	25.90	26.01
	(4.49)	(4.45)
Full time (hours of work ≥ 35)	45.14	41.51
	(8.56)	(5.83)

Notes: The sample is restricted to those who worked at least 20 hours per week. Standard deviations are in parentheses.

Table 1.11: Five-year Cumulative Wage Returns to Tenure and Experience, by Hours of Work Per Week

	Part time (hours of work < 35)		Full time (Hours of work ≥ 35)					
			Overall		35-45 hours		≥ 45 hours	
	male	female	male	female	male	female	male	female
Overall experience	0.482***	0.432***	0.239***	0.278***	0.230***	0.252***	0.295***	0.420***
Firm tenure	0.113	-0.132	-0.069***	-0.020	-0.059	-0.021	-0.106**	-0.034
Occupational tenure	0.116	0.143	0.132***	0.022	0.062	-0.008	0.202***	0.242*
Industry tenure	-0.165	-0.031	0.026	0.062*	0.099*	0.103***	-0.022	-0.128
Observations	1899	4448	21118	16431	12503	13505	8615	2926

Hypothesis tests:
H_0: Wage growth with various types of experience equal across genders.

	Part time	Full time (overall)	Full time (35-45 hours)	Full time (≥ 45 hours)
	χ^2 statistic (p-value)	χ^2 statistic (p-value)	χ^2 statistic (p-value)	χ^2 statistic (p-value)
Overall experience	0.19 (0.666)	2.52 (0.112)	0.64 (0.422)	3.53 (0.060)
Firm tenure	0.88 (0.349)	2.12 (0.146)	0.67 (0.412)	0.76 (0.383)
Occupational tenure	0.01 (0.925)	6.45 (0.011)	1.75 (0.185)	0.10 (0.748)
Industry tenure	0.26 (0.611)	0.72 (0.398)	0.01 (0.941)	1.34 (0.247)

Notes: The five-year accumulative wage returns are calculated based on the IV estimates in pooled regressions for men and women. The models are estimated separately by part time and full time and by categories of hours of work per week. Standard errors are in parentheses. *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level, respectively.

Table 1.12: Gender Differences in Five-year Cumulative Wage Returns to Tenure and Experience, With Controls for Hours of Work Per Week

	(1) No controls for hours of work	(2) With control for full time/part time	(3) With controls for hours of work in continuous measure
Gender gap in wage growth with:			
Overall experience	-0.028	-0.020	-0.012
Firm tenure	-0.027	-0.021	-0.013
Occupational tenure	0.101*	0.056	0.042
Industry tenure	-0.049	-0.008	-0.029

Hypothesis tests:
H_0: Gender gap in wage growth with various types of experience do not change after controlling for hours of work.

		χ^2 statistic (p-value)	χ^2 statistic (p-value)
Overall experience		2.74 (0.098)	5.52 (0.019)
Firm tenure		0.07 (0.791)	0.96 (0.326)
Occupational tenure		5.07 (0.024)	6.10 (0.013)
Industry tenure		2.62 (0.106)	1.22 (0.269)

Notes: The five-year accumulative wage returns are calculated based on the IV estimates in pooled regressions for men and women, with controls for part time and full time, or controls for hours of work per week. Standard errors are in parentheses. *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level, respectively.

Table 1.13: Occupational Sex Segregation

	female dominated occupations	sex integrated occupations	male dominated occupations
occupational distribution			
men	5.3%	47.1%	47.6%
women	46.6%	47.8%	5.6%
one-digit occupation code			
Professional, Technical	nurses, elementary and secondary school teachers	accountants computer specialists	engineers, science technicians
Managers, Administrators		managers administrators	
Sales Workers		salesmen	
Clerical, Unskilled Workers	secretaries, cashiers	storekeepers, shipping clerks	
Craft			carpenters, mechanics, repairmen
Operatives		drivers, assemblers, machine operatives	Welders, flamecutters
Laborers		stock handlers animal caretakers	construction laborers freight handlers
Service Workers	waiters, cleaners, health aides	cooks, janitors, bartenders	

Notes: The gender composition of each three-digit occupation is calculated by using IPUMS 1980, 1990, and 2000. Sample occupations are given for each category.

Table 1.14: Five-year Cumulative Wage Returns to Tenure and Experience and Occupational Sex Segregation

	female dominated occupations		sex integrated occupations		male dominated occupations	
	male	female	male	female	male	female
Overall experience	0.327***	0.270***	0.290***	0.355***	0.286***	0.368***
Firm tenure	0.089	-0.061	-0.063	0.006	-0.062	-0.223
Occupational tenure	-0.121	0.097	0.167***	-0.035	0.075	0.030
Industry tenure	0.024	0.001	-0.011	0.099*	0.051	0.323
Observations	1213	9664	10664	9908	10996	1162

Hypothesis tests:
H_0: Wage growth with various types of experience equal across genders.

	female dominated occupations	sex integrated occupations	male dominated occupations
	χ^2 statistic (p-value)	χ^2 statistic (p-value)	χ^2 statistic (p-value)
Overall experience	0.51 (0.475)	3.22 (0.073)	1.31 (0.252)
Firm tenure	1.26 (0.261)	1.96 (0.161)	1.00 (0.317)
Occupational tenure	2.11 (0.146)	12.05 (0.001)	0.07 (0.786)
Industry tenure	0.03 (0.865)	3.14 (0.076)	2.50 (0.114)

Hypothesis tests:
H_0: Occupational feminization has no effect on wage growth with various types of experience.

	male	female
	χ^2 statistic (p-value)	χ^2 statistic (p-value)
Overall experience	4.02 (0.134)	0.15 (0.929)
Firm tenure	2.01 (0.366)	2.83 (0.243)
Occupational tenure	6.69 (0.035)	0.06 (0.807)
Industry tenure	0.61 (0.736)	1.43 (0.489)

Notes: The accumulative wage returns are calculated based on the IV estimates. Standard errors are in parentheses. *, ** and *** denote statistical significance at the 5%, 1% and 0.1% level, respectively.

Table 1.15: Annual Occupational Mobility Rate, NLSY 1979-1993

	Male	Female	gender difference
overall	0.3082 (18793)	0.3149 (16788)	-
Unmarried	0.3848 (10967)	0.3522 (9043)	$+^{***}$
Married	0.1996 (7826)	0.2706 (7745)	$-^{***}$
No Children	0.3458 (12624)	0.3166 (10543)	$+^{***}$
Have Children	0.2288 (6169)	0.3120 (6245)	$-^{***}$
High school or less	0.3045 (10225)	0.3162 (7903)	-
More than High school	0.3123 (8568)	0.3138 (8885)	-

Notes: Number of person-year observations in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.16: Occupational Mobility Regression (Marginal Coefficients from Probit Model Specifications)

	(1) All ages	(2) $\leq$ 25 years old	(3) All ages & excluding potential occupational changes for family reasons
Female	-0.0712**	-0.0704*	-0.0779**
	(0.0259)	(0.0317)	(0.0260)
Married	-0.188***	-0.183***	-0.192***
	(0.0295)	(0.0424)	(0.0294)
Female*Married	0.128***	0.0977	0.0720
	(0.0381)	(0.0541)	(0.0385)
Parental status	0.0891**	0.154***	0.0772*
	(0.0315)	(0.0466)	(0.0313)
Female*Parental Status	0.0497	0.0610	-0.0207
	(0.0410)	(0.0619)	(0.0416)
More than high school	0.171***	0.177***	0.176***
	(0.0311)	(0.0371)	(0.0312)
Female*More than high school	0.0247	0.0635	0.0309
	(0.0430)	(0.0504)	(0.0433)
Observations	35581	18330	34994

Notes: Control variables include gender dummy, age, age squared, marital status and its interaction with gender, parental status and its interaction with gender, education and its interaction with gender, AFQT score, union status, occupational tenure, general experience, year dummies, region dummies, and one-digit occupation/industry dummies. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 2

Negative Equity and Occupational Mobility

2.1 Introduction

Occupational change is an important adjustment mechanism through which the labor market adapts to changes in occupational structure (Kambourov and Manovskii 2008). It also plays a significant role in the process of occupational matching, especially for young workers. During the recent great recession and the subsequent subprime mortgage crisis that started in 2007 in which millions of homeowners were trapped in negative equity, occupational mobility rate in the U.S.A. reached the lowest levels of the past two decades recorded in U.S. Census Bureau statistics[1]. Let us, however, partition workers into those who rented, those who were homeowners with positive housing equity, and those who were homeowners with negative housing equity, the calculation using data from the Panel Study of Income Dynamics (PSID) shows that the occupational mobility rate of homeowners who were underwater dropped by 20-40% from its pre-crisis level, while in the same period homeowner who were not underwater on their mortgages experienced a drop of 10-20% in their occupational mobility, and those who rented experienced a slight drop only[2]. This suggests that negative equity status might impede workers' occupational mobility.

There has been a concern that, all else equal, a decline in occupational mobility during a recession will make the labor market adjust more slowly to shocks. If it is indeed the case, then workers are less flexible to switch away from occupations hit by negative productivity shock to insure against income risk, potentially prolonging recessions and reducing growth.

[1]Statistics for the Current Population Survey (CPS) sample show that, between 1991 and 2006, the average level of occupational mobility was around 10.2% at the three-digit level. From 2007 to 2009 when the trough was reached, occupational mobility was only 7.7%, dropped by one quarter from the pre-recession level. The recovery since 2009 has been weak. Occupational mobility from 2010 to 2012 was 8.7% on average, still much lower than the levels before the recession.

[2]See Table 2.3 for details.

It also potentially prolongs the occupational matching process for young workers. It is thus imperative to identify the potential drivers of the decline in occupational mobility observed in recent mortgage crisis. In this paper, I empirically examine whether negative housing equity affects occupational mobility. Specifically, I test whether homeowners with negative housing equity are less likely to switch occupations than renters and homeowners who are not underwater.

In my empirical analysis, I use the data from the PSID to identify the effect of negative housing equity on homeowners' occupational switching decision. The estimation is based on observations from 2003 to 2011, which covers 3 phases of the recent U.S. housing market: boom, bust and recovery. The challenge of this identification is that unobserved individual characteristics may be correlated with both the level of home equity and occupational mobility. For instance, an individual that is inherently less likely to switch occupations to insure against income shock may inherently have a low propensity to save and accumulate home equity. As house prices fall, homeowners with low home equity will disproportionately end up with negative equity. If they are also inherently less likely to switch occupations, failure to control for unobserved individual heterogeneity would result in biased estimation of the impact of negative equity. The panel data from the PSID longitudinal survey enable me to use regressions with personal-specific fixed effects to control for unobserved time-invariant individual characteristics. The regression results do not provide any strong evidence that negative equity affects homeowners' occupational mobility in recourse or non-recourse states.

Why might negative equity impede occupational mobility? One potential explanation is financial constraint faced by homeowners in negative equity, the situation which the outstanding mortgage balance exceeds the current market value of the home. Negative equity is usually caused by the sufficient falling of housing price combined with high loan-to-value (LTV), and disappears when housing markets boom. Negative equity would potentially prevent homeowners from geographic relocation if they don't have enough liquidity to pay off the loan balance which is required by the sale of property, or if they don't want to default on housing debt. When occupational switching is associated with geographic moving, inability to move geographically will prevent inter-occupation mobility. Even when they could pay off the housing debt, the costs associated with the potential loss on sale of an "underwater" home increases the cost of occupational switching, and thus change the cost-benefit calculus[3]. Much previous research focusing on financial constraint indicates that falling housing prices can 'lock-in' people to their homes, and consequently reduce household mobility (Quigley (1987), Stein (1995), Genesove and Mayer (1997, 2001), Chan (2001), Engelhardt (2003), Ferreira, Gyourko and Tracy (2010)). Thus, the "house lock" effect of

[3]The loss aversion literature supports this conjucture by suggesting that nominal loss aversion leads the household not to sell the homes after home price has fallen but to wait for house market to recover.

reduced geographic mobility operates as an unobserved link between negative equity and individual decision on occupational switching. This theoretical consideration suggests that, in the case that occupational change is associated with geographic moving, the occupational mobility rates are likely to be lower for homeowners in negative equity status than renters and homeowners who are not underwater.

On the other hand, even if a geographic move is not required when a worker wants to switch occupations, negative equity may still affect the decision. The studies of Kambourov and Manovskii (2009a), Sullivan (2010), Zangelidis (2008) and Dobbie et al. (2014) suggest that human capital is occupation-specific rather than firm-specific or industry-specific[4]. It implies that a substantial amount of human capital may be destroyed in an occupation switch. As a result, in exchange for potentially greater long-term growth in earnings, workers may suffer short-term earning losses when they switch occupations. Reduced earning upon occupation switching may limit the ability of a worker to pay off his home mortgage. When the house is not underwater, a homeowner could adjust monthly mortgage payment through refinancing or changing the status of ownership in response to the reduction of short-term earning. However, if the house is underwater, borrowing constraints faced by the homeowner may prevent him from accepting short-term earning losses and investing in new occupation-specific skills. This is another channel through which negative equity might affect homeowners' decisions on occupation switches. As investment in occupation-specific human capital is an important determinant of earnings, negative equity thus may slow or prevent homeowners from improving life-cycle earning through switching occupations.

As discussed above, negative equity might reduce occupational mobility. However, the picture is more complex because with underwater mortgages, some individuals might switch occupations more frequently. When demand shock or productivity shock are local and are independent across occupations, a displaced worker will weigh the cost of a geographic move to preserve his occupation-specific skills against the cost of staying put geographically and switching occupations. As mentioned in Markey and Parks (1989), in 1986, one in eight workers who changed occupations, or 1.3 million workers, made involuntary occupational changes because they lost their previous jobs[5]. Since negative housing equity will increase the cost of homeowners' geographic moving to preserve their occupation-specific human capital, it will increase the possibility that homeowners choose to switch occupations

[4]Sullivan (2010) allows the returns to human capital to vary across occupations. Using data from NLSY79, he finds that human capital is primarily occupation-specific in occupations such as craftsman and service, is primarily industry-specific in occupations such as managerial employment, and is both occupation-specific and industry-specific in occupations such as professional employment. In contrast, sales and clerical workers realize significant wage gains from general human capital instead of occupation or industry specific human capital.

[5]In 1986, nearly 10 million persons changed occupations. The majority had changed voluntarily, but 1.3 million workers made involuntary occupational changes because they lost their previous jobs. The data is from January 1987 Current Population Survey.

in order to stay put geographically. Thus, negative equity may lead to more involuntary occupational changes. Since the negative equity effects on voluntary and involuntary occupational mobility are opposite, the net effect of negative equity on overall occupational mobility will be ambiguous. To distinguish between the offsetting effects of being underwater on voluntary and involuntary occupational changes, I examine the negative equity effect on upward/downward occupational mobility, the effect on job-related moving, and the effect on occupational mobility for the subsample of displaced workers. I don't find strong evidence that the status of negative housing equity impedes homeowners' voluntary occupational changes to insure against negative productivity shocks or to improve occupational matching, or does it result in more involuntary occupational changes for displaced workers.

This paper is intended to complement the existing literature on the impact of negative equity on the labor market. Some research has been conducted in recent years on how negative home equity affects residential moving and job mobility. Using the American Housing Survey from 1985-2009, Ferreira, Gyourko and Tracy (2010, 2011) study the impact of negative equity on residential mobility. Based on their finding that homeowners with negative equity are about 30% less mobile than those with non-negative equity, they argue that, at least in the past, the lock-in effect dominated default-induced mobility. However, their work is susceptible to questionable sample selection procedures because they drop some permanent moves in a non-random way due to missing information on physical location and economic ownership. Schulhofer-Wohl (2011) reproduces the work of Ferreira, Gyourko and Tracy (2010) by using the same data but counting all cases dropped by them as a move. Schulhofer-Wohl's (2011) estimation shows contrasting results that negative equity does not make homeowners less mobile, and notably, homeowners with high levels of negative equity are more likely to move. But his work is also subject to possible misclassification of many transitions between temporary moving and permanent moving. Molloy, Smith and Wozniak (2011) use data from the Current Population Survey (CPS), the Internal Revenue Service (IRS) and the American Community Survey (ACS) 2006-2009 to compare changes in migration rates of homeowners and renters among states with different percentages of mortgages with negative equity. Their finding that migration doesn't fall more in states with a larger share of underwater mortgages also suggests that negative equity played only a small role in impeding the recent labor market recovery. Demyanyk et al. (2017) examine whether negative home equity leads to reduced job-related mobility for home-owners located in depressed local labor markets. They find that unemployed individuals with negative home equity are more likely to move to another metro area. These findings challenge the conjecture that home negative equity significantly hampers labor market adjustment.

