Three Essays in Labor Economics

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(ABSTRACT)

This dissertation comprises three autonomous essays on topics in labor economics. The first chapter investigates the impact of socio-cultural, technological, and other transformative factors on employees' labor market decisions over recent decades, focusing specifically on the mobility of young workers in terms of job and occupation transitions. Data from the National Longitudinal Surveys of Youth (NLSY79 and NLSY97) indicate a marked increase in job mobility among young participants across different cohorts. Analysis of these datasets demonstrates that the influence of age on the likelihood of changing jobs has become more negative for the second cohort. This shift is primarily driven by changes in the impact of age for specific socio-demographic groups of respondents. Additionally, there is a notable between-cohort rise in the relationship between both upward and downward job transitions and occupational mobility.

The second essay explores the consequences of the rise in industrial robot installations on shifts in population size and employment within local labor markets, which may be substantially affected by the rapid advancement of robotics technology in recent decades. The cross-sectional study reveals discernible gender disparities in the impacts of robot adoption. The effect of robotization on the labor force participation rate is negative for men and unmarried women yet positive for married women. As industrial robots are predominantly programmed to perform routine tasks in manufacturing industries traditionally associated with heavy manual male-dominated labor, the anticipated impact of robot exposure on employment in the manufacturing sector is predictably negative for male workers. For women,

this effect is conversely positive. It was also found that robot penetration leads to an increase in the share of family income attributed to females within married-couple households.

The extended cross-sectional analysis in the third chapter indicates that the impact of robotization on local labor markets is more negative for younger people. Fixed-effects models using panel data analysis reveal that robot adoption unexpectedly reduces migration but enhances labor force participation, opposing recent scholarly findings. Employing an alternative robot adoption variable that is based on technology adoption within individual industries and, therefore, can only be utilized to analyze employment-related dependent variables yields more robust and statistically significant results, indicating a negative impact of robot exposure on employment. Nevertheless, panel data analysis does not support the previous chapter's findings regarding gender differences in the impact of robot penetration. These discrepancies may be attributed to differences in the structure, methodology, and nature of cross-sectional versus panel data and the methodological differences in measuring robotization.

Three Essays in Labor Economics

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(GENERAL AUDIENCE ABSTRACT)

This work consists of three separate essays on labor economics. The first chapter looks at how cultural, technological, and other big changes have affected people's job choices over the past few decades. Data from two surveys of young people show that young workers are changing jobs more often now. Age is found to have a bigger negative effect on job changes for the younger cohort. This change mainly affects specific socio-demographic groups. There is also a stronger link between moving up or down in jobs and changing occupations.

The second essay examines how the increase in the use of industrial robots affects the population and employment in local labor markets. The study finds that robots affect men and unmarried women negatively but have a positive impact on married women. Since robots usually do routine tasks in manufacturing, which is a male-dominated field, this hurts male workers' job prospects but helps women. Robots also lead to a higher share of family income coming from women in married households.

The third chapter shows that robots impact younger people in local job markets more negatively. Using different data, it is found that robots surprisingly reduce migration but increase labor force participation. This finding is different from those of other studies. A new way of measuring robot use within specific industries shows that robots negatively affect employment. However, this new analysis does not support the earlier findings about gender differences. These differences may come from how data is collected and analyzed and the methods used to measure robot use.

Dedication

Dedicated to my family.

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Chapter 1

Changes in Job and Occupational Mobility: Evidence from NLSY79 and NLSY97

1.1 Introduction

Job mobility has always been a pivotal topic in the field of economics because it reveals the impact of labor - a fundamental resource to produce goods and services - on both production and economic growth. Job mobility is one of the key indicators of labor market flexibility and is a significant factor contributing to wage inequality (Fuller [47], Jovanovic [61]). Between 1998 and 2011, the overall job mobility rate in the United States, measured by the combined rate of hires and separations, stood at a relatively high 31% (Haltiwanger et al. [54]). This figure is, for example, nearly double that of Norway, a European nation with a comparable standard of living to the United States (Hijzen et al. [55]). Recognizing the established inverse relationship between age and job mobility (see Mobley et al. [75], among others), it is likely that this overall job mobility rate is strongly correlated with the mobility rate of younger individuals. In an effort to deepen our understanding of how this important measure of labor market mobility has evolved, this paper investigates the determinants of job mobility, with a particular focus on the job mobility of young workers aged 18 to 33.