The work I conduct is also related to a substantial literature regarding house lock-in effect. Oswald (1997) was the first to propose the hypothesis that home ownership leads to higher unemployment rates or longer duration of unemployment spells since high transaction costs of selling and buying houses limit geographic mobility. The work of Green and

Hendershott (2001) supports Oswald's hypothesis by finding limited geographic mobility among prime age individuals. By using Danish microdata, Munch, Rosholm and Svarer (2006) do not find strong support for lock-in effect. Instead, they find a negative effect of home ownership on job mobility in their later study in 2008.

The recent subprime mortgage crisis and subsequent great recession in the United States led economists to renew their focus on house lock-in effect on labor market outcomes including the effect of housing downturn on unemployment rate, residential and job mobility, unemployment duration, and job matching. Donovan and Schnure (2011) use data from the American Community Survey 2007-2009 to examine the effect of the downturn in the housing market on geographic moving. They find that the large decline in house price reduced within-county mobility only, and didn't result in fewer moves out-of-state. Since moving to a job is more likely associated with cross metro area or cross state moving rather than within-county moving, they thus conclude that higher unemployment rate during recession is not due to housing market lock-in. Using the data from Displaced Workers Survey (DWS), Schmitt and Warner (2011) show that displaced workers' likelihood to move did not depend on the extent to which house values fall. Their research results suggest that housing lock didn't cause structural unemployment. Farber (2012) examines DWS and CPS on mobility rate by home ownership status for displaced workers, and does not find any evidence either to support the house lock-in effect. With the expectation that house lock extends job search in the local labor market for homeowners whose home value has declined, Valetta (2013) compares the unemployment duration of renters and homeowners across geographic areas with substantial variation in the decline in home prices. Relying on microdata from the monthly CPS, he finds no evidence that unemployment duration of homeowners rose relative to renters in states experience a larger decline in house prices. Barnichon and Figura (2011) document the dramatic fall in matching efficiency measured by hiring intensity and the ratio of vacancies to unemployment following the onset of the great recession in the states that suffered a large drop in home prices and a large number of foreclosures, but find no evidence that matching efficiency was affected by a house-lock.

There are also rich literature examining the effect of housing wealth shock on other aspects of economic outcomes such as marital stability, fertility choices, and college choices. The study of Farnham, Schmidt and Sevak (2011) indicates that house value depreciation reduces divorce probability for homeowners while increases divorce probability for renters. Lovenheim and Mumford (2010) find that house price growth increases fertility rate. The findings of Johnson (2011) and Lovenheim and Reynolds(2012) suggest that house value appreciation increases the likelihood that the child attends college and the quality of attended school. In addition, there is evidence that foreclosure crisis negatively affects the academic performance of students and health (Been et al. (2011), Currie and Tekin (2011)).

In this paper, I investigate whether negative equity status impedes homeowners' voluntary occupational mobility, and accordingly deter economic recovery. The remainder of the paper proceeds as follows. Section 2.2 provides some background on the U.S. housing market during subprime mortgage crisis, and introduces recourse and non-recourse mortgages. Section 2.3 contains a description of the data. In Section 2.4, I outline the model used to be estimated, and describe my empirical specification and results. Robust tests are gathered in Section 2.5. Section 2.6 concludes.

2.2 Background

2.2.1 Decreasing Home Equity during the Subprime Mortgage Crisis

In 2006, immediately before the housing bust, the U.S. housing market was characterized by high home ownership rates and high LTV. According to the U.S. Census, in the 1990s, around 65% of households were homeowners[6], and two-thirds of homeowners had an outstanding mortgage[7]. The fewer years the household has owned the house, the more likely it is that the homeowner has a mortgage. Data from Dataquick shows that, in the San Francisco Bay Area, the typical LTV on a home purchase was fairly stable around 80% until the end of 2002. Beginning in 2003, as the minimum down payment required for home buyers dropped from 20% typically to 10% or even lower, a sharp increase in LTV was witnessed that the median LTV hit 90% in 2004, and stayed at that high level until 2007[8]. Other markets, such as Boston, also experienced similar swings in LTV ratios over time. Meanwhile the home ownership rate for the U.S. markedly rose to nearly 70% in 2006.

With the bursting of the housing bubble in 2007, more and more houses fell into the negative equity zone. From the peak in early 2007 through the end of 2011, nominal home prices across the U.S. fell about 16% on average. But the pattern varies substantially across regions. Some areas in California witnessed a decline of about 63% from peak, while some areas in Texas saw an increase of about 20%. When High LTV combined with the dramatic drop in home value, a significant quantity of homeowners were trapped in negative housing equity. According to a Zillow negative equity report[9], the national negative equity rate reached its peak in the first quarter of 2012, when 31.4% of U.S. homeowners with a mortgage were underwater. This represents approximately 16 million homeowners nationwide. Figure 2.1 shows the overall trend in underwater mortgages between 1997-2014. The percentage of housing units under water is calculated based on 3 datasets: American Housing Survey, CoreLogic, and Zillow. The long term trend starting from 1997 is based on

[6]Refer to statistics on home ownership rates published by U.S. Census Bureau, https://www.census.gov/housing/hvs/index.html

[7]The calculation is based on federal census data,
https://factfinder.census.gov/faces/nav/jsf/pages/searchresults.xhtml?refresh=t

[8]Refer to figure 2 of Ferreira et al. (2010)

[9] http://www.zillow.com/research/negative-equity-2014-q3-8532/

the American Housing Survey only. Overall, the percentage of housing units under water remained stable at the level of 4-5% until 2007. In 2009, it shot up to 12%. It continued to rise in 2011, and then declined in 2013, but remained at a significant higher level than in 2007.

However, the national numbers hide considerable variations in the extent of the problem across states. The percentage of underwater mortgages was higher in the regions suffering the worst price declines. By the end of 2009, 65% of homeowners were underwater in Nevada, 48% of mortgage borrowers in Arizona were underwater, and the numbers for Florida, Michigan, and California are 45%, 37%, and 35%, respectively[10]. In addition, Carter (2012) shows regional difference in trends in underwater mortgage percentage. For example, as the northeast saw a dramatic drop in the percentage of underwater mortgages from 2005 to 2007, more and more homeowners in the west were trapped in negative equity. Although the percentage of underwater units began to rise in all regions in 2007, the rate of increase was quite different across regions. In 2005, the west had a relatively smaller percentage of underwater homes compared with other regions, but in 2009, the highest rates were in the west.

Not only were significant numbers of homeowners underwater, but many were underwater by substantial amounts. By the second quarter of 2009, of homeowners with negative equity, around 16% had negative equity exceeding 20% of their home's value, and over 22% had negative equity exceeding 10% of their home's value[11]. Again, the situation was worse in the states suffering the worst price declines. A large number of homeowners were underwater by hundreds of thousands of dollars. In Nevada, for example, 47% of homeowners had negative equity exceeding 25% of their home's value. The numbers for Florida, Arizona, and California are 30%, 29%, and 25%, respectively.

2.2.2 U.S. Foreclosure Law: Recourse vs. Non-Recourse Mortgages

Recourse or the lack thereof is fundamental in any residential or business loan as it deals with the lender's ability to collect upon default and delinquency. A non-recourse residential mortgage is a type of loan in which recourse is limited to the value of the collateral, normally the house itself. In other words, if the proceedings from a foreclosure sale are not enough to pay off the loan, the borrower is not liable for the outstanding loan amount and the lender must accept the loss. As discussed by Pavlov and Wachter (2009), a non-recourse mortgage provides the borrower with a put option: the borrower is entitled to capture all capital gains

[10]Media Alert, 2009 Q3 Negative Equity Report, *supra* note 10. Outstanding Nevadan mortgage debt values were almost sixteen billion dollars, or 14% greater than the underlying property values these loans secured. While Nevada was the only state, as of 2009, with a loan-to-value ratio over 100% (signifying negative net homeowner equity), residents of Arizona (91%), Florida (87%), and Michigan (84%) had negative net equity with loan-to-value ratios close to 100%.

[11]See Second Quarter Negative Equity Summary, *supra* note 1.

from the appreciation of the property but has no obligation for capital losses due to the depreciation of the property because he can simply use the put option to sell the asset to the bank and walk away, free and clear.

In contrast, for borrowers with recourse mortgages, foreclosure is not the end of the story. The borrower must repay the full amount of the loan. By obtaining a deficiency judgement, the lender may be able to lay claim to assets other than the mortgaged property such as personal assets or future income. Such borrowers are less likely to return their house to the lender even if it is deeply underwater. Given the difference between recourse and non-recourse loans in the ability of the lender to claim the assets of the borrower if the debt is not paid, a borrower with a non-recourse loan has more incentive to use strategic default to reduce the loss on the house.

An exceptional feature of American residential mortgages is that they are non-recourse in some U.S. states[12]. Based on state foreclosure law, out of fifty states and the District of Columbia, forty are categorized as recourse and eleven as non-recourse. Table 2.1 shows the list of recourse and non-recourse states. Arizona and California, two of the leading foreclosure states[13], are among non-recourse states.

2.3 Data

In order to explore how a house wealth shock affects a worker's occupational mobility, it is optimal to have longitudinal data where respondents are surveyed continuously even if they move. Furthermore, since some personal characteristics that affect the home ownership decision and the loan-to-value ratio may also be related to decisions on occupational changes, a panel dataset that observes individuals over time allows me to control for unobservable personal heterogeneity. The Panel Study of Income Dynamics (PSID) provides the best US-oriented data for these purposes.

The PSID is a longitudinal study conducted since 1968 with a nationally representative sample of nearly 5,000 families in 40 states. The survey was conducted annually until 1997, and every two years since. The PSID records a broad range of social and economic information on the same households over time, including data on housing, wealth and income, employment, health, education, and numerous other topics. Specifically, it collects consistent data on occupations of employed heads and spouses, whether they rent or own a house, and current house values and mortgages if they are homeowners. My data for this analysis cover the period from 2003 to 2011, which covers the pre-recession housing boom

[12]Some scholars allege that all US residential mortgages are, in practice, non-recourse because of the US bankruptcy regime. Refer to: Ankoor Jain and Cally Jordan, *Diversity and Resilience: Lessons From the Financial Crisis*, 32 U.N.S.W.L.J. 416, 423 (2009).

[13]see http://www.realtytrac.com/contentmanagement/pressrelease.aspx?channelid=9&accnt=0&itemid=7856

(2003-2006), housing crash that coincided with the financial crisis and subprime mortgage crisis (2007-2009), and the subsequent recovery period (2009-2011). To construct variables of occupational change and occupational tenure, I need repeated observations of occupation. For example, to identify whether a worker changed occupations between 2011 and 2013, the observations of occupation in survey year 2011 & 2013 are indispensable. Similarly, I need pre-2003 survey data to calculate workers' cumulative experience in their current occupations. Thereby, I need the full set of the PSID data from 1968 to 2013 for this study.

My sample is restricted to male heads of household[14], aged 22 to 65, who worked for pay, and who were employed in non-military jobs. After excluding observations with missing values for my analysis variables, I have 11,972 person-year observations. I make one further sample restriction in that I exclude 1,602 person-year observations for respondents who at the time of the interview worked in the industry of construction and real estate. In this paper, the identification assumption of the model is that house price movements are conditionally exogenous to occupational switching decisions. Any direct effect of housing market conditions and occupational switching decisions would result in biased estimation of the impact of negative equity. However, it is reasonable to believe that weak housing market reduces the labor demand in industries such as construction and real estate[15], which would violate the identifying assumption. Excluding these observations does not significantly change the estimated effect of ownership and negative equity. My final data sample consists of 3,117 individuals who contribute a total of 10,370 person-year observations.

The information on occupations of employed heads of household provided at each survey in the PSID enables me to identify occupational mobility. The PSID defined occupations using the three-digit classifications used by the 1970 Census of Population and Housing (1970 OCC) until 2003 when the three-digit 2000 Census code (2000 OCC) became standard[16]. If the occupation of a worker doesn't change over the two year period between the survey conducted in year t and the subsequent survey conducted in year t+2, I classify him as an occupation stayer. Otherwise, he is an occupation switcher. Due to the well-known coding error problem[17] for occupation, I follow a widely used method to identify genuine occupation

[14]As women's greater domestic commitments such as marriage, childbirth, and family care responsibilities make them more prone to employment interruptions and gaps, my study focus on male only.

[15]Barnichon et al. (2010) find that the drop in matching efficiency was particular pronounced in the industries of construction, trade, transportation and utilities. The decline in house prices and construction activity during subprime mortgage crisis was rather steep in the states of Arizona, California, Florida, and Nevada. In these states concentrated with labor market depression and house market depression, low geographical mobility maybe due to workers being reluctant to sell houses that fall in value. Schmitt and Warner (2011) confirm that during subprime mortgage crisis, construction workers were more likely to be displaced than workers in other industries.

[16]Alphabetical index of industries and occupations issued by the U.S. Department of Commerce and the Bureau of the Census please refer to www.census.gov/hhes/www/ioindex/ioindex.html for complete listings.

[17]For more details about coding error problem on occupation, see Kamborov and Manovskill (2009).

switches. That is, an occupation switch observed in the original PSID data is treated to be genuine if and only if it coincides with an employer switch. An employer switch is identified if the responder worked for the current employer for less than 2 years[18]. To construct the occupational tenure variable, I track data back to the first observation year 1968. For year 1968, I set occupational tenure to be equal to employer tenure. For any subsequent year in which the individual was surveyed as household head for the first time, I use the same strategy to set the initial value of his occupational tenure. If an individual did not switch occupation, then his occupational tenure increments by one year for survey years prior to 1997 or two years for survey years after 1997. If the individual switched occupation between survey years, his occupational tenure is reset to equal his employer tenure. Since the PSID changed its occupation coding system in 2003, I use the crosswalk from 1970 OCC to 2000 OCC to identify occupational switching between 2001 and 2003[19].

The PSID collects detailed information on housing including type of dwelling and whether the house is currently owned or rented. This information enables me to construct the indicator for home ownership. To construct the indicator for home equity status, I first construct the homeowner's current LTV ratio using the self-reported current value of the home[20] and the remaining principal owed from all mortgages or land contracts on the home. I then code the indicator for home equity status that takes a value of one when the current LTV exceeds 100%[21].

The PSID contains a rich set of detailed demographic information that is useful to control for the factors that influence occupational mobility. One set of variables I employ as controls is age and age squared. As observed in Kambourov and Manovskii (2008),

[18]The PSID interview was usually conducted roughly between March through November, with some exceptions into December. Interviews are seldom taken exactly twenty four months apart for the same family from wave to wave. As a result, interview intervals may longer or shorter than 2 years.

[19]The crosswalk used in this study is based on the crosswalks constructed by the Census Bureau (https://usa.ipums.org/usa/volii/occ_ind.shtml). There are 443 occupation categories in the 1970 census occupational classification system, and 510 categories in the 2000 census occupational classification system. The Census Bureau didn't construct direct crosswalk from 1970-2000. Instead, they create a new occupational classification scheme which is a modified version of 1990 OCC and contains 389 categories, and then construct crosswalks between the modified 1990 OCC and occupational classification schemes in various decades. Thus, the modified 1990 OCC provides a bridge between 1970 OCC and 2000 OCC. The crosswalk from 1970-2000 does not give 1 to 1 match. Some occupations are combined with others into a more general occupation, while some occupations break out into more specific occupations. For example, "college administrators" (1970 code 235) and "elementary and secondary school administrators" (1970 code 240), two occupation categories in 1970 OCC, are together coded as "education administrators" (2000 code 23) in 2000 OCC. Conversely, persons coded as "electrical end electronic engineers" (1970 code 12) in 1970 OCC are coded in two more specific occupations in 2000 OCC: "computer hardware engineers" (2000 code 140), and "electrical and electronics engineers" (2000 code 141).