It can be posited that the economic, socio-cultural, technological, and political transformations of the past several decades have profoundly influenced worker behavior in the labor market. This paper seeks to estimate the effects of these changes by comparing job mobility patterns between two cohorts from the National Longitudinal Surveys of Youth: the 1979 cohort (NLSY79) and the 1997 cohort (NLSY97). Key socio-demographic factors such as age, gender, race, marital status, and educational attainment are identified as critical determinants of job mobility. The incentives for job changes fluctuate significantly over an individual's lifetime, thus making the life-cycle profile of respondents a valuable framework for understanding their labor market decisions. By leveraging longitudinal data and focusing on the notable differences in the life-cycle profiles of job transition probabilities between the cohorts[1], this study examines age effects for both cohorts while controlling for other individual and job-related variables.

For some employees, job changes are accompanied by shifts in occupations. Occupational mobility refers to the propensity to move from one occupation to another. It is an important factor of labor market efficiency, particularly due to the associated transition costs (Cortes and Gallipoli [33]. Contemporary research indicates that occupational mobility is a significant factor driving income inequality (Kambourov and Manovskii [65]), thereby having substantial welfare implications for workers.

Previous studies (Kambourov and Manovskii [63], among others) have identified an increase in occupational mobility. However, much of the recent research has analyzed changes in this labor market indicator using either single panel survey data, such as the PSID or NLSY79, or data from the Current Population Survey (CPS). This paper seeks to compare the occupational mobility characteristics of young participants from the NLSY79 and NLSY97 surveys. The objective is to assess shifts in occupational mobility over time resulting from

[1] For more details, see Figure 1, which demonstrates the difference in probabilities of a job change by age for two cohorts.

socio-cultural, technological, and other changes and to determine the impact of key determinants on these shifts. This analysis is conducted using occupational groups that encompass 22 aggregated categories of occupations.

Downward (upward) job mobility refers to the act of transitioning to a new employer where wages are lower (higher) compared to the previous job. Both forms of job mobility can be linked to motivations for changing occupations, and this relationship may vary over time. Therefore, understanding this interplay might be important for examining wage inequality, which is the focus of this study. The findings indicate a notable cohort-based increase in the marginal effects of both upward and downward job transitions on the likelihood of switching occupational groups.

This paper makes several contributions to existing literature. It aims to investigate changes in job and occupational mobility across two cohorts spanning the periods 1979-2000 and 1997-2017. By conducting a comparative analysis of these cohorts, this research sheds light on whether there have been shifts in mobility patterns over time. The multigenerational examination of labor market decisions among young workers concludes that the observed significant increase in job mobility between cohorts is influenced by differences in observable characteristics of its determinants, such as age and other individual characteristics.

By comparing the marginal effects of key determinants of job mobility on the probability of job changes between two generations, this study demonstrates that the negative regression estimate of age on job change is more pronounced for the younger cohort (NLSY97). This increase in the impact of age is observed when considering other individual and job-related factors, and it appears to be driven by shifts in the effect of this variable for male, white, unmarried, and less educated workers.

Finally, this paper identifies a noticeable association between various types of job transitions (upward, downward, and horizontal) and occupational mobility after controlling for individual and occupational characteristics. The between-cohort comparison of these estimations highlights a significant increase in the marginal effects of both upward and downward job mobility on the likelihood of changing occupational groups.

The rest of the paper is organized as follows. Section 2 reviews the literature related to job and occupational mobility. Section 3 demonstrates the data and descriptive statistics. Section 4 describes the empirical framework. The results are presented in Section 5. Section 6 concludes.

1.2 Related Literature

1.2.1 Theoretical Models of Job Mobility

Theoretical standpoints describe processes of job mobility mostly related to the relationship between mobility and earnings. One of the oldest models of job mobility is the mover-stayer model (Blumen et al. [22]), which states that underlying workers' characteristics lead "good" (or high productivity) employees to stay in their jobs, while "bad" (or low productivity) workers experience frequent job changes. According to this model, the job mobility of "movers" remains consistent over time, and there is a negative association between job mobility and wages. The reason for this negative relation is that job mobility is correlated with unobserved characteristics of employees that determine workers' productivity. Accounting for the relationship between these unobserved individual effects and job mobility suggests that mobility may not necessarily correlate with wages.

The human capital model (Becker [15], Oi [85]) emphasizes the inverse relationship between job mobility and investments in job-specific skills. This model suggests that job turnovers could potentially result in substantial wage gains. However, it does not ascertain whether the wage growth between jobs for "movers" exceeds the wage growth within jobs for "stayers" as a return on their job-specific training.