[20]The current value of the home means about how much would it bring if the homeowner sold it at the date of interview.

[21]Home equity status may be wrongly coded due to the inaccuracy of the self-reported home value. See Section 2.5 for a discussion on this issue.

young workers are more likely to change occupations than are old workers. Another set of controls is marital status and the presence of children. These controls have important mobility implications because they may proxy for preferences over job stability and career progression. For example, when an occupation switch is associated with a geographic move, the labor force attachment of the spouse and the presence of children will increase the relevant moving cost, and accordingly affect the occupational switching decision. Other characteristics of household heads such as race and education are captured by individual effects since they do not change over time.

In addition to control for demographic characteristics of household heads, I allow for changes in local labor market conditions to affect occupational switching decisions. I use the unemployment rate at the state level as the proxy of local labor market conditions. The regional labor market shock is defined as the change in unemployment rate since the last interview year[22].

Table 2.2 contains descriptive statistics for the sample used in the estimation. Averaging across years 2003-2011, around 66% of observations are homeowners. This matches up with aggregate national statistics published by U.S. Census Bureau[23]. Regarding financial characteristics of housing units, on average over the observation period, 4.1% of homeowner observations involve a household in a negative equity situation[24]. The average occupational mobility rate at the three-digit level over two-year period for the whole sample is 19.2%[25]. Renters have much higher occupational mobility rates than homeowners, 30.6% and 13.4% respectively, and underwater homeowners are more likely to change their occupations than homeowners who are not in negative equity zones. As shown in this table, on average, renters are younger than homeowners, and underwater homeowners are younger than homeowners who are not underwater but are older than renters. This seems reasonable since young workers tend to borrow more on their homes, thus are more likely to be underwater as home price falls. Similar facts can be found on the variable occupational tenure. Regarding marital status and family status, homeowners are more likely to be married than renters, while the probability of being married for homeowners with negative equity is quite close to the probability for homeowners without negative equity. Underwater homeowners have the highest probability of having kids. Regarding schooling, on the whole, homeowners are more educated than renters. 67% of homeowners have a college degree or postgraduate degree. In contrast, less than 50% of renters have some college or higher level education. The

[22]Let u_{st} denote the annual unemployment rate in the state of residence s in year t. The regional labor market shock is defined as $\triangle u_{st} = u_{st} - u_{s,t-1}$.

[23]see https://www.census.gov/housing/hvs/index.html for details

[24]The information of the share of underwater mortgages for each observation year are shown in Table 2.4.

[25]Based on the Survey of Income and Program Participation (SIPP), Xiong (2008) shows that the 3-digit yearly occupational mobility rate is 13% in early 2000's.

educational attainment of homeowners suffering from negative equity is slightly lower than that of homeowners without negative equity, but still much higher than that of renters. A higher share of white people own a house, and non-white homeowners are more likely to be trapped in negative housing equity.

2.4 Regression Specifications and Results

2.4.1 Occupational Mobility Rate, Home Ownership Rate, and the Share of Negative Equity

Table 2.3 shows how the occupational mobility rate, computed as the fraction of workers in year t who switched their occupations between year t and t+2, changed before and after the subprime mortgage crisis. As shown in the first column of Table 2.3, the overall occupational mobility rate dropped approximately 6% in 2011-2013 from the pre-crisis average. The occupational mobility rate of renters shows a similar trend. However, the decline in occupational mobility for underwater homeowners is much larger than for those with non-negative equity: from around 20% to 12.61% versus from above 14% to 11.11%. The biggest fall in occupational mobility is for homeowners with negative equity.

Table 2.4 shows the changes in the home ownership rate and the changes in the share of negative equity amongst homeowners over years. The trend in the home ownership rate shown in this table is consistent with the U.S. Census Bureau data showing that home ownership rates in the U.S. have dropped since the end of 2007. My calculation also shows that the decline in the home ownership rate in recourse states is slightly larger than that in non-recourse states. The home ownership rate in recourse states dropped from 68.3% in 2007 to 61.7% in 2011, while in non-recourse states, it dropped from 67.4% to 64.2% over the same period. Accompanying the decline in the home ownership rate is an increase in the proportion of homeowners with underwater mortgages. The trend of negative equity share is consistent with the statistics shown in Figure 2.1. Before the crisis, the share of negative equity was as low as 1%. Since 2007, as house prices dropped, more and more homes were trapped in negative equity. Based on my calculation, about 10% of homeowners were in the negative equity zone in the period of 2011-2013. Similar trends are found for recourse/non-recourse groups.

2.4.2 Regression Specification

I estimate the impact of negative equity on occupational mobility using the following linear probability model[26]:

[26]Fixed effect is not allowed in probit model.

$$P(OM_{it}) = \gamma_1 Own\_Rec_{it} + \gamma_2 Own\_NonRec_{it} + \gamma_3 NE\_Rec_{it} + \gamma_4 NE_{it}\_NonRec_{it} + X_{it}\beta + \theta_i + \phi_t + state_{s(it)} + \varepsilon_{it} \quad (2.1)$$

where OM_{it} is an indicator variable that equals 1 if individual i changed occupations between year t and t+2, zero otherwise. Own_Rec_{it} and Own_NonRec_{it} denote ownership in recourse/non-recourse states. $Own\_Rec_{it}/Own\_NonRec_{it}$ takes a value of one if individual i is a homeowner residing in a recourse/non-recourse state at the time of interview in year t, and zero if he is a renter. NE_Rec_{it} and NE_NonRec_{it} are indicator variables that equal one if individual i in year t is a homeowner with negative home equity residing in a recourse/non-recourse state, zero otherwise. X is a vector of time-variant regressors including age and age squared, occupational tenure and occupational tenure squared, marital status, parental status, and regional labor market shock. θ_i are fixed individual effects, ϕ_t capture fixed year effects, $state_{s(it)}$ capture fixed state effects[27], and ε_{it} is the stochastic error term. I cluster standard errors by individuals in the regressions. In this model, I assume that the changes in house price in the state in which an individual resides are exogenous.

As explained previously, when an underwater homeowner succumbs to foreclosure, the ability of the lender to take the assets of the borrower differs between recourse loans and non-recourse loans when the loan is not paid. As the house price drops, homeowners in non-recourse states can use strategic default to reduce the financial loss on their home while homeowners in recourse states have to pay off the full amount of the loan even if they default. Pavlov and Wachter (2009) show that the put option contained in non-recourse loans is typically underpriced in equilibrium. As legal recourse lowers the value of the default option, the choice between renting and purchasing a housing unit might be affected by state foreclosure law. The coefficients of Own_Rec_{it} and Own_NonRec_{it} capture the effect of home ownership in recourse and non-recourse states separately[28]. Similarly, the negative equity effect might be different between recourse and non-recourse states. As legal recourse lowers the borrower's sensitivity to negative equity, borrowers in non-recourse states are more likely to default, and thus become more geographically flexible. The result of Ghent and Kudlyak (2011) supports this conjecture and shows that borrowers in non-recourse states are 30% more likely to default than those in recourse states. The coefficients of NE_Rec_{it} and NE_NonRec_{it} capture the responses of homeowners with negative housing equity relative to homeowners who are not underwater in recourse/non-recourse states.

[27] There was no change in the state legislation on recourse versus non-recourse since 2000.

[28] Bao and Ding (2016) find that non-recourse states experience faster price growth during the boom period (2000-2006), a sharper price drop during the bust period (2006-2009) and faster price recovery in the rebound period after a crisis (2009-2013).

2.4.3 Empirical Results

I start the estimation of the determinants of occupational mobility in a specification without controlling for individual heterogeneity. As the same individuals are being followed over time in panel data, all standard errors in this pooled OLS regression are clustered at the individual level. The OLS estimates are shown in Table 2.5. The first column is based on a specification without controlling for any fixed effects, the second reports the estimates controlling for year effect only, the third controls for state effect only, while the last column shows the estimates controlling for both year effect and state effect.

The coefficients of the variables of interest reported in Table 2.5 provide basic information on how home ownership and negative equity affect occupational mobility. In both recourse and non-recourse states, home ownership significantly reduces the probability of occupational switching. In recourse states, home ownership reduces the the probability of occupational switching by 7.5 percentage points, while in non-recourse states, occupational mobility for homeowners is 5.5 percentage points lower than renters. Compared with the baseline mobility rate of 30% for renters shown in Table 2.3, the impact of home ownership is economically large. The coefficients of negative equity are not significantly different from zero in recourse or non-recourse states. The OLS regressions do not provide strong evidence that being underwater reduces homeowners' occupational mobility.

To control for unobservable personal heterogeneity, I estimate the linear probability model with personal fixed effect. The results are shown in Table 2.6. Again, column (1) reports the estimates without controlling for either year effect or state effect, column (2) and (3) control for year effect and state effect respectively, and column (4) controls for both. Contrary to the OLS estimates, the coefficient of home ownership in both recourse and non-recourse states becomes insignificant in fixed effect estimation.

In fixed effect estimation, the coefficients of negative equity are still not significantly different from zero in recourse or non-recourse states. No strong evidence shows that the occupational mobility of underwater homeowners is significantly different from that of homeowners who are not underwater. In recourse states, it is probably because of nominal loss aversion that homeowners who are not trapped in negative housing equity don't tend to be more flexible than underwater homeowners. As homeowners face the same decline in house price no matter what housing equity status they are in, nominal loss aversion leads homeowners with positive equity not to sell the homes after the home price has fallen but to wait for the housing market to recover. In non-recourse states, not as expected, underwater homeowners don't tend to be more mobile than their counterparts even if it is in their best interest to strategically default on their mortgages. This result is consistent with the observation that when more and more underwater homeowners use strategic default to "walk away" from their mortgages, the vast majority of underwater homeowners continue to make their mortgage payments, even in non-recourse states such as Arizona and California.

Behavioral economists explain that this is because homeowners are not fully aware that it would be in their financial best interest to default. White (2009) points out that this is the result of emotional forces and the desire to avoid the shame and guilt of foreclosure and exaggerated anxiety over foreclosure's perceived consequences. Statistics show that the overall strategic default rate among all homeowners is only 2.5% to 3.5%. These findings suggest that the overall impact of negative equity on geographic flexibility through strategic default is quite limited; thus negative equity would not have a significant effect on occupational mobility.

Neither the OLS estimates nor fixed effect estimates provide strong evidence that negative housing equity reduces homeowners' occupational mobility. As discussed in the first section, negative housing equity might affect occupational switching in two directions. On one hand, negative equity reduces voluntary occupational mobility. This is because negative equity increases the cost of geographic moving and thus increases the cost of occupational change whenever occupational change is associated with geographic moving. On the other hand, negative equity limits homeowners' ability to move for a job to preserve their occupation-specific human capital; so displaced homeowners may be forced to switch occupations to stay put. Statistics from Markey and Parks (1989) show that, in 1986, one in eight workers who changed occupations did so involuntarily. These two effects are opposite and the net effect of negative equity on occupational switching depends on which effect dominates. Therefore, the estimated insignificant net effect of negative equity on occupational mobility does not necessarily imply that the effects of being underwater on homeowners' voluntary and involuntary occupational mobility are insignificant as well. It is thus important to distinguish between these two offsetting effects.

My data do not provide direct information on whether an individual changes his occupation voluntarily or involuntarily. Instead, I can tell if an individual moves to a higher paying occupation (upward occupational mobility) or moves to a lower paying occupation (downward occupational mobility). By using IPUMS-USA 2000 5% sample, I rank occupations by median wage. An occupational change is identified as downward occupational mobility if the median wage of the terminal occupation is lower than 95% of the median wage of the initial occupation, otherwise identified as upward occupational mobility[29]. Given that upward occupational mobility tends to be voluntary occupational mobility, and downward occupational mobility is more likely to be involuntary, it is expected that being underwater reduces the probability that an individual upgrades his occupation, and increases the probability that an individual downgrades his occupation. I thus estimate separate models to examine the effects of negative equity on upward occupational mobility and downward

[29]In my sample, there are 2257 observations showing occupational change. 1497 (66%) of them are identified as upward occupational mobility, and 760 observations (34%) are identified as downward occupational mobility.

occupational mobility; fixed effect estimates are shown in column (2) and (3) of Table 2.7, respectively. The insignificant coefficients of negative equity in either model do not provide strong evidence that negative equity affects homeowners' upward/downward occupational mobility in recourse or non-recourse states. This finding suggests that homeowners' decision on voluntary/involuntary occupational change are not likely to be affected by their negative equity status.

As some occupational changes are associated with geographic moving, to explore negative equity effects on voluntary and involuntary occupational change, I also examine whether negative equity affects job-related moving. The PSID survey asked whether the head moved within two years prior to the interview, as well as reasons for moving. One answer option for that question is to take another job. This information enables me to identify a job-related move. I am thus able to estimate the personal fixed effect model with job-related moving as dependent variable[30]. Column (2) of Table 2.8 shows that none of the coefficients of interest is significant, indicating that homeowners with negative equity do not have a significantly lower probability of job-related moves compared to homeowners who are not underwater. This result supports my conclusion from Table 2.7 that no strong evidence shows that negative equity status impedes voluntary occupational changes that are associated with geographic moving, or results in more involuntary occupational changes due to underwater homeowners' inability to move for a job to preserve their occupation-specific human capital.

Another piece of useful information collected by the PSID that I can use to identify the negative equity effect is whether the head had ever been displaced due to company closure, layoff, or seasonal work completion. Given that displaced workers are more likely to have involuntary occupational changes if they cannot move to a job in the current occupation, I then explore different effects of negative equity for displaced workers and their counterparts. Column (3)-(4) of Table 2.8 show the estimates in the fixed effect model. For those who were not displaced, the effects of negative equity on the probability that a homeowner changes his occupation are insignificant. This result does not suggest that negative equity impedes voluntary occupational change. For the subsample of displaced workers, there is no evidence that underwater homeowners have higher occupational mobility compared with homeowners who are not underwater. The estimation conditional on the status of displacement provides some suggestive evidence that negative equity has no signficant impact on voluntary/involuntary occupational mobility.

As discussed above, in their best interest, some underwater homeowners may succumb to foreclosure, making them as geographically flexible as renters. Thus, the impact of negative equity may be different for those who choose to default on their residential mortgages and for

[30]Out of 2257 observations showing occupational switch, 138 observations coincide with the occurrence of job-related moving during the same observation period. For the group of 8113 observations without occupational change, 118 observations are reported to have a job-related moving.

those who don't default. To tell how negative equity influences homeowners' occupational mobility without mortgage default, I estimate the model using a sample that excludes individuals who had ever transitioned from being underwater to renting. In my sample, 26 out of 3117 individuals experienced a transition from underwater homeowner to renter[31]. Regression results from column (2) of Table 2.9 still do not privide any evidence that home ownership and negative housing equity have significant effect on homeowners' occupational mobility.

Schulhofer-Wohl (2011) examines the relationship between geographic mobility and the depth of negative equity. He finds that a homeowner whose debt greatly exceeds the value of the home will be more likely to default and thus be more geographically flexible than a homeowner whose debt only slightly exceeds the value of the home. To allow the negative equity effect on occupational mobility change with the depth of negative equity, I regress occupational mobility on a continuous measure of LTV interacted with the indicator for negative equity instead of the indicator of being underwater only. Column (3) of Table 2.9 shows the result. The insignificant coefficients of the variables of interest do not suggest that occupational mobility of underwater homeowners is significantly different from that of homeowners with positive housing equity, or change significantly as housing equity gets more negative.

In summary, in this section, there is no strong evidence that negative equity affects homeowners' occupational mobility. The regression analyses on upward/downward occupational mobility, on job-related moving, and the analysis for the subsample of displaced workers do not provide any evidence that the status of negative housing equity impedes homeowners' voluntary occupational changes to insure against negative productivity shocks or to improve occupational matching, or does it result in more involuntary occupational changes for displaced workers.

2.4.4 Variation in the Negative Equity Effect Across Demographic Groups and Occupations

The analysis so far estimates an average effect of negative equity on occupational mobility. I have not allowed this relationship to vary with other personal demographics. I explore these interactions here by estimating the effect for subgroups defined by race and educational attainment. This exercise serves two goals. One is to characterize heterogeneity in the effect of negative housing equity. The second is to test for spurious inference. As documented above, the status of ownership or housing equity differs greatly across race and educational attainment. It is plausible that the effect of negative equity on the decision of switching occupations may be partially attributable to the demographic differences rather than the

[31]Out of 3117 individuals, 229 are observed to transition from homeowners who are not underwater to being underwater and vice versa.

status of housing equity. I explore this channel of negative equity effect by estimating the model separately across the categories of race and educational attainment.

I first examine the heterogeneity in the negative equity effect across races. As observed in Table 2.2 and discussed in Section 2.3, white workers are more likely to be homeowners, and less likely to be underwater compared with other workers. This is consistent with the finding of Krivo and Kaufman (2004) that black and Hispanic householders had lower levels of home equity than White householders. Additionally, Carter (2012) documents different trends of underwater mortgage ratios by race. During the subprime mortgage crisis, the percentage of underwater units rose in all race categories, but the change was lowest for white homeowners.

Table 2.10 reports estimates from the fixed effect model for homeowners who are white, black, or other races separately in columns (2) to (4). To make the results comparable with my basic result, column (1) in Table 2.10 reports the estimated coefficients from the basic specification. Sample sizes are considerably reduced by these splits, especially for those who are not white. Precision falls accordingly. In general, I do not see a robust negative equity effect for all groups. In contrast, the home ownership effect in non-recourse states is significant for white homeowners. The magnitude of the coefficients of interest for whites only are larger than the coefficient estimated in overall effect shown in column (1). White homeowners who are not underwater on their mortgages in non-recourse states are less likely to switch occupations than white renters by 8.9 percentage points. The “lock-in" effect is not significant for other race groups.

Education is another demographic characteristic that is positively related to higher home equity levels. Carter (2012) shows that householders with college educations or more were less likely than those with less than a high school education to be underwater in all years in the 2010s. To explore the heterogeneity in the negative equity effect across education, I divide individuals into three groups based on their completed education level: high school graduates or dropouts (at most 12 years of schooling), some college and college graduates (12 to 16 years of schooling), and post-graduates (at least 17 years of schooling), and then estimate separate models for each group. In Table 2.11, I see a sizable home ownership lock-in effect in non-recourse states only for homeowners with some college or college graduates, but not for homeowners who are high school graduates or dropouts, or post-graduates. For those with some college or college graduates, homeowners in general are 12.5 percentage points less likely to change their occupations than renters. In both recourse and non-recourse states, negative equity effects are insignificant for all education groups.

Considering that the degree of occupational specificity varies vastly across occupations, I then investigate heterogeneity in the negative equity effect across occupations. Some occupations are intrinsically more stable than others because of the relatively high entry cost or the specificity of the skills required and tasks performed for the occupation. For example, the specific skills required to be a dentist may not be as valuable for other medical occupations. In contrast, bank tellers, bookkeepers and file clerks share similar types of main tasks and skills. My calculation based on the data from PSID 1968-1997 shows that the propensity to switch away from current occupation at the three-digit level for dentists and physicians is lower than 0.01, while the corresponding number for clerical workers is as high as 0.12.

I divide the individuals into two groups: those whose current occupation is professional, managerial or the like, and those who are working in other occupations. I then estimate separate models for each group. Table 2.12 shows the results. For each occupation group, there is no evidence that negative housing equity affects the chance that a homeowner will switch his occupation.

2.5 Robustness Check

In this section, I analyze the robustness of my results in response to the concern of measurement error on the negative equity variable due to home value overestimates. Specifically, I examine robustness by using adjusted home value with fixed effect model. Table 2.14 reports the result of this robustness check.

In this paper, the variable of negative equity is constructed by using the self-reported current value of the home and the remaining principal owed from all mortgages or land contracts on the home. The accuracy of home value estimates was first examined by Kish and Lansing (1954). By using appraisal data and national data from the Survey of consumer Finance, they find that homeowners overstate their home values by about 4 percent. Kain and Quigley (1972) replicate Kish and Lansing's work on a single city, and find that home value estimate errors were systematically related to the respondents' socioeconomic characteristics. Kiel and Zabel (1999) compare self-reported home value data from American Housing Survey with sales prices of houses sold in the 12 months before the survey interview. They find that self-reported home values, on average, are 5.1 percent higher than stated sales prices. They also find that differences between respondent's estimates and sales prices are related to the length of home tenure. For those who bought their homes recently, self-reported home values are 8.4 percent higher than stated sales prices. Unlike Kain and Quigley (1972), they don't find the relationship between overestimates and responders' socioeconomic characteristics. They conclude that self-reported home values are still reliable, but that home values are consistently overestimated. Recent research by Benitez-Silva et al. (2015) suggests that homeowners who purchase their homes in a booming housing market are more accurate in assessing their home values.

To examine the concern on home value overestimates, I adjust the variable of home value by decreasing the self-reported current home value by 5%. Then I reconstruct the LTV ratio using adjusted home value and original data on remaining mortgage loan, and recode the indicator variable of negative equity. As adjusted home value is lower, there are more homeowners with underwater mortgages. The change in the share of negative equity by year is shown in Table 2.13. The recoded negative equity share is closer to the statistics shown in Figure 2.1, especially closer to the statistics derived from American Housing Survey. This also shows a consistent trend with Figure 2.1. In the period of 2003-2005, the recoded negative equity share is 3 percentage points higher than in original data. In the period of 2011-2013, as house price continued to drop and more homeowners became underwater, the recoded negative equity share is 6 percentage points higher than in original data. A similar trend applies for recourse/non-recourse groups. The higher negative equity share as a result of home value recoding implies that, as house price declined, even when some homeowners still held positive home equity, their positive equity was very low.

The estimates using the recoded indicator variable of negative equity are shown in column (2) of Table 2.14. The effects of negative equity and home ownership are still insignificant. Thus, my result on the impact of negative equity on occupational mobility is robust to the measurement error on the status of housing equity.

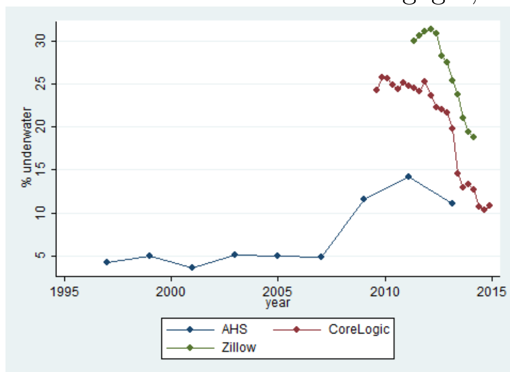
2.6 Conclusions

In this paper, I studied the effect of negative housing equity on occupational switching decisions, motivated by remarkable rises in the percentage of underwater mortgages and low occupational mobility during the recent recession. Negative housing equity might affect occupational switching in a couple of ways. On the one hand, for those who want to change occupations either to switch away from occupations hit by negative productivity shocks or to improve occupational matching, negative equity tends to reduce occupational mobility, especially when occupational change is associated with a geographic move. On the other hand, for displaced workers, negative equity prevents them from moving to preserve their occupation-specific human capital, and thus forces them to make involuntary occupational changes. In either direction, negative equity delays the adjustment of labor markets to shocks and leads to inefficient allocation of workers across occupations. From the standpoint of the individual, a worker cannot insure against income shock via mobility.

To analyze if the effect of income shocks is potentially magnified by negative equity, I used panel data from the Panel Study of Income Dynamics (PSID) for years 2003-2011, and employed fixed effect specifications to control for unobservable personal heterogeneity and other factors that may influence occupational mobility. I don't find any strong evidence that the overall effect of negative equity on homeowners' occupational mobility is significant in recourse or non-recourse states. Furthermore, to distinguish between the offsetting effects of being underwater on voluntary and involuntary occupational changes, I examined the negative equity effect on upward/downward occupational mobility, the effect on job-related moving, and the effect on occupational mobility for displaced workers. The estimates do not provide any supportive evidence that negative housing equity does have an effect on homeowner's voluntary/involuntary occupational mobility.

My research is focused on short-term effects only; that is, I observe occupational mobility within two years from the interview. The choice of a short observation window may lead to a large number of observations where no mobility occurred, and thus may undervalue the potential effect of negative equity on workers' choices. It is of interest to have a robustness check to a longer observation window when more rounds of survey become available. In addition, looking into thick-market effects on voluntary and involuntary occupational mobility for underwater homeowners would be a valuable subject for future research. Bleakley & Lin (2012) find that displaced workers change occupations less in more densely populated areas, while younger workers with less than 10 years of labor market experience switch occupations more in areas that are more densely populated. It is thus expected that the negative equity effect might vary with labor market density. If more detailed information on geographic area of residence (e.g. CMSA) becomes available, my work could be extended by investigating heterogeneity in the negative equity effect across local labor markets with substantial variation in population density.

Figure 2.1: Trend in Underwater Mortgages, 1997-2014



Notes: (1) American Housing Survey (AHS), 1997-2013: self-reported home value and outstanding principal, owner-occupied housing unit with a mortgage. (2) CoreLogic, 2009-2014: outstanding principal from public record data on mortgage debt outstanding, AVM (Automated Valuation Models)- estimated home values, both occupied and vacant single-family residential properties with a mortgage. (3) Zillow, 2011-2014: outstanding mortgage balance from TransUnion, Zillow-estimated home values, all owner-occupied single-family, condominium and cooperative properties with a mortgage.

Table 2.1: State Foreclosure Laws

State	Recourse Classification	State	Recourse Classification
Alabama	recourse	Montana	non-recourse
Alaska	non-recourse	Nebraska	recourse
Arizona	non-recourse	Nevada	recourse
Arkansas	recourse	New Hampshire	recourse
California	non-recourse	New Jersey	recourse
Colorado	recourse	New Mexico	recourse
Connecticut	recourse	New York	recourse
Delaware	recourse	North Carolina	non-recourse
District of Columbia	recourse	North Dakota	non-recourse
Florida	recourse	Ohio	recourse
Georgia	recourse	Oklahoma	recourse
Hawaii	recourse	Oregon	non-recourse
Idaho	recourse	Pennsylvania	recourse
Illinois	recourse	Rhode Island	recourse
Indiana	recourse	South Carolina	recourse
Iowa	non-recourse	South Dakota	recourse
Kansas	recourse	Tennessee	recourse
Kentucky	recourse	Texas	recourse
Louisiana	recourse	Utah	recourse
Maine	recourse	Vermont	recourse
Maryland	recourse	Virginia	recourse
Massachusetts	recourse	Washington	non-recourse
Michigan	recourse	West Virginia	recourse
Minnesota	non-recourse	Wisconsin	recourse
Mississippi	recourse	Wyoming	recourse
Missouri	recourse		

Notes: information on state foreclosure law are from RealtyTrac (http://www.realtytrac.com/real-estate-guides/foreclosure-laws/) and AllLaw (http://www.alllaw.com/articles/nolo/foreclosure/anti-deficiency-laws.html).

Table 2.2: Descriptive Statistics

variable	overall	renter	homeowner: overall	homeowner: homeowner without negative equity	homeowner: homeowner with negative equity
Occupational switch	0.192	0.306	0.134	0.133	0.160
	(0.394)	(0.461)	(0.341)	(0.340)	(0.367)
Home ownership	0.662	0.000	1.000	1.000	1.000
	(0.473)	(0.000)	(0.000)	(0.000)	(0.000)
Negative equity	0.027	0.000	0.041	0.000	1.000
	(0.162)	(0.000)	(0.198)	(0.000)	(0.000)
Live in recourse state	0.792	0.797	0.790	0.790	0.786
	(0.406)	(0.402)	(0.407)	(0.407)	(0.411)
Occupational tenure	9.307	5.529	11.234	11.328	9.036
	(9.218)	(6.611)	(9.748)	(9.821)	(7.545)
Age	42.845	37.566	45.537	45.703	41.640
	(11.049)	(10.768)	(10.185)	(10.163)	(9.947)
Marital status	0.739	0.475	0.874	0.874	0.864
	(0.439)	(0.499)	(0.332)	(0.331)	(0.344)
If have kids	0.427	0.331	0.476	0.471	0.614
	(0.495)	(0.471)	(0.499)	(0.499)	(0.488)
College graduate	0.458	0.382	0.497	0.498	0.474
	(0.498)	(0.486)	(0.500)	(0.500)	(0.500)
Post-graduate	0.146	0.093	0.172	0.174	0.139
	(0.353)	(0.291)	(0.378)	(0.379)	(0.347)
Black	0.107	0.182	0.069	0.069	0.078
	(0.310)	(0.386)	(0.254)	(0.253)	(0.269)
Other race	0.072	0.084	0.066	0.064	0.110
	(0.258)	(0.277)	(0.248)	(0.245)	(0.313)
Economic shock	0.626	0.664	0.607	0.581	1.207
	(2.001)	(2.037)	(1.982)	(1.937)	(2.776)
Number of observations	10370	4348	6022	5750	272

Notes: "Occupation switch" is a dummy variable that equals 1 if an individual switched his occupations in the following two years. "Ownership" is a dummy variable that equals 1 if an individual owned a house. "Negative equity" is a dummy variable that equals 1 if a homeowner had negative home equity. "Live in recourse state" is a dummy variable that equals 1 if recourse was allowed in the state of residence. "Marital status" is a dummy variable that equals 1 if an individual was married. "If have kids" is a dummy variable that equals 1 if an individual had kids. "Economic shock" is defined as the change of local unemployment rate in a 2-year period. Standard deviation in parentheses.

Table 2.3: Occupational Mobility Rates (%)

			homeowner		
year	overall	renter	overall	homeowner without negative equity	homeowner with negative equity
2003	19.93	31.27	14.56	14.52	17.32
	(2034)	(786)	(1248)	(1230)	(18)
2005	19.85	31.13	14.47	14.31	30.69
	(2073)	(814)	(1259)	(1244)	(15)
2007	18.62	29.81	13.39	13.28	19.13
	(2081)	(827)	(1254)	(1227)	(27)
2009	18.95	29.75	13.07	12.76	16.77
	(2067)	(915)	(1152)	(1054)	(98)
2011	18.66	30.84	11.26	11.11	12.61
	(2115)	(1006)	(1109)	(995)	(114)

Notes: The table shows occupational mobility rates calculated based on the data from the PSID. It reports the fraction of workers in year t who switched their occupations between year t and t+2. The rates have been multiplied by 100. Number of observations in parentheses.

Table 2.4: Home Ownership Rate, and the Share of Negative Equity amongst Homeowners

	2003	2005	2007	2009	2011
A) Overall					
Home ownership rate	67.9%	67.7%	68.2%	64.8%	62.2%
	(2034)	(2073)	(2081)	(2067)	(2115)
The share of negative equity amongst homeowners	1.3%	1.0%	1.9%	7.9%	9.7%
	(1248)	(1259)	(1254)	(1152)	(1109)
B) Live in recourse state					
Home ownership rate	68.1%	67.6%	68.3%	64.0%	61.7%
	(1642)	(1679)	(1694)	(1690)	(1735)
The share of negative equity amongst homeowners	1.6%	0.9%	1.7%	7.8%	9.7%
	(1003)	(1009)	(1010)	(919)	(885)
c) Live in non-recourse state					
Home ownership rate	67.1%	68.1%	67.4%	67.6%	64.2%
	(392)	(394)	(387)	(377)	(380)
The share of negative equity amongst homeowners	0.2%	1.3%	2.9%	8.2%	9.6%
	(245)	(250)	(244)	(233)	(224)

Notes: The table shows home ownership rate and the share of negative equity among homeowners by year and by the type of state foreclosure laws. The numbers in parentheses below home ownership rates are the numbers of all observations including renters and homeowners. The numbers in parentheses below the share of negative equity are the numbers of homeowners.