In job matching models, job mobility refers to voluntary transitions individuals make to seek more productive employment relationships. If the quality of a match (or the productivity of the match) is initially uncertain but becomes apparent over time, a job change occurs when the match proves to be less favorable than originally expected (Johnson [59], Jovanovic [62]). Consequently, there is a downward adjustment in wages, prompting individuals to seek alternative employment. In these models, jobs are considered "experience goods," where job mobility largely stems from evolving perceptions of job quality over time. Therefore, in such cases, job mobility remains associated with wages, even if the correlation between wages and unobserved, time-invariant individual and job effects is taken into account and controlled.

When the quality of a job match is known in advance, categorizing jobs as "search goods," workers tend to gravitate towards higher-quality matches, leading to a decrease in job mobility over time (Burdett [27], Mortensen [76]). In this context, wages are influenced not just by job mobility itself but primarily by the quality of the match, which is a characteristic that remains constant over time. Integrating this search model with specific capital models, Jovanovic [61] introduced a framework for permanent job separations with endogenous firm-specific capital and varying levels of on-the-job search intensity. Empirical work by Farber [41] provided evidence supporting that workers' mobility and wage dynamics can be effectively explained by models emphasizing firm-specific capital. However, this study also highlighted that models accounting for workers' heterogeneity could provide additional insights into job mobility.

Another strand of literature explores the macroeconomic implications of job mobility. Davis and Haltiwanger [37] found that the volatility of employment opportunities among manufacturing establishments correlates with fluctuations in the business cycle. Moreover, his research revealed that gross job flows in labor markets, encompassing both job creation and destruction rates, play a significant role. The search and matching theory, as articulated by Blanchard and Diamond [19] and Petrongolo and Pissarides [86], posits that the process of matching unemployed workers with available jobs can be encapsulated by a well-behaved function that relates the number of jobs created to the number of job seekers, firms seeking workers, and a few other variables. Shimer [96] extended this theory by distinguishing between the traditional search and matching process, where unemployed workers actively seek new employers after leaving their old jobs, and his dynamic model of mismatch, which emphasizes the attachment of unemployed workers to their geographic locations and occupations.

1.2.2 Determinants of Job Mobility

The turnover model proposed by March and Simon [70] serves as the foundational framework for understanding job turnover processes. This model delineates two primary phases: the desirability of a job change and the subsequent ease of making that move. Following this pioneering work, subsequent literature has categorized factors influencing voluntary job changes into three main groups: "organizational," "environmental," and "individual" factors.

The first group comprises factors that are internal to an organization. Among these, job satisfaction stands out as a key determinant of job mobility. Previous research consistently supports the notion that job satisfaction significantly influences turnover intent, showing a negative relationship between job satisfaction and turnover (Arnold and Feldman [9], Freund [46], Williams and Hazer [106]). Higher satisfaction with pay and financial rewards is linked to lower expected levels of turnover behavior (Porter and Steers [87]). According to Mobley et al. [74], the relationship between turnover and job satisfaction is moderated by workers' intentions. Lambert et al. [66] found that the work environment is more important in shaping worker job satisfaction than demographic characteristics. Other factors from this group that have a significant association with job mobility include levels of autonomy and responsibility on the job (Chung-Yan [31], Mowday and Spencer [79]), performance-reward contingencies (Allen and Griffeth [5], Dreher [38]), and perceptions of work experience (Spencer and Steers [98]).

The second group of determinants influencing job mobility includes external factors such as family size and responsibilities, household income levels, the status of being a wage earner in the household, and perceived job alternatives (Boyar and Keough [24], Dansereau et al. [35], Mobley et al. [75]). It is generally expected that primary household wage-earners exhibit lower job turnover rates due to their greater responsibility for household financial stability. Mobley et al. [74] noted that the expectancy of finding a satisfactory job alternative positively correlates with the intention to leave a job, although this intention does not always lead to actual quitting; however, the intention to quit does increase the likelihood of turnover. Swider et al. [99] presented empirical evidence suggesting that the relationship between job search activity and turnover is stronger when workers perceive higher levels of available job alternatives.

Individual characteristics form the third group of predictors of job turnover. Age, for instance, consistently shows a significant negative relationship with job mobility (Ng and Feldman [82], Price [88]). Farber [41] observed a negative correlation between tenure and turnover. However, given that tenure is closely associated with age as a covariate, the impacts of these two factors are generally expected to be similar (Bedeian et al. [16]).