Table 2.5: The Effect of Negative Equity on Occupational Mobility, OLS Estimation

	(1)	(2)	(3)	(4)
Ownership in recourse states	-0.073***	-0.074***	-0.074***	-0.075***
	(0.012)	(0.012)	(0.013)	(0.013)
Ownership in non-recourse states	-0.073***	-0.074***	-0.055**	-0.055**
	(0.016)	(0.016)	(0.022)	(0.022)
Negative equity in recourse states	0.014	0.017	0.018	0.021
	(0.027)	(0.027)	(0.028)	(0.028)
Negative equity in non-recourse states	-0.016	-0.013	-0.020	-0.017
	(0.044)	(0.044)	(0.047)	(0.047)
Occupational tenure	-0.024***	-0.024***	-0.023***	-0.023***
	(0.002)	(0.002)	(0.002)	(0.002)
Occupational tenure squared	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.015***	-0.015***	-0.014***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)
Age squared	0.014***	0.014***	0.013***	0.013***
	(0.004)	(0.005)	(0.005)	(0.005)
Marital status	-0.037***	-0.037***	-0.040***	-0.040***
	(0.013)	(0.013)	(0.013)	(0.013)
If have kids	0.003	0.003	0.002	0.002
	(0.011)	(0.011)	(0.011)	(0.011)
Economic shock	-0.000	-0.004	-0.000	-0.003
	(0.002)	(0.006)	(0.002)	(0.006)
year effect	N	Y	N	Y
state effect	N	N	Y	Y
Constant	0.758***	0.765***	0.761***	0.769***
	(0.077)	(0.078)	(0.087)	(0.088)
number of observations	10370	10370	10370	10370
number of individuals	3117	3117	3117	3117

Notes: The table reports OLS estimates. The sample is restricted to male heads of household, aged 22 to 65, who worked for pay, and employed in non-military jobs. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: The Effect of Negative Equity on Occupational Mobility, Fixed Effect Model

	(1)	(2)	(3)	(4)
Ownership in recourse states	-0.012	-0.013	-0.009	-0.009
	(0.023)	(0.023)	(0.022)	(0.022)
Ownership in non-recourse states	-0.062	-0.064	-0.061	-0.062
	(0.040)	(0.040)	(0.043)	(0.043)
Negative equity in recourse states	0.031	0.033	0.026	0.028
	(0.033)	(0.034)	(0.033)	(0.033)
Negative equity in non-recourse states	-0.047	-0.045	-0.040	-0.038
	(0.055)	(0.055)	(0.050)	(0.050)
Occupational tenure	0.031***	0.031***	0.031***	0.031***
	(0.003)	(0.003)	(0.003)	(0.003)
Occupational tenure squared	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.048***	-0.017	-0.048***	-0.017
	(0.009)	(0.020)	(0.009)	(0.020)
Age squared	0.035***	0.035***	0.034***	0.035***
	(0.010)	(0.010)	(0.010)	(0.010)
Marital status	-0.010	-0.008	-0.005	-0.003
	(0.022)	(0.022)	(0.021)	(0.021)
If have kids	0.005	0.005	0.002	0.002
	(0.017)	(0.017)	(0.017)	(0.017)
Economic shock	0.000	-0.002	0.000	-0.002
	(0.002)	(0.006)	(0.002)	(0.006)
year effect	N	Y	N	Y
state effect	N	N	Y	Y
Constant	1.355***	0.121	1.540***	0.305
	(0.191)	(0.741)	(0.239)	(0.747)
number of observations	10370	10370	10370	10370
number of individuals	3117	3117	3117	3117

Notes: The table reports fixed effect estimates. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: The Effect of Negative Equity on Upward and Downward Occupational Mobility, Fixed Effect Model

	(1) overall	(2) upward occupational mobility	(3) downward occupational mobility
Ownership in recourse states	-0.009	-0.017	0.012
	(0.022)	(0.021)	(0.017)
Ownership in non-recourse states	-0.062	0.001	-0.082**
	(0.043)	(0.037)	(0.040)
Negative equity in recourse states	0.028	0.035	0.011
	(0.033)	(0.032)	(0.022)
Negative equity in non-recourse states	-0.038	-0.052	0.015
	(0.050)	(0.038)	(0.042)
Occupational tenure	0.031***	0.025***	0.018***
	(0.003)	(0.003)	(0.003)
Occupational tenure squared	-0.000***	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)
Age	-0.017	-0.017	-0.009
	(0.020)	(0.019)	(0.016)
Age squared	0.035***	0.039***	0.005
	(0.010)	(0.009)	(0.008)
Marital status	-0.003	-0.012	0.015
	(0.021)	(0.021)	(0.017)
If have kids	0.002	0.009	-0.010
	(0.017)	(0.016)	(0.011)
Economic shock	-0.002	0.000	-0.006
year effect	Y	Y	Y
state effect	Y	Y	Y
Constant	0.305	0.103	0.466
	(0.747)	(0.725)	(0.588)
number of observations	10370	9610	8873
number of individuals	3117	3036	2919

Notes: The table reports fixed effect estimates. In column (1), the model is estimated using the full sample. In column (2) and (3), negative equity effect is estimated on upward occupational mobility and downward occupational mobility respectively. Occupations are ranked by median wage which is estimated by using IPUMS-USA 2000 5% sample. An occupational switch is identified as upward occupational mobility if the individual moves up or stays in a similar place in the occupational distribution, otherwise identified as downward occupational mobility. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: The Effect of Negative Equity on Job-Related Moving, the Effect of Negative Equity on Occupational Mobility Conditional on Whether the Worker Had Ever Been Displaced, Fixed Effect Model

	(1)	(2)	(3)	(4)
	overall		not displaced	displaced
	occupational mobility	job-related moving	occupational mobility	occupational change
Ownership - rec.	-0.009	0.006	-0.013	-0.086
	(0.022)	(0.012)	(0.024)	(0.112)
Ownership - non-rec.	-0.062	-0.020	-0.037	-0.479***
	(0.043)	(0.028)	(0.044)	(0.185)
Negative equity - rec.	0.028	0.006	0.026	0.030
	(0.033)	(0.012)	(0.032)	(0.096)
Negative equity - non-rec.	-0.038	0.004	-0.023	0.334
	(0.050)	(0.023)	(0.048)	(0.225)
Occupational tenure	0.031***	0.001	0.027***	0.040**
	(0.003)	(0.001)	(0.003)	(0.019)
Occupational tenure^2	-0.000***	0.000	-0.000**	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Age	-0.017	-0.006	-0.002	-0.031
	(0.020)	(0.009)	(0.020)	(0.087)
Age squared	0.035***	0.004	0.027***	0.009
	(0.010)	(0.003)	(0.009)	(0.080)
Marital status	-0.003	-0.011	0.006	-0.088
	(0.021)	(0.010)	(0.021)	(0.107)
If have kids	0.002	-0.001	-0.005	-0.002
	(0.017)	(0.007)	(0.016)	(0.077)
Economic shock	-0.002	-0.000	-0.006	-0.032
	(0.006)	(0.002)	(0.006)	(0.040)
year effect	Y	Y	Y	Y
state effect	Y	Y	Y	Y
Constant	0.305	0.405	-0.055	0.872
	(0.747)	(0.329)	(0.757)	(2.507)
Observations	10370	10370	9172	1198
Individuals	3117	3117	2952	909

Notes: The table reports fixed effect estimates. In column (1), the model is estimated using the full sample. In column (2), the effect on job-related moving is estimated. In column (3) and (4), the model is estimated conditional on if the worker is displaced or not. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: The Effect of Negative Equity on Occupational Mobility, Fixed Effect Model

	(1)	(2)	(3)
Ownership in recourse states	-0.009	-0.005	-0.010
	(0.022)	(0.023)	(0.022)
Ownership in non-recourse states	-0.062	-0.053	-0.063
	(0.043)	(0.044)	(0.043)
Negative equity in recourse states	0.028	0.046	
	(0.033)	(0.034)	
Negative equity in non-recourse states	-0.038	-0.009	
	(0.050)	(0.053)	
LTV X negative equity - recourse			0.025
			(0.025)
LTV X negative equity - non-recourse			-0.028
			(0.034)
Occupational tenure	0.031^{***}	0.032^{***}	0.031^{***}
	(0.003)	(0.003)	(0.003)
Occupational tenure squared	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)
Age	-0.017	-0.020	-0.017
	(0.020)	(0.020)	(0.020)
Age squared	0.035^{***}	0.036^{***}	0.035^{***}
	(0.010)	(0.010)	(0.010)
Marital status	-0.003	-0.003	-0.003
	(0.021)	(0.022)	(0.021)
If have kids	0.002	0.005	0.002
	(0.017)	(0.017)	(0.017)
Economic shock	-0.002	-0.002	-0.002
	(0.006)	(0.006)	(0.006)
year effect	Y	Y	Y
state effect	Y	Y	Y
Constant	0.305	0.393	0.305
	(0.747)	(0.752)	(0.747)
number of observations	10370	10264	10370
number of individuals	3117	3091	3117

Notes: The table reports fixed effect estimates of the effect of negative equity on occupational mobility. In column (1), the model is estimated using the full sample. In column (2), the model is estimated using a sample that excludes individuals who transition from being underwater to renting. In column (3), occupational mobility is regressed on a continuous measure of LTV interacted with the indicator for negative equity rather than the indicator of being underwater only. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.10: Heterogenous Effect by Race, Fixed Effect Model

	(1) overall	(2) white	(3) black	(4) other
Ownership in recourse states	-0.009	-0.006	0.017	-0.054
	(0.022)	(0.025)	(0.064)	(0.052)
Ownership in non-recourse states	-0.062	-0.089**	0.143	0.246
	(0.043)	(0.044)	(0.170)	(0.164)
Negative equity in recourse states	0.028	0.020	0.037	0.110
	(0.033)	(0.038)	(0.106)	(0.084)
Negative equity in non-recourse states	-0.038	-0.034	-0.006	-0.093
	(0.050)	(0.054)	(0.037)	(0.119)
Occupational tenure	0.031***	0.030***	0.038***	0.036***
	(0.003)	(0.004)	(0.010)	(0.014)
Occupational tenure squared	-0.000***	-0.000**	-0.001**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.017	-0.017	0.022	-0.086
	(0.020)	(0.021)	(0.070)	(0.088)
Age squared	0.035***	0.034***	0.023	0.029
	(0.010)	(0.011)	(0.036)	(0.041)
Marital status	-0.003	0.007	0.016	-0.227***
	(0.021)	(0.023)	(0.074)	(0.072)
If have kids	0.002	0.007	-0.087	0.054
	(0.017)	(0.018)	(0.066)	(0.089)
Economic shock	-0.002	-0.003	0.018	-0.005
	(0.006)	(0.007)	(0.019)	(0.026)
year effect	Y	Y	Y	Y
state effect	Y	Y	Y	Y
Constant	0.305	0.195	-0.744	2.995
	(0.747)	(0.813)	(2.400)	(3.075)
number of observations	10370	6760	2809	801
number of individuals	3117	1992	914	335

Notes: The table reports fixed effect estimates. In column (1), the model is estimated using the full sample. In column (2)-(4), the model is estimated for each race group. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11: Heterogenous Effect by Education, Fixed Effect Model

	(1) overall	(2) high school or lower	(3) some college	(4) post-graduate
Ownership in recourse states	-0.009	-0.011	-0.022	-0.039
	(0.022)	(0.039)	(0.031)	(0.059)
Ownership in non-recourse states	-0.062	-0.018	-0.125***	-0.167
	(0.043)	(0.079)	(0.048)	(0.183)
Negative equity in recourse states	0.028	-0.017	0.074	0.102
	(0.033)	(0.049)	(0.052)	(0.084)
Negative equity in non-recourse states	-0.038	-0.010	-0.095	-0.027
	(0.050)	(0.051)	(0.087)	(0.052)
Occupational tenure	0.031***	0.036***	0.038***	0.048***
	(0.003)	(0.005)	(0.005)	(0.010)
Occupational tenure squared	-0.000***	-0.000**	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.017	-0.032	-0.031	-0.001
	(0.020)	(0.030)	(0.031)	(0.062)
Age squared	0.035***	0.034**	0.028*	0.066**
	(0.010)	(0.016)	(0.015)	(0.028)
Marital status	-0.003	0.012	0.009	0.020
	(0.021)	(0.038)	(0.031)	(0.048)
If have kids	0.002	-0.032	0.026	0.013
	(0.017)	(0.029)	(0.026)	(0.048)
Economic shock	-0.002	-0.005	0.003	0.001
	(0.006)	(0.009)	(0.009)	(0.016)
year effect	Y	Y	Y	Y
state effect	Y	Y	Y	Y
Constant	0.305	0.836	0.941	-1.011
	(0.747)	(1.095)	(1.133)	(2.429)
Number of observations	10370	4636	4539	1195
Number of individuals	3117	1563	1552	443

Notes: The table reports fixed effect estimates. In column (1), the model is estimated using the full sample. In column (2)-(4), the model is estimated for each education group. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.12: Heterogeneous Effect by Occupation, Fixed Effect Model

	(1) overall	(2) professional, management, and related	(3) other occupations
Ownership in recourse states	-0.009	-0.036	-0.008
	(0.022)	(0.035)	(0.031)
Ownership in non-recourse states	-0.062	-0.034	-0.045
	(0.043)	(0.077)	(0.048)
Negative equity in recourse states	0.028	0.065	0.020
	(0.033)	(0.056)	(0.044)
Negative equity in non-recourse states	-0.038	-0.053	0.003
	(0.050)	(0.126)	(0.038)
Occupational tenure	0.031***	0.041***	0.028***
	(0.003)	(0.005)	(0.005)
Occupational tenure squared	-0.000***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)
Age	-0.017	0.021	-0.039
	(0.020)	(0.032)	(0.026)
Age squared	0.035***	0.029*	0.025**
	(0.010)	(0.015)	(0.013)
Marital status	-0.003	-0.001	-0.004
	(0.021)	(0.028)	(0.029)
If have kids	0.002	-0.015	-0.003
	(0.017)	(0.026)	(0.024)
Economic shock	-0.002	0.005	-0.004
	(0.006)	(0.009)	(0.009)
year effect	Y	Y	Y
state effect	Y	Y	Y
Constant	0.305	-1.251	1.327
	(0.747)	(1.236)	(0.942)
number of observations	10370	3543	6827
number of individuals	3117	1292	2431

Notes: The table reports fixed effect estimates. In column (1), the model is estimated using the full sample. In column (2), the model is estimated for those who work in the occupation of professional, management and related. And column (3) reports the estimation result for those who work in all other occupations. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.13: The Share of Negative Equity amongst Homeowners, Original and Recoded

	2003	2005	2007	2009	2011
A) Overall					
Original	1.3%	1.0%	1.9%	7.9%	9.7%
Recoded	4.2%	4.0%	5.8%	13.2%	15.4%
Number of homeowners	1248	1259	1254	1152	1109
B) Live in recourse state					
Original	1.6%	0.9%	1.7%	7.8%	9.7%
Recoded	4.4%	3.1%	5.2%	13.4%	15.8%
Number of homeowners	1003	1009	1010	919	885
c) Live in non-recourse state					
Original	0.2%	1.3%	2.9%	8.2%	9.6%
Recoded	3.0%	7.4%	7.9%	12.3%	13.8%
Number of homeowners	245	250	244	233	224

Notes: The table shows the share of negative equity amongst homeowners. Recoded negative equity share is calculated by using adjusted home value which is 5% lower than the reported home value.

Table 2.14: Robustness Check

	(1)	(2)
		home values overestimates
Ownership in recourse states	-0.009	-0.008
	(0.022)	(0.023)
Ownership in non-recourse states	-0.062	-0.056
	(0.043)	(0.042)
Negative equity in recourse states	0.028	0.003
	(0.033)	(0.025)
Negative equity in non-recourse states	-0.038	-0.059
	(0.050)	(0.047)
Occupational tenure	0.031***	0.031***
	(0.003)	(0.003)
Occupational tenure squared	-0.000***	-0.000***
	(0.000)	(0.000)
Age	-0.017	-0.016
	(0.020)	(0.020)
agesq	0.035***	0.035***
	(0.010)	(0.010)
Marital status	-0.003	-0.004
	(0.021)	(0.021)
If have kids	0.002	0.003
	(0.017)	(0.017)
Economic shock	-0.002	-0.003
	(0.006)	(0.006)
year effect	Y	Y
state effect	Y	Y
Constant	0.305	0.284
	(0.747)	(0.748)
number of observations	10370	10370
number of individuals	3117	3117

Notes: The table reports fixed effect estimates. In column (1) , estimation is based on original reported home value. In column (2), the model is estimated by using recoded indicator of being underwater. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3

Changes in Occupational Structure and Occupational Mobility Trend: 1968-1997

3.1 Introduction

This paper is inspired by two empirical findings on the U.S. labor market. The first one is the substantial increase in occupational mobility among men over the 1968-1997 period documented by Kambourov and Manovskii (2008, "KM08" hereafter)[1]. The second empirical finding is first noted in Acemoglu (1999) and then depicted in greater detail in Autor, Katz, and Kearney (2006), and shows that employment growth in the U.S. over the period 1980 through 2005 has been disproportionate in the top and bottom of the occupation skill distribution. As employment in both high-skill, high-wage occupations and low-skill, low-wage occupations grew substantially in relative size by 10-25% over this period, the share of employment in occupations in the middle of the skill distribution contracted rapidly. This phenomenon is termed as "job polarization". In this paper, I examine whether the change in occupational structure can account for the observed upward trend in occupational mobility.

Shifts in occupational structure might potentially affect gross occupational mobility rates through two key channels. Firstly, some occupations are intrinsically more stable than others because of the relatively high entry cost or the specificity of the skills required and tasks performed for those occupations, thus a shift in employment from more to less stable occupations would account for the increase in occupational mobility. As noted by Moscarini and Vella (2003), a more accurate view of the level and trends in occupational mobility requires an occupation distance measure that can be used to weight moves across

[1]Their finding is generally consistent with Xiong (2008)'s result for the overlap period. But Moscarini and Vella (2003) document a pro-cyclical and mildly declining pattern for 1976 to the early 1990s. The difference is due to different sample restrictions that workers aged 16-22 and government workers are excluded from KM08.

various occupations. Recent literature on occupation distance (Gathmann and Schonberg (2007), Poletaev and Robinson (2008, 2011), Yamaguchi (2008), Cortes (2012)) finds that the probability of workers switching away from occupations that are vastly different from other occupations in terms of skill required and/or task performed (e.g. health diagnosing occupations) is much lower than for those who are in occupations that share similar types of main tasks with many other occupations (such as management occupations). Given the heterogeneity in mobility across occupations, it is thus important to distinguish compositional effects from other factors affecting occupational mobility. Another channel through which shifts in occupational structure and occupational mobility are interrelated is that negative occupational employment shocks induce more occupation switches. As the labor demand in an occupation declines, workers have an incentive to switch away from current occupation to insure against the shocks.

In this paper, I examine the extent to which shifts in occupational structure can explain the observed upward trend in occupational mobility during the period of 1968-1997. By using panel data from the Panel Study of Income Dynamics (PSID) for years 1968-1997 to measure occupational mobility and using IPUMS 1970-2000 to measure the change in occupational composition, I firstly estimate the time trend in occupational mobility in the probit and linear probability models. My estimation indicates that the occupational mobility rate for the overall sample rose over that period by around 0.26% annually. The time trend in occupational mobility varies across age-education subgroups.

I then examine the effects of the changes in occupational structure on the time trend of occupational mobility by controlling for occupations and negative occupational employment shocks. My estimation results show that shifts in occupational composition can partially explain the rising occupational mobility trend for less educated young workers and more educated workers. An approximate 10-20% reduction in the estimated mobility trend when occupation is controlled for implies that occupational composition generally shifted to less stable occupations. In addition, when negative occupational employment shocks are controlled for, workers in most age-education subgroups exhibit higher increases in occupational mobility.

The related literature on the investigation of the causes of the change in mobility rate is very limited. KM08 examines whether the observed occupational mobility trend is due to the change in population age structure and education structure. When the structure of age and education are held fixed over time, they still find a substantial upward time trend in occupation mobility. KM08 also examines whether the mobility trend is caused by sectoral shifts between manufacturing and service industries. However, the researchers do not control for occupation categories. Instead, they only calculate occupational mobility in broad sectors, and use the findings that occupational mobility within the growing sectors was lower than within declining ones to conclude that shifting to less mobile sectors cannot explain the upward mobility trend. In addition, Kambourov and Manovskii (2009b) argue in a general equilibrium model that the mobility trend was not likely to be caused by a decline in the costs of switching occupations. In the study of Hollister and Smith (2013), the role of occupational structure change is examined in explaining the diverging trend in job tenure by gender. Their results show that shifts in work across different occupations and industry sectors can explain most of the decline in job tenure among men and never-married women in the period before 1996.

The remainder of the paper proceeds as follows. In Section 3.2, I document the changing occupational structure in the U.S. during 1970-2000. Section 3.3 contains a description of the data. Section 3.4 presents some supportive evidence that some occupations are more intrinsically stable than the others. In Section 3.5, I outline my estimation framework, and present and discuss the role the shifts in occupational structure play in explaining the time trend of occupational mobility. Section 3.6 concludes with a brief summary and discussion of further extensions.

3.2 The Changing Occupational Structure over 1970-2000

In this section, I document occupational structure changes over the period 1970-2000. The data used for the analysis of changing occupational employment patterns are from decennial censuses, adjusted by the Integrated Public Use Microdata Series (IPUMS) from the University of Minnesota's Minnesota Population Center. Specifically, I use Census IPUMS 1% sample for year 1970, and 5% samples for years 1980, 1990, and 2000 to measure employment shares of occupations. As IPUMS provide substantially larger samples than PSID or other data sources, they are better suited for an analysis of occupational employment trends within finer groups. Each census for these decades originally used different schemes to classify occupations, and census-based coding schemes changed significantly from 1970 to 1980 and from 1990 to 2000. In order to provide researchers with a consistent classification of occupations across census, IPUMS imposed a modified version of the 1990 Census Bureau occupational classification scheme on data from each census from 1950 onward. This enables me to determine decade-to-decade changes in employment shares across occupations[2]. The sample used for measuring occupational employment share is restricted to those aged between 16-65, and who were in the labor force in the year before the survey year. Unpaid family workers are excluded.

To give an overview of how occupational structure shifted over the period 1970-2000, occupational employment share across OCC1970 two-digit categories in each decade is shown

[2]The broad trends for occupation groups at the one-digit or two-digit level and many occupations at the three-digit level can be measured directly. But due to definitional changes, some occupations at the three-digit level are not comparable over decades. For example, classification for legislators (occupation code 3) and chief executives and public administrators (occupation code 4) were not available in census year 1970. To deal with the comparability problem, I follow Acemoglu and Autor (2011) to do some minor changes in coding and construct a balanced panel of occupations.

in Figure 3.1. Of the 23 major occupation groups listed, those with growing employment shares are concentrated in occupations that require nonroutine tasks. For example, occupations in medical and paramedical fields, accountants and auditors, teachers, judges and lawyers, and other professional specialized and technical occupations, exhibited steady growth as a percent of total employment throughout the entire period. These occupations are normally high-skill, high-pay occupations, and their core activities are “abstract" tasks (e.g., problem-solving, creativity, complex interpersonal interactions) - one category of nonroutine tasks. Meanwhile, employment growth also took place in low-skill, low-pay occupations, for example, among private household workers, and service workers. “Manual" tasks (e.g., situational adaptability, visual and language recognition, in-person interactions) - the other category of nonroutine tasks - are most intensive in these occupations.

Accompanying the employment growth of occupations intensive in nonroutine tasks was the decline in employment shares of occupations such as clerical (secretaries, stenographers, typists), crafts, operative (except transport), foremen, two farm groups (farm laborers and foremen, farmers and farm managers). Among the big occupation groups, the greatest decline in employment share took place in operative occupations (except transport) which sharply dropped from 14% in 1970 to 5.9% in 2000, as well as in crafts occupations which declined from 13.6% to 9.6% during three decades. Sales dropped significantly in the 1970s, but declined slowly thereafter. For these occupations, the core job tasks are routine cognitive and manual activities, which correspond to middle-skill, middle-pay jobs.

In summary, the marked pattern of non-neutral occupational employment change depicted in Figure 3.1 is generally in line with the “job polarization" in the U.S. observed by Acemoglu (1999) and Autor, Katz, and Kearney (2006). A leading explanation for the displacement of occupations intensive in routine tasks is that skill-biased technical change, augmented by off-shoring, reduced the demand for middle-skilled routine jobs (Acemoglu, 1999; Autor, Levy, and Murnane 2003; Autor, Katz, and Kearney, 2006; Autor and Dorn, 2008). As the routine tasks of many middle-skilled cognitive and manual jobs were increasingly codified in computer software and performed by machines or, alternatively, offshored to foreign worksites facilitated by advances in information and communication, demand for local labor in these occupations declined accordingly. In turn, the displacement of routine job tasks raised relative demand for non-routine job tasks in which workers hold a comparative advantage over current technology, in particular in performing “abstract" tasks and “manual" tasks. As a result, occupational structure in 2000 was substantially different from that in 1970.

3.3 The Data

3.3.1 Sample Restrictions

This study uses two main data sources. For the analysis on occupational mobility, I use data from the Panel Study of Income Dynamics (PSID) for the period of 1968-1997[3]. To evaluate the impact of the changes in occupational structure on mobility, I use U.S. decennial censuses from 1970 to 2000 to measure employment share by occupation, and its change over decades.

The PSID is a longitudinal study conducted since 1968 with a nationally representative sample of nearly 5,000 families. To make my work comparable with KM08, I follow their sample selection criteria by restricting the main sample to male heads of household, aged 23-61, who are not self-employed and are not working for the government. As demonstrated by KM08, the exclusion of women, workers younger than 23[4], and self-employed workers does not significantly affect the estimates on the level and the trend of aggregate mobility[5]. My final data sample from PSID consists of 4,911 individuals who contribute a total of 46,988 person-year observations.

3.3.2 Occupation Affiliation Data

The PSID defines occupations consistently using the 1970 Census occupation codes throughout the 1968-1997 period. Prior to 1981, occupation affiliation was originally coded at the one-digit or two-digit level, and after that, three-digit occupation codes were used. In 1999, the PSID released the Retrospective Occupation-Industry Supplemental Data Files in which the PSID recoded occupations and industries of household heads and wives at the three-digit level for the period 1968-1980. The originally and retrospectively assigned occupation and industry codes were produced based on the same written records of the respondents' descriptions of their occupations and industries. However, the methodology employed by the PSID in constructing these data were different. When originally coding occupation

[3] After 1997, the survey is conducted once every two years. This makes it difficult to measure occupational mobility within one-year observation period.

[4] As mentioned by KM08, workers younger than 23 are excluded in their paper because they are more interested in switches other than occupational matching in early career search process. In this paper, I follow their sample selection criteria for similar reason that rule out occupational shopping.

[5] According to KM08, the empirical results are sensitive to the exclusion of government workers. Occupational mobility of government workers is two time lower than the mobility of private-sector workers, and shows sharp downward trend during the period, which is in contrast to the upward trend of mobility of private-sector workers. As a result, including government workers in the sample decreases the overall level and flattens the upward trend in occupational mobility. On possible explanation for the downward trend of mobility of government workers is the changes of government regulation. For example, contracting out of many government-provided services results in a change in the occupational mix employed by the government. To investigate the drivers of mobility trends other than the effect of government regulation change, I follow KM08 to exclude government workers from the sample.

affiliation, the PSID coders had no access to the respondents' descriptions of their past occupations, so the coders could not compare the current year description to the one in the previous year. As a result, for a responder who is in the same occupation in consecutive years, similar occupational descriptions could end up being coded differently. In contrast, when retrospectively coding the occupation, as reported in the PSID (1999), "the coders coded all occupations and industries for each person across all required years before moving on to the next case." Access to the respondents' descriptions of occupation in all interview years allowed the coders to compare these descriptions, judge how they are similar, and assign the same occupational codes where appropriate. As discussed by Kambourov and Manovskii (2008, 2009a), the Retrospective Files are more reliable than the originally coded data.

In this study, I use the data from the Retrospective Files to identify occupational mobility prior to 1981, and use the originally coded data to identify mobility since 1981. If the occupation of a worker changes over a one year period between the survey conducted in year t and the subsequent survey conducted in year $t+1$, I classify that worker as an occupation switcher. Otherwise, he is an occupation stayer. Due to the well-known coding error problem[6] for occupation, I follow a widely used method to identify genuine occupation switches. That is, an occupation switch observed in the PSID data is treated as genuine if and only if it coincides with an employer switch. An employer switch is identified if the responder worked for the current employer for less than one year.

3.4 Are Some Occupations More Intrinsically Stable Than Others?

Since my explanation on changing occupational mobility is based on the hypothesis that some occupations are more intrinsically stable than others, I begin here by presenting some supportive evidence of occupational heterogeneity in the propensity to leave current occupation.

For the PSID sample that I use to explore the effect of shifts in occupational structure on occupational mobility trend, Table 3.1 shows annual occupational mobility rates at the three-digit level across occupations. Throughout the period of 1968-1997, the occupational mobility rate for all jobs is 10.8%. But the rate varies widely across occupations. Medical and health professionals such as physicians, dentists, chiropractors, pharmacists and dieticians, have a relatively low propensity to leave their current occupations. Only $0 \sim 5.3\%$ of observations in these occupations record a new occupation within one year from previous survey. Occupational mobility rates of workers in professional occupations such as judges and lawyers, accountants and auditor, architects, engineers, and scientists are around $3.8 \sim$

[6]For more details about coding error problem on occupation, see Kambourov and Manovskii (2009a).

7.2%, which are also lower than the economy-wide average. In contrast, occupational mobility rates of unskilled laborers and service workers are more than double that of professional jobs. Workers in low-skill occupations such as fisherman, gardeners, garbage collectors, and farm laborers, have probabilities of around $0.177 \sim 0.188$ of switching to a different occupation on a yearly basis. The number for service workers is also as high as 0.174. The mobility rates of workers in middle skill occupations are around the economy wide average. Craftsmen tend to change their occupations with a probability of 0.087, and the numbers for operatives (except transport), transport equipment operatives, and clerical workers are 0.125, 0.116, and 0.125, respectively. Overall, these statistics suggest that some occupations are indeed more stable than others. In general, occupational mobility rates decrease with the level of skill. They are highest in low-skill, low-pay occupations in which nonroutine manual tasks are the core activities, and lowest in high-skill, high-pay occupations in which abstract tasks are most intensive.

When workers face occupational transition decisions, the costs of occupational mobility play an important role in decision making. According to Cortes and Gallipoli (2017), the largest share of occupational mobility costs are attributable to occupation-specific entry costs. These occupation entry costs reflect institutional barriers such as professional qualifications, specific training or other requirements, and also convey information about the relative attractiveness of occupations[7]. Cortes and Gallipoli (2017) show that occupation-specific entry costs vary widely in size, and are positively correlated with the desirability of any given occupation. For example, dentistry (OCC 1970 code: 62) is an attractive occupation[8] to many people, but also a difficult (costly) one to get into due to its task-related barriers. In contrast, clerical occupations, including work as cashiers (OCC 1970 code: 310), bookkeepers (OCC 1970 code: 305), and secretaries (OCC 1970 code: 372), tend to have relatively low entry costs, but are not particularly attractive for some workers. As workers change their occupations, professional qualification or specific training for source occupations may not be valued in new occupations. The variation in occupation-specific access costs will thus result in differences in costs associated with leaving current occupation, and accordingly influence workers' decisions on occupational transition.