Johnson [60] highlighted a positive correlation between education and job mobility, suggesting that higher education levels may incentivize greater mobility, or conversely, higher mobility may incentivize higher education levels. Supervisory positions, which typically require more experience and education, exhibit significantly lower turnover rates compared to less educated line-level employees (Lu et al. [69]). According to Viscusi [103], women quit more than men, but this observation is not informative because of the essential heterogeneity of worker characteristics, job characteristics, and regional economic conditions. Royalty [94] suggested that differences in job mobility between men and women stem from the turnover behavior of less educated women, whose mobility patterns differ significantly from those of more educated women and both education groups of men; in contrast, the turnover behavior of more educated women resembles that of men. Cotton and Tuttle [34] found that unmarried workers are more likely to leave their jobs compared to married employees.

In addition, factors from the second and third groups exert a more pronounced influence on the job mobility of part-time workers, whereas factors from the first group have minimal impact on turnover behavior among part-time employees (Mcbey and Karakowsky [72]).

1.2.3 Determinants of Occupational Mobility

The patterns of occupational mobility exhibit variations across the lifespan, with age being a significant predictor. Similar to job changes, occupational mobility tends to decrease over time (Rosenfeld [92]). Besides this, occupational mobility shows a strong negative correlation with the duration of time spent in the current job and the level of occupational training while demonstrating a positive correlation with job mobility and industrial mobility (Byrne [28], Longhi and Brynin [68]).

Empirical evidence regarding gender as a determinant of occupational mobility presents mixed findings. Some studies have indicated that men express a greater intention to change occupations compared to women (Blau [20], Felmlee [43], Markham et al. [71]), while others suggested a little difference between genders in overall occupational mobility (Gabriel [48], Rosenfeld and Sorensen [93]) or found that women are more likely than men to switch occupations (Ranson [89]).

Another important determinant of individual upward occupational mobility is education (van Ham et al. [102]). More educated workers tend to have fewer distinct occupations over the course of their careers, leading to a lower likelihood of changing occupations (Sicherman and Galor [97]). Since human capital is often specific to occupations (Kambourov and Manovskii [64]) and investment in occupation-specific skills is a strong determinant of income (Shaw [95]), the duration spent in a particular occupation generally correlates negatively with occupational mobility (Kambourov and Manovskii [63]).

Some occupations are relatively closed, and entry into these occupations is restricted to workers with determined credentials (Redbird [90], Weeden [105]). Employees in these particular occupations typically enjoy higher wages (Bol and Weeden [23]), which reduces the attractiveness of leaving such occupations.

1.2.4 Dynamics and Cohorts Comparison

Kambourov and Manovskii [63] found a significant increase in occupational mobility among employed men in the Panel Study of Income Dynamics (PSID) sample in the USA from 1968 to 1997. Moscarini and Thomsson [77], analyzing monthly data from the Current Population Survey (CPS), observed that occupational mobility tends to be pro-cyclical. It increased from the early 1980s to the early 1990s, declined from the mid-1990s onward, and experienced a cyclical rebound after 2004. Similar patterns have been noted in job mobility since 1994. Hyatt and Spletzer [58] showed that employment dynamics in the USA declined during the first decade of the century.

Bernhardt et al. [17] examined men from two cohorts of the NLS (Original Cohort of Young Men started in 1966 and NLSY79) and found that men in the more recent cohort exhibited higher rates of job turnover compared to the earlier cohort. Hollister [56], using the same cohorts and taking into account the declines in transitions out of the labor force for women, reported that the increase in occupational mobility between the two cohorts was largely similar for both men and women.

1.3 Data and Descriptive Statistics

1.3.1 Data and Sample Construction

This study on job and occupational mobility utilizes data from the National Longitudinal Surveys of Youth (NLSY) 1979 and 1997. The NLSY79 survey tracks 12,686 American youth born between 1957 and 1964 across 28 survey rounds spanning from 1979 to 2018[2]. The NLSY97 survey includes 8,984 respondents born between 1980 and 1984, covering 18 survey rounds from 1997 to 2017. Both panel datasets offer extensive information on job and occupational changes over time.

The NLSY79 employment history file records a week-by-week timeline spanning 2,082 weeks over 40 years from 1978 to 2017. Similarly, the weekly array of the NLSY97 history file covers 1,292 weeks across 25 years from 1994 to 2018. Using these employment history files, I construct a comprehensive timeline of all jobs held by each respondent in the sample. This sample consists of annual and biannual employment reports. The NLSY79 respondents reported annually from 1979 to 1994 and biannually after 1994. The NLSY97 consists of annual reports from 1997 to 2011, transitioning to biannual reports thereafter. Following

[2] This paper was written in 2020-2021 and submitted as a third-year paper in 2021.

the previous literature, I drop observations involving jobs lasting for less than three months (Topel and Ward [101]) and observations comprising dual job holdings (Yankow [108]).

In order to compare the two cohorts, I restrict observations to individuals within the age range of 18-33 years in both the NLSY79 and NLSY97 surveys. Additionally, I exclude jobs where reported hours per week are less than 20 or more than 90, as well as jobs held by high school or college students. After applying these criteria and removing cases with missing values, the initial sample for this study comprises 113,716 observations (see Table 1.1) in which respondents reported their jobs in two subsequent surveys (period $t-1$ and period t). Of these, 77,135 observations are from the NLSY79 survey (1979-2000), and 36,581 are from the NLSY97 survey (1998-2017).

This paper attempts to evaluate the impact of various determinants of job and occupational mobility, including organizational (job-related) factors. Therefore, observations, where respondents were unemployed or out of the labor force in either period $t-1$ or in period 1, are not the focus of this study. However, exploring these transitions (from employment to unemployment or out of the labor force and vice versa) could be a valuable direction for future research in this field.

Out of the total sample of 113,716 observations, there were 34,664 instances (30.48%) of job changes reported by respondents. Among these, 27,940 observations had both jobs categorized into occupational groups with complete data for independent variables, comprising the second sample used in this study. Specifically, 17,247 observations were from the NLSY79 survey and 10,693 from the NLSY97 survey. Within these observations of job changes, occupational group shifts were reported in 16,923 cases (60.57%).

1.3.2 Variables

Dependent Variables

The dependent variables of this study are job-to-job transitions (a job mobility measure) for the first sample and changes in occupational groups (an occupational mobility measure) for the second sample. Both dependent variables are binary dummy variables, which are assigned a value of one if respondents switch their jobs or occupational groups and zero if no such change occurs. Descriptive statistics of these variables are presented in Table 1.1. The share of observations in which participants reported a job change is significantly higher for the NLSY97 cohort (34.21%) compared to the older cohort (28.72%). The values for the second dependent variable are nearly identical for both cohorts, with 60.31% of respondents from the NLSY79 sample and 60.98% from the NLSY97 sample changing their occupational groups. However, these proportions are conditional on job changes. The fractions of respondents who shifted their occupational groups as the shares of the total samples for the NLSY79 and NLSY97 are 16.87% and 20.98%, respectively.

This paper uses occupation classification codes of the Current Population Surveys (CPS) provided by the U.S. Census Bureau. The occupations are aggregated into 22 detailed groups. Table 1.2 demonstrates the list of occupational groups. The main objective to analyze occupational mobility using occupational groups instead of occupations is twofold.

First, this distinction enables the identification of substantial shifts (e.g., from 4030 ”Food preparation workers” to 5860 ”Office clerks”) as opposed to minor changes in occupations (e.g., from 4030 ”Food preparation workers” to 4020 ”Cooks”). While both instances involve occupational changes, only the former represents a shift in occupational groups (from 13 ”Food Preparation and Serving Related Occupations” to 17 ”Office and Administrative Support Occupations”). Shifts in occupational groups are of greater research interest compared to insignificant changes in occupations within the same occupational groups.

Second, some respondents may use slightly different terms to describe their occupations, and coders might interpret identical terms differently across different years. Consequently, there may be erroneously reported shifts in occupations, though these closely related occupations are likely within the same groups. Employing occupational groups instead of specific occupations can help researchers mitigate issues arising from such discrepancies.

Independent Variables

The individual characteristics used in this paper for both job and occupational mobility models include age, age squared, gender, race, marital status, and level of education. The age range (18-33) is consistent for both cohorts. Figure 1.1 illustrates the probability of job and occupational group changes by age. Since both cohorts have U-shaped curves of the probability of a job change (Panel A), it is reasonable to include the age-squared variable in the models. Panel A shows that the probability of a job change for both cohorts decreases until the age of 28-30, but the NLSY97 cohort exhibits a much steeper curve. Therefore, it is anticipated that the marginal effects of age on the probability of a job change will differ significantly between the two cohorts.[3] Panel B does not indicate essential differences in the life-cycle profiles of the probability of occupational group shifts between the two cohorts.

Race is represented by a binary variable that takes the value of one for white respondents and zero for black and Hispanic participants. Marital status is captured by a binary variable that is set to one if respondents are married and zero otherwise. Education is defined as a binary variable where individuals are assigned a value of 1 if they have more than 12 years of education and 0 otherwise. Geographic dummy variables are constructed for four

[3] One possible reason for this difference is the considerably different attrition rates between the two cohorts (Figure A.1 of Appendix A).

statistical regions defined by the United States Census Bureau (Northeast, Midwest, South, and West). Additionally, a numerical variable for family size is included to account for family responsibilities.