Another significant component of the costs of switching occupations relates to occupation distance, that is, the degree of skill transferability across occupation pairs. The idea of occupational skill transferability was first introduced by Shaw (1984). Instead of following

[7] In Cortes and Gallipoli (2017), relative attractiveness of source occupation is estimated using data on workers' outflows from that occupation conditional on the task variables and destination occupation fixed effect. An occupation is estimated to be more desirable if outflows from that occupation are relatively low.

[8] According to a 2012 survey by the Society of Human Resource Management, an attractive occupation has the following features: the opportunity to use skills and abilities in a meaningful way, job security, competitive compensation, professional development opportunities, flexibility, alignment with workers' values and interests.

the standard hypothesis that human capital from the former occupation will fully depreciate during an occupation switch, Shaw notes in her paper that a worker “would be able to transfer a certain amount of his/her occupation skills during the occupation switch depending on the ‘transferability’ between those two occupations" (pp. 320-321). Ormiston (2006) then developed an occupational skills transferability index based on the knowledge, skill, and ability categories (defined by O*NET) shared across occupation pairs. His study shows that there is a positive relationship between skills transferability and occupation switches among blue-collar workers. Using the methodology developed in Ormiston (2006) for measuring occupational skill transferability, Nawakitphaitoon and Ormiston (2015) find that post-displacement earning losses of reemployed displaced workers are negatively correlated with the degree of similarity between the pre- and post-displacement occupations. In addition, Gathmann and Schonberg (2010) proposed the concept of task-specific human capital to measure the transferability of skills. Their results show that workers are more likely to move to occupations in which similar tasks are performed as in their source occupation, and more than 40% of wage growth can be attributed to the portable skills from the source occupation. Studies of Poletaev and Robinson (2008), Cortes (2012) and Cortes and Gallipoli (2017) also provide evidence that occupation distance increases the cost of switching occupations.

All of these studies indicate that occupation distance plays an important role in occupational change decisions. As skills required and tasks performed in some occupations are so ‘specific’, the degree of their transferability is relatively lower than others, which leads to a higher cost of leaving occupations that entail these ‘specific’ skills/tasks. For example, dentists (OCC 1970 code: 62) and other medical occupations such as physicians (OCC 1970 code: 65) have somewhat different sets of skills and perform some different tasks. And the distance between dentists and occupations out of medical and health fields are even larger. In contrast, bank tellers (OCC 1970 code: 301), bookkeepers (OCC 1970 code: 305), and file clerks (OCC 1970 code: 325) share similar types of main tasks and skills. Transitions among these clerical occupations involve only a minor adjustment in the mix of tasks performed. In this case, due to easier transferability of human capital of workers in clerical occupations compared to the specific human capital of dentists, occupational mobility costs for dentists are potentially higher than for clerks; dentists thus have less incentive to switch to other occupations than workers in clerical occupations. Overall, studies on occupational mobility costs support my hypothesis that some occupations are more intrinsically stable than others.

3.5 Regression Specification and Results

3.5.1 Methodology

Building upon KM08, I study the trend in occupational mobility by estimating regression models with an indicator variable for occupation switch as the dependent variable and a linear time trend as the key independent variable. The marginal effect of this time trend variable estimates the average annual change in occupational mobility rate, controlling for other variables. The baseline model is:

$$
\begin{aligned}
E(OM_{it}|X_{it}) = f(&\beta_0 + \beta_1 Time_t + \beta_2 Break_t + \beta_3 Unemp_{it} \\
&+ \gamma_1 A_{it} + \gamma_2 Time_t * A_{it} + \gamma_3 Break_t * A_{it} + \gamma_4 Unemp_{it} * A_{it}) \quad (3.1)
\end{aligned}
$$

where OM_{it} is a binary indicator variable that equals one if individual i reports a current occupation in survey year t different from the one he reported in year t+1, zero otherwise. $Time$ denotes a time trend and $Unemp_{it}$ is the current level of unemployment in the state of residence[9]. As discussed in Section 3.3, the coding procedure changed in survey year 1981. To capture the possible effect of the coding change on the measurement of occupational mobility, a dummy variable $Break_t$, which assumes the value of one if the survey year is in the period 1981-1997, and zero otherwise, is also included in the model. An individual's occupation switch is also modeled to be dependent on a set of controls A_{it} which include age, age squared, education, interaction between education and age, and interaction between education and age squared. Individuals are divided into two educational groups: those who have 12 years of education or less and those who have more than 12 years of education. Further, in order to allow different age-education groups to have different mobility trends over time and over the business cycle, and to have different changes in mobility as a result of the change in the coding procedure in 1981, A_{it} is interacted with the time trend $Time_t$, the macroeconomic condition variable $Unemp_{it}$, and the *break* variable. In this paper, I use two models to predict the mobility trend: probit model, and linear probability model. Note that the data used in this study is panel data and the same individuals are followed over time. Robust standard errors are adjusted for clustering at the individual level.

In this study, I assume that the coding error presented in the originally coded data results only in an affine shift in the level of occupational mobility relative to that obtained

[9] I use unemployment level in the state of residence to capture local labor market situations as macroeconomic conditions affect worker occupational mobility decisions. The data of state level unemployment rate is from the Bureau of Labor Statistics of the U.S.

on the Retrospective Files[10]; thus the overall sample over the entire time period will identify the time trend. The time trend is calculated as the derivative of function $f(\cdot)$ with respect to $Time$. It is computed around the sample mean of all variables. The time trends in mobility identified in this specification is economy-wide time trends in mobility.

To explore the effect of the change in occupational structure on gross occupational mobility, I first examine the compositional effect by comparing economy-wide time trends in mobility, which average over occupation categories, to within-occupation time trends. Given the hypothesis on occupational heterogeneity in the propensity to leave current occupation, the difference between economy-wide time trend and within-occupation time trend is informative of the extent to which the observed changes in occupational mobility rate is driven by workers shifting between more or less stable occupations, versus by changes in switching behavior within detailed occupations.

The within-occupation time trends in mobility condition on occupation identity. That is, I augment the regression model described above with occupation effects. These encompass some observed and unobserved occupational characteristics. The occupation effects measure inter-occupation differences in mobility rates, conditional on individual characteristics A_{it}, local macroeconomic condition $Unemp_{it}$, and coding procedure variable $Break_t$. The time trends in mobility identified in this specification is thus the within-occupation time trends as adding occupation effects into the regression model removes the effects of inter-occupation differences in mobility rates. Given that omitted variable bias can be represented as least squares coefficients in an artificial regression[11], I examine the effect of the change in occupational composition on mobility by comparing estimated time trend in mobility in specifications with and without occupation effects, that is, by comparing economy-wide time trends in mobility to within-occupation time trends. This analysis is, of course, based on a strong assumption that the propensity to switch away from current occupation is not affected by the change in employment share of that occupation.

Secondly, I examine whether the change in mobility behavior in response to occupational demand shocks can explain the time trend in occupation mobility. As occupational structure shifts over time, changing job opportunities may lead to workers' reallocation across occupations. When an occupation shrinks, workers face an incentive to exit the occupation to insure against the labor demand shock, and at the same time, firms may react to changing demands for occupations by reducing hiring. It is thus expected that workers in shrinking occupations are more likely to switch away from their occupations than those who are not in shrinking occupations. By using the reliable data from the Retrospective Files for the

[10]KM08 tests this assumption formally, in both probit model and linear probability model. All tests' results suggest that the coding error leads to an affine shift in mobility with a minor effect on the time trend.

[11]See, e.g., Greene (2007)

1969-1980 period, KM08 provides supportive evidence that occupational mobility within growing sectors was lower than within declining ones. I therefore examine if occupational demand shock may partially explain the observed changes in occupational mobility in the 1968-1997 period.

The change in employment share of an occupation over decades is measured as $\triangle Eshare_{ot'} = Eshare_{o,t'+10}/Eshare_{ot'} - 1$ where $Eshare_{ot'}$ denotes the share of occupation o in total employment at time t'. Note that a negative value of this measure means that the employment share of the occupation declines, but does not necessarily mean that employment in that occupation declines. It might be the case that employment in an occupation increases but at a lower rate than in other increasing occupations, thus relative to the total, its employment share declines. Let $AVG_{t'}$ denote percentage change in total employment over the decade from year t'. Based on the measure of the change in occupational employment share, occupations are divided into two categories - "shrinking occupations", where $\triangle Eshare_{ot'} < -AVG_{t'}/(1 + AVG_{t'})$, and "growing occupations", where $\triangle Eshare_{ot'} > -AVG_{t'}/(1 + AVG_{t'})$. An indicator variable is used to identify if the employment of an occupation declines. It takes a value of one if the occupation shrinks over a decade. My calculation shows that 89 out of 316 occupations experienced shrinking demand in the 1970s, and 25% observations during that period worked in declining occupations. In the 1980s, employment in 116 out of 384 occupations declined over the decade, and 31% observations worked in those shrinking occupations. The corresponding numbers in the 1990s are 148 out of 378 and 49%, respectively.

In the second estimation, in addition to controlling for occupation effects, occupational demand shocks, and their interaction, the interactions between occupational demand shocks and age, age squared, education and macroeconomic condition variable $Unemp_{it}$ are also included in the regression. Adding these interaction terms into the regression model allows the effect of occupational demand shocks to vary across age-education groups and to change with macroeconomic conditions. This is motivated by the finding of Autor and Dorn (2009) that the mean age of a declining occupation's workforce rose substantially faster than average. Their explanation for this finding is that skill specificity makes the costs of occupational mobility higher for older than younger workers, therefore as an occupation contracts, older workers will have an incentive not to leave the occupation while younger workers will face an incentive not to enter. The interaction terms between occupational demand shock variable and age and age squared capture the different opportunity set faced by workers at different ages.

3.5.2 Empirical Results

I start the estimation of the regression model in a specification without controlling for changes in occupational structure. The estimated coefficients of the variables of interest are presented in Table 3.2. The first column reports the estimates from a probit regression, and the second column corresponds to a linear probability model. As the same individuals are being followed over time in panel data, all standard errors in these pooled regressions are clustered at the individual level. Based on the estimates shown in Table 3.2, the time trends in occupational mobility for the overall sample and for various age-education subgroups are calculated accordingly and shown in Table 3.3.

The trends in occupational mobility reported in Table 3.3 are consistent with the findings in KM08 as well as the findings in Markey and Parks II (1989) based on the January CPS supplements. For the overall sample, the estimate from the probit regression indicates that the occupational mobility rate rose over the period 1968-1997 by around 0.26% annually which is statistically significant at the 1% level. Upward mobility trends are also presented for most age-education subgroups. For instance, those who are 23-35 years old and are high school graduates or dropouts exhibit the highest rise in mobility rate compared to other subgroups, where their mobility rate rose by 0.36% annually. In contrast, occupational mobility did not change significantly for less educated workers who are older than 49. Table 3.3 also shows that the rise in occupational mobility of young workers (23-35 years old) is greater than that of middle-aged workers (36-48 years old) for both education groups. However, old workers (49-61 years old) behave differently across education groups. Among less educated workers, old workers exhibit the lowest rise in occupational mobility, while among more educated workers, occupational mobility of old workers rose more than the other two age groups. The estimates of the time trend in occupational mobility obtained from the linear probability model (column (2) of Table 3.3) are highly consistent with the estimates from the probit regression.

To explore whether mobility trends can be explained by the shifts in occupational structure, I then add occupation related controls into the regressions. Table 3.4 shows the estimated coefficients of the variables of interest in the probit model. To make the results comparable with my basic result, column (1) reports the estimates from the baseline model without controlling for occupations, which is economy-wide time trends in mobility. Column (2) reports the estimates of a regression that includes dummy variables for occupations at the three-digit level, which is within-occupation time trends in mobility. In column (3), the model is estimated with controls for both occupations and negative occupational demand shocks. The corresponding time trends in occupational mobility for the overall sample and various age-education subgroups are calculated and shown in Table 3.5.

Estimated time trends in occupational mobility when occupation is controlled for (column (2) of Table 3.5) are positive and statistically significant for the overall sample and various age-education subgroups. A comparison with the estimated mobility trends from the baseline model (column (1) of Table 3.5) shows that including occupation controls in the regression substantially shifts the time trend estimates to less positive values for the overall sample and most age-education subgroups. For the overall sample, the annual rise in occupational mobility decreases from 0.26% to 0.24% when detailed occupation is controlled for. The change in the estimated mobility trend due to the inclusion of occupation controls in the regression (i.e., (1)-(2), the difference between economy-wide time trends in mobility and inter-occupation time trends in mobility) is shown in column (3), and the result of the Hausman test on compositional effects indicates that the decrease in the estimated trend is significant. It implies that shifts in occupational composition can partially account for the rising mobility trend. Similar effects occur for some subgroups. For less educated workers who are younger than 35, estimated mobility trends decrease from 0.36% to 0.29% when detailed occupations are controlled for. This result suggests that occupational compositions for this group of workers shifted toward less stable occupations, which accounts for about one fifth of the increase in mobility. For more educated workers who are younger than 35 or older than 48, estimated mobility trends decrease from 0.29% to 0.26% and from 0.34% to 0.3%, respectively, suggesting that the over time change in occupational structure can explain around 10% of the rise in occupational mobility for these two groups of workers. In contrast, the estimated time trend for less educated workers who are older than 48 increases when occupation controls are included in the regression. Their estimated mobility trend slightly increases from 0.1% to 0.11%, but the Hausman test result shows that the compositional effect is not significant. For middle-aged workers in each education group, the estimated mobility trends do not change significantly when occupation is controlled for, suggesting that the change in occupational structure has no overall effect on their occupational mobility. Evidently, less educated young workers are generally employed in low-skill low-pay unattractive occupations. The analysis of Groes and Manovskii (2015) shows that the low earners tend to switch to new occupations with lower average wages. With the decline of manufacturing and the rise of the service industry during the period 1970-2000, job polarization moves young low-skill workers toward low-pay less stable jobs, and thus affects them most among all workers.

The estimates shown in column (4) of Table 3.5 are based on a specification with both occupation controls and controls on occupational employment shocks. For the overall sample and all age-education subgroups, estimated time trends in mobility are positive and significant. Column (5) gives the difference in time trends between the one from baseline estimation and the one reported in column (4), representing the overall effect of the change in occupational structure. Column (6) gives the difference in time trends reported in column (2) and (4), representing the effect of negative occupational employment shocks on mobility trends. For the overall sample, the mobility trend reported in column (4) is significantly lower than the estimate from the baseline model, but is significantly higher than the estimate in column (2) when only occupation is controlled for. This result indicates that negative occupational demand shocks did influence occupational mobility trends, and negative occupational demand shocks declined over time. Similarly, the estimated mobility trend for less educated young workers significantly increases from 0.29% to 0.31% when occupational demand shocks are controlled for, indicating that the shocks they suffered influenced their mobility trends[12]. In total, the compositional effect on occupational mobility trends dominates the effect of occupational demand shocks.

Table 3.6 reports the estimates in a linear probability model with the same controls as in Table 3.4. The corresponding time trend in occupational mobility are shown in Table 3.7. In general, the estimates from the linear probability model are consistent with the probit estimates. Occupational mobility rose for the overall sample and various age-education subgroups. When occupation is controlled for, the estimated mobility trend decreases for most subgroups. In the probit model, the compositional effect is not significant for less educated older workers. While in the linear probability model, the significant compositional effect for this subgroup suggests that occupational compositions for less educated older workers shift to more stable positions. In addition, based on estimation results from the linear probability model, the estimated within-occupation mobility trends increase for most age-education subgroups when occupational employment shocks are controlled for, implying that occupational employment shocks declined over time.