In addition to these variables, I include restrictions on job mobility and occupational mobility as independent variables in the models for job changes and occupational group changes, respectively. As potential constraints on job mobility, I include job tenure (measured in weeks), the natural logarithm of wage, and hours worked per week. Variables that may limit occupational mobility include the direction of job transitions, occupational group-specific human capital, and characteristics of occupational groups such as unemployment rates, closure (licensure) levels, and skill demand levels.

Following the previous literature (see Mouw and Kalleberg [78] among others), I define the direction of the job transition as upward and downward when a worker moves to a new employer with higher and lower wages, respectively. Dwyer [39] argues that most job changers experience some degree of wage change. Therefore, I establish a $\pm 10\%$ threshold to classify job transitions as upward, downward, or horizontal (lateral).

Occupational group-specific human capital is quantified by the duration a worker has spent in a particular occupational group, measured here as occupational group tenure in months. Unemployment rates for each occupational group are computed using annual IPUMS CPS data (Flood et al. [44]).

Occupational group licensure variables serve as proxy indicators for occupational group closure. Two numerical variables are derived based on the proportions of licensed workers and occupations within occupational groups for the years 1983 and 2012, as detailed by Redbird [90]. Using these proportions from 1983 and 2012, I calculate the proportions of licensed workers and occupations across all 22 occupational groups for the NLSY79 (1983) and NLSY97 (2012) cohorts.

Occupational group skill demand level dummy variables are different for the two cohorts. For the NLSY97, they are created using the Occupational Information Network (O*NET). O*NET Data descriptors are categories of occupational information collected and available for O*NET-SOC occupations. This network provides the values of importance of each skill from six groups (basic skills, complex problem-solving skills, resource management skills, social skills, systems skills, and technical skills) for every occupation. For each occupational group, I calculate the average values of the importance of these skills and obtain three skill demand levels for occupational groups for all six variables. These levels are labeled high, medium, and low.

Corresponding variables for the NLSY79 cohort are created based on the revised fourth edition of the Dictionary of Occupational Titles (DOT). The DOT data provide values of the physical demand strength rating, values of Specific Vocational Preparation (SVP), and three values of General Educational Developments (reasoning, mathematical, and language) for each occupation. The strength rating represents the strength requirements that are considered to be important for average, successful work performance. SVP quantifies the time typically needed for a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation. Similar to O*NET Data, for each occupational group, I calculate the average values of strength requirements, SVP, and GED values and obtain the same three skill demand levels (high, medium, and low) for occupational groups for five variables (Physical strength demand, SVP demand, Reasoning skills demand, Mathematical skills demand, and Language skills demand).

Descriptive statistics of independent variables used for modeling job mobility are presented in Table 1.3. The average age of respondents decreased from 26.17 in the NLSY79 to 25.35

in the NLSY97. The share of women in the sample did not noticeably change (45.1% and 45.8%), and the portion of nonwhite participants rose by about seven percentage points (42% and 48.6%). This table shows a decrease in the proportion of married people (from 44.4% to 27.2%), as well as a considerable increase in the percentage of more educated respondents (43.1% in the NLSY97 against 34.6% in the NLSY79). The mean values of the regional dummy variables did not essentially change. The NLSY97 participants have slightly greater average family size (3.3) than their NLSY79 counterparts (3.1)[4]. The average job tenure significantly decreased from 184.9 weeks for the NLSY79 to 78.3 weeks for the NLSY97. The mean value of hours per week worked also declined (from 41.6 to 36.7), and the natural logarithm of wage became greater from 6.6 for the NLSY79 to 6.9 for the NLSY97.

Table 1.4 demonstrates descriptive statistics of the sample used for modeling occupational mobility. There is a between-cohort drop in the average age from 25.47 to 24.23 and an insignificant rise in the fraction of female participants from 44.1% to 45.5%. The portion of married respondents went down from 37% to 20.7%. The share of more educated people increased by almost four percentage points (29.8% in the NLSY79 and 33.5% in the NLSY97). The average occupational group tenure increased from 13.4 to 19.4 months. The mean value of the occupational group unemployment rate insignificantly decreased from 0.077 (the NLSY79) to 0.072 (the NLSY97). Both average proportions of workers and occupations licensed increased from 0.149 to 0.185 and from 0.119 to 0.171, respectively. Finally, the proportion of upward job transitions decreased from 0.523 to 0.486, whereas the fraction of downward job transitions did not considerably change (0.255 and 0.242). Descriptive statistics of occupational group skills demand levels variables might be found in Table A.1 of Appendix A.

[4] This increase in family size, although not very significant, looks counterintuitive given the expectations of a decrease in the average family size over the recent decades due to various demographic and societal factors such as delayed marriage, increased cohabitation, reduced fertility, and higher rates of multigenerational living.

1.4 Empirical Framework

A job transition (or a job change) is identified when a respondent who was employed at the time of the interview in period $t-1$ had switched jobs at the time of the interview in period t. The initial specification of the linear probability model examining the impact of basic predetermined job mobility factors of individual i on the probability of a job transition in time t can be written as follows:

$$\begin{aligned} JobChange_{it} =& \beta_0 + \beta_1 Age_{it-1} + \beta_2 Age^2_{it-1} + \beta_3 Female_i + \beta_4 Nonwhite_i + \\ & \beta_5 Married_{it-1} + \beta_6 Educated_{it-1} + \beta_7 Region_{it-1} + \\ & \beta_8 FamSize_{it-1} + u_t + \varepsilon_{it} \end{aligned} \tag{1.1}$$

where $Region$ is the set of four dummy variables ($Northeast, Midwest, South$, and $West$) and u_t is the set of year dummy variables. The explained binary dummy variable, $JobChange_{it}$, equals one if individual i has different jobs in years t and $t-1$, and it equals zero if this respondent works at the same job in both time periods.

The second specification of this model includes three additional organizational determinants of job mobility:

$$\begin{aligned} JobChange_{it} =& \beta_0 + \beta_1 Age_{it-1} + \beta_2 Age^2_{it-1} + \beta_3 Female_i + \beta_4 Nonwhite_i + \\ & \beta_5 Married_{it-1} + \beta_6 Educated_{it-1} + \beta_7 Region_{it-1} + \\ & \beta_8 FamSize_{it-1} + \beta_9 JobTenure_{it-1} + \\ & \beta_{10} HoursWorked_{it-1} + \beta_{11} LogWage_{it-1} + u_t + \varepsilon_{it} \end{aligned} \tag{1.2}$$

These three factors are expected to be significant predictors of job mobility. However, including potentially endogenous variables in the model might lead to inconsistency of estimators of the model parameters and hence the estimated coefficients should be interpreted with precaution.

Table 1.1 shows that the probability of a job change is higher for the NLSY97 cohort. I use Oaxaca decomposition techniques to determine how much of the overall cohort difference in the probability of a job change is attributable to cohort differences in observable characteristics of explanatory variables and how much is due to differential magnitudes of regression coefficients. These decomposition techniques, first introduced by Oaxaca [84] and Blinder [21], utilize the property that the linear regression line goes through the means of the predictors and hence the observed cohort difference in an outcome is the difference between the coefficients from cohort-specific regressions evaluated at the cohort-specific variable means. Neumark [81] suggested using coefficients from a pooled sample regression as the set of reference coefficients.

These decompositions require estimating the probability of the job change equation (1) for three different samples: the NLSY79, NLSY97, and the pooled sample denoted respectively by $h = \{79, 97, PS\}$. Let the coefficient estimates of the three regressions be represented by β_h. Let P_h denote the cohort-specific probability of a job change and X_h denote the transpose of a vector of cohort-specific means, including a constant term. The Neumark decomposition based on coefficients from the pooled regression is

$$
\begin{aligned}
P_{97} - P_{79} &= X_{97}\beta_{97} - X_{79}\beta_{79} \\
&= (X_{97} - X_{79})\beta_{PS} + [X_{97}(\beta_{97} - \beta_{PS}) - X_{79}(\beta_{79} - \beta_{PS})] \qquad (1.3)
\end{aligned}
$$

where the first term, $(X_{97} - X_{79})\beta_{PS}$, is the part of the overall cohort difference in the probability of a job change due to differences in characteristics ("explained" differences). The second term, $[X_{97}(\beta_{97} - \beta_{PS}) - X_{79}(\beta_{79} - \beta_{PS})]$, is the part of the overall cohort difference in the probability of a job change due to differences in the responses of the two cohorts, where response is measured by differences in coefficients (”unexplained” differences).

An occupational group change occurs when a worker who was employed at the time of the interview in time period $t-1$ and had switched a job at the time of the interview in period t also has shifted to a different occupational group. The dependent variable, $OGChange_{it}$, is the binary dummy variable that equals one if an individual i has different occupational groups in years t and $t-1$, and zero if the occupational group remains the same. I start with a simple specification of the linear probability model to estimate the impact of fundamental determinants of occupational mobility on the probability that individual i decides to switch occupational groups at time t:

$$\begin{aligned} OGChange_{it} = &\beta_0 + \beta_1 Age_{it-1} + \beta_2 Age^2_{it-1} + \beta_3 Female_i + \beta_4 Nonwhite_i + \\ &\beta_5 Married_{it-1} + \beta_6 Educated_{it-1} + \beta_7 Region_{it-1} + \\ &\beta_8 FamSize_{it-1} + u_t + \varepsilon_{it} \end{aligned} \tag{1.4}$$

where u_t is the set of year dummy variables.