In summary, the rising trend in occupational mobility during the period of 1968-1997 can be partially explained by the shifts in occupational structure. Regression results from the probit and linear probability models indicate that, for less educated young workers and all more-educated workers, around 10-20% of the upward mobility trend can be attributed to the shifting of occupational composition to less stable occupations. In addition, when occupational mobility shocks are controlled for, workers in most age-education subgroups exhibit higher increases in occupational mobility.

3.6 Conclusions

In this paper, I examine the extent to which shifts in occupational structure explain the trend in occupational mobility during the period of 1968-1997. By using panel data from the Panel Study of Income Dynamics (PSID) for years 1968-1997 to measure occupational mobility and using IPUMS 1970-2000 to measure changes in occupational composition, I firstly estimate the time trend in occupational mobility in the probit and linear probability models. Regression results indicate an upward mobility trend for the overall sample and various age-education subgroups.

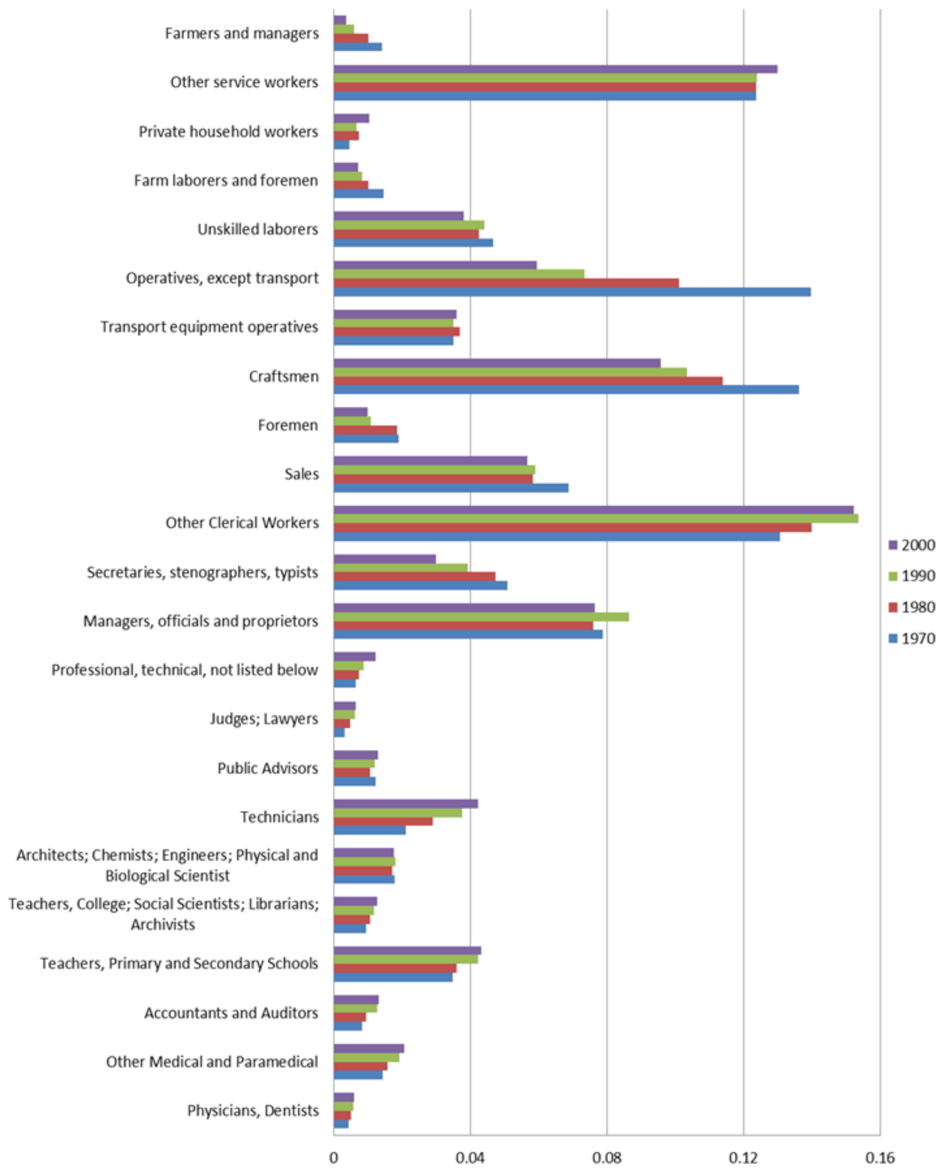
I then examine the effects of changes in occupational structure on the time trend of occupational mobility by controlling for occupations and negative occupational employment shock. My estimation results show that the rising occupational mobility trends for less educated young workers and more educated workers can be partially explained by the shifts in occupational composition. An approximate 10-20% reduction in the estimated mobility

[12]The test statistic for the overall effect of the change in occupation structure is negative for more educated middle-aged workers, which is a fairly common finite-sample occurrence for Hausman tests and is usually interpreted as rejection of the null hypothesis.

trend when occupation is controlled for implies that occupational composition generally shifted to less stable occupations. In addition, when negative occupational employment shocks are controlled for, workers in most age-education subgroups exhibit higher increases in occupational mobility.

In view of the fact that significant upward trends in occupational mobility still exist even after occupations are controlled, the next step is to investigate other causes of that trend. One potential research question is to relate the changes in occupational matching quality to the changes in occupational mobility. Due to the advancement of information and communication technology, has occupational matching quality been improved over time? Has the matching process shortened? How might it potentially affect occupational mobility trends? I believe the exploration of occupational mobility trends will help us to further understand human capital formation and growth.

Figure 3.1: Occupational Employment Share, 1970 - 2000



Note: Occupational employment share, representing employment in a specific occupation or occupation group as a percent of total employment in the economy, is calculated by using Census IPUMS 1% sample for year 1970, and 5% samples for years 1980, 1990, and 2000. The sample is restricted to those aged between 16-65, were in the labor force in the year before the survey year. Unpaid family workers are excluded. Occupations are grouped based on OCC1970 at the two-digit level.

Table 3.1: Propensity to Switch Away from Current Occupation

Current occupation	♯ of obs.	Prob.
Dentist, physicians (medical and osteopathic)	118	0
Chiropractors, optometrists, pharmacists, veterinarians, nurses, therapists, etc.	177	0.053
Accountants and Auditors	612	0.06
Teachers (primary and secondary schools)	427	0.101
Teachers (college), social scientists, librarians, archivists, mathematical specialists	417	0.104
Architects, engineers, life and physical scientists	1981	0.072
Computer specialists, foresters, operations and systems researchers and analysts, airplane pilots and navigators, health technicians, engineering and science technicians, embalmers, flight engineers, radio operators, tool programmers, etc.	2206	0.096
Public advisors: clergymen, editors and reporters, farm and home management advisors, personnel and labor relations workers, public relations persons, etc.	646	0.11
Judges, lawyers	128	0.038
Vocational counselors, writers, artists, athletes, musicians, painters, sculptors, radio and television announcers, and professional, etc.	258	0.112
Managers, officials and proprietors (except farm)	6184	0.09
Secretaries, stenographers, typists	27	0.206
Clerical workers (bank tellers, cashiers, bookkeepers, library attendants, etc.), office machine operators (payroll clerks, receptionists, etc.), storekeepers, telegraph or telephone operators, station and express agents, shipping clerks, statistical clerks	2441	0.125
Sales workers (manufacturing industry, wholesale, retail, service, etc.)	2157	0.15
Foremen, n.e.c.	1421	0.085
Craftsmen (bakers, carpenters, electricians, jewelers, etc.), mechanics and repairmen (aircraft, automobile, air conditioning, heavy equipment,household appliance, etc.)	9720	0.087
Transport equipment operatives (boat, bus, truck, fork lift, taxicab, etc.)	3739	0.116
Operatives, except transport (precision machines, textile, assemblers, drillers, etc.)	6701	0.125
Unskilled laborers, nonfarm (fishermen, lumbermen, garbage collectors, etc.)	3548	0.188
Farm laborers and foremen	878	0.177
Private household workers (cooks, child care, housekeeping, maids, laundresses)	25	0.229
Other service workers (cleaning, food, health, personal service, protective service)	3062	0.174
Farmers (owners and tenants) and managers	115	0.073
Total	46988	0.108

Note: Observations are from PSID 1968-1997. Probability to leave current occupation is measured based on the three-digit level of OCC 1970.

Table 3.2: Estimation Results, Baseline Model

	Probit	LPM
Time	0.0109	0.0115
	(0.0438)	(0.0092)
Time*Age	0.0003	-0.0004
	(0.0023)	(0.0005)
Time*Age^2/100	-0.0007	0.0003
	(0.0029)	(0.0005)
Time*Edu	0.0079	-0.0046
	(0.0711)	(0.0152)
Time*Edu*Age	-0.0010	0.0001
	(0.0038)	(0.0008)
Time*Edu*Age^2/100	0.0023	0.0001
	(0.0047)	(0.0009)
Number of observations	46988	46988

Note: The dependent variable is whether there was an occupational switch or not. The other explanatory variables include a dummy variable *Break* which assumes the value of one if the survey year is in the period 1981-1997, zero otherwise; unemployment level in the state of residence *Unemp*, age and age squared, Education, and their interactions $Break*Age$, $Break*Age^2$, $Break*Edu$, $Break*Edu*Age$, $Break*Edu*Age^2$, $Unemp*Age$, $Unemp*Age^2$, $Unemp*Edu$, $Unemp*Edu*Age$, $Unemp*Edu*Age^2$, $Edu*Age$, and $Edu*Age^2$. Errors clustered by individual. Standard deviation in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 3.3: Time Trend in Occupational Mobility, Baseline Model

	(1)	(2)
Age (♯ of observations)	Probit	LPM
	A. Overall	
23-61 (46988)	.0026***	.0027***
	B. High School and Less	
23-35 (13344)	.0036***	.0036**
36-48 (9937)	.0018***	.0018**
49-61 (7247)	.0010	.0011
	C. Some College and More	
23-35 (8308)	.0028***	.0027***
36-48 (5644)	.0026***	.0028***
49-61 (2508)	.0034***	.0040***

Note: Based on the estimation results shown in Table 3.2, the time trend is calculated by taking the derivative of the function with respect to time. The number of observations for the overall sample or for each age-education subgroup is reported in parentheses. For the overall sample, the time trend is computed around the mean of all variables. For various age-education subgroups, the time trend is computed around the variables' means for that particular subsample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.4: Estimation Results, Probit Model

	(1)	(2)	(3)
Time	0.0109	-0.0043	-0.0042
	(0.0438)	(0.0443)	(0.0445)
Time*Age	0.0003	0.0009	0.0010
	(0.0023)	(0.0024)	(0.0024)
Time*Age^2/100	-0.0007	-0.0011	-0.0012
	(0.0029)	(0.0029)	(0.0029)
Time*Edu	0.0079	0.0237	0.0270
	(0.0711)	(0.0719)	(0.0728)
Time*Edu*Age	-0.0010	-0.0017	-0.0018
	(0.0038)	(0.0038)	(0.0039)
Time*Edu*Age^2/100	0.0023	0.0028	0.0030
	(0.0047)	(0.0048)	(0.0048)
Occupations controls	No	Yes	Yes
Shrinking occupations controls	No	No	Yes
Number of observations	46988	46988	46988

Note: The results are from a linear probability regression in which the dependent variable is whether there was an occupational change or not. Column (1) reports the estimates of the baseline model. In column (2), the model is estimated with controls for occupations at the three-digit level. In column (3), the model is estimated controlling for occupations, if the employment in a specific occupation declines, and its interaction with occupations at the two-digit level, and interactions with variables Age, Age^2, Edu, $Edu * Age$, $Edu * Age^2$, $Unemp * Age$, $Unemp * Age^2$, $Unemp * Edu$, $Unemp * Edu * Age$, $Unemp * Edu * Age^2$. Errors clustered by individual. Standard deviation in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.5: Time Trend in Occupational Mobility, With Occupation-related Controls, Probit Model

Age	(1) Baseline model	(2) Control for occupations	(3) Difference (1)-(2)	(4) Control for occupations & shrinking job market	(5) Difference (1)-(4)	(6) Difference (2)-(4)
			A. Overall			
23-61	.0026***	.0024***	.0002**	.0024***	.0002*	-.0001***
			B. High School and Less			
23-35	.0036***	.0029***	.0007***	.0031***	.0005**	-.0002*
36-48	.0018***	.0018***	.0000	.0019***	-.0001	-.0001
49-61	.0010	.0011*	-.0002	.0012*	-.0002	-.0001
			C. Some College and More			
23-35	.0029***	.0026**	.0002**	.0026***	.0002	.0000
36-48	.0026***	.0023***	.0003	.0022***	.0004+	.0001+
49-61	.0034***	.0030***	.0004**	.0028***	.0006**	.0002

Note: Column (1) reports the economy-wide trend in occupational mobility which is calculated based on the estimates of the baseline model shown in column (1) of Table 3.4. Within-occupation time trends shown in column (2) & (4) are calculated based on the estimates in column (2) & (3) of Table 3.4, respectively. + indicates a negative Hausman test statistic. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Estimation Results, Linear Probability Model

	(1)	(2)	(3)
Time	0.0115	0.0085	0.0085
	(0.0092)	(0.0091)	(0.0091)
Time*Age	-0.0004	-0.0003	-0.0003
	(0.0005)	(0.0004)	(0.0004)
Time*Age^2/100	0.0003	0.0003	0.0002
	(0.0005)	(0.0005)	(0.0005)
Time*Edu	-0.0046	-0.0016	-0.0009
	(0.0152)	(0.0150)	(0.0151)
Time*Edu*Age	0.0001	-0.0000	-0.0001
	(0.0008)	(0.0007)	(0.0007)
Time*Edu*Age^2/100	0.0001	0.0001	0.0002
	(0.0009)	(0.0009)	(0.0009)
Occupations controls	No	Yes	Yes
Shrinking occupations controls	No	No	Yes
Number of observations	46988	46988	46988

Note: The results are from a linear probability regression in which the dependent variable is whether there was an occupational change or not. Column (1) reports the estimates of the baseline model. In column (2), the model is estimated with controls for occupations at the three-digit level. In column (3), the model is estimated controlling for occupations, if the employment in a specific occupation declines, and its interaction with occupations at the two-digit level, and interactions with variables Age, Age^2, Edu, $Edu * Age$, $Edu * Age^2$, $Unemp * Age$, $Unemp * Age^2$, $Unemp * Edu$, $Unemp * Edu * Age$, $Unemp * Edu * Age^2$. Errors clustered by individual. Standard deviation in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.7: Time Trend in Occupational Mobility, With Occupation-related Controls, Linear Probability Model

Age	(1) Baseline model	(2) Control for occupations	(3) Difference (1)-(2)	(4) Control for occupations & shrinking job market	(5) Difference (1)-(4)	(6) Difference (2)-(4)
			A. Overall			
23-61	.0027***	.0025***	.0002***	.0026***	.0001+	-.0001+
			B. High School and Less			
23-35	.0036***	.0030***	.0007***	.0032***	.0005***	-.0002+
36-48	.0018**	.0018**	-.0000	.0020***	-.0002***	-.0002+
49-61	.0011	.0016**	-.0005+	.0017**	-.0006+	-.0001+
			C. Some College and More			
23-35	.0027**	.0024**	.0003	.0025**	.0002	-.0001+
36-48	.0028***	.0025***	.0003*	.0025***	.0003+	.0000+
49-61	.0040***	.0038***	.0002+	.0039***	.0001+	-.0001+

Note: Column (1) reports the economy-wide trend in occupational mobility which is calculated based on the estimates of the baseline model shown in column (1) of Table 3.6. Within-occupation time trends shown in column (2) & (4) are calculated based on the estimates in column (2) & (3) of Table 3.6, respectively. + indicates a negative Hausman test statistic. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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