The second specification of the model includes several additional variables (job mobility directions and occupation-specific factors):

$$\begin{aligned} OGChange_{it} = &\beta_0 + \beta_1 Age_{it-1} + \beta_2 Age^2_{it-1} + \beta_3 Female_i + \beta_4 Nonwhite_i + \\ &\beta_5 Married_{it-1} + \beta_6 Educated_{it-1} + \beta_7 Region_{it-1} + \\ &\beta_8 FamSize_{it-1} + \beta_9 JobMobility_{it} + \beta_{10} OGTenure_{it-1} + \\ &\beta_{11} OGUnempRate_{it-1} + \beta_{12} OGLicensure_{it-1} + v_{it-1} + u_t + \varepsilon_{it} \end{aligned} \tag{1.5}$$

where $JobMobility$ is the set of three dummy variables (upward, downward, and latent job mobility), $OGLicensure$ is the set of two variables (proportions of licensed workers and licensed occupations), v_{it-1} is the set of skill demand variables (five variables for the NLSY79 and six variables for the NLSY97), and u_t is the set of year dummy variables.

I employ linear probability models for all equations presented above. According to Angrist and Pischke [8], estimates of marginal effects from linear probability models, which is a special case of Ordinary Least Squares (OLS) regression, closely resemble results from logit and probit models. Based on their recommendation that linear probability models offer simplicity and straightforward interpretability of results, I use them to estimate the effects of independent variables on the probabilities of job changes and occupational group changes.

Additionally, my study involves comparing these effects across various socio-demographic groups. Previous research demonstrates that comparing coefficients across groups is problematic in logit and probit models because coefficients in these models are confounded with residual variation (unobserved heterogeneity). Differences in the degree of residual variation across groups can produce differences in coefficients that are not indicative of true differences in causal effects (Allison [6]). However, using linear probability models for group comparisons may also have limitations. Holm et al. [57] demonstrated that differences in coefficients from these models can arise not only from genuine differences in effects but also from variations in outcome truncation, scale parameters, and the distributional shape of predictor variables.

Finally, the following two regression models measure the effect of the set of predictors (including the $JobChange$ or $OGChange$ variables) on the difference in natural logarithms of wages of individual i in time periods t and $t-1$ and take the forms:

$$\begin{aligned} LogWage\Delta_{it} =& \beta_0 + \beta_1 Age_{it} + \beta_2 Age^2_{it} + \beta_3 Female_i + \beta_4 Nonwhite_i + \\ & \beta_5 Married_{it} + \beta_6 Educated_{it} + \beta_7 Region_{it} + \\ & \beta_8 FamSize_{it} + \beta_9 JobChange_{it} + u_t + \varepsilon_{it} \end{aligned} \tag{1.6}$$

$$\begin{aligned} LogWage\Delta_{it} =& \beta_0 + \beta_1 Age_{it} + \beta_2 Age^2_{it} + \beta_3 Female_i + \beta_4 Nonwhite_i + \\ & \beta_5 Married_{it} + \beta_6 Educated_{it} + \beta_7 Region_{it} + \\ & \beta_8 FamSize_{it} + \beta_9 OGChange_{it} + u_t + \varepsilon_{it} \end{aligned} \tag{1.7}$$

For each model presented in this chapter, the regressions are employed separately for the NLSY79 and NLSY97 in order to explore the differences in coefficients. For all regressions I report standard errors that account for clustering of observations. For all between-cohort or between-group comparisons, I reject the null hypothesis that there is no difference between the estimated coefficients of two cohorts or groups. The p-values of chi-squared tests of these differences are presented in corresponding tables.

1.5 Results

1.5.1 Job Changes Models

Table 1.5 presents results from both specifications of the linear probability model with the probability of a job change as the dependent variable. Using ordinary least squares, estimations of equations (1) and (2) strongly indicate that age is an important determinant of the explained variable. The regression results suggest that estimated coefficients of the *Age* variable are highly statistically significant, and the one-year increase in age is associated with a decrease in the probability of a job change by 0.0635 for the NLSY79 respondents and 0.0940 for the NLSY97 participants. For the second specification, the marginal effects for the two cohorts are 0.0543 and 0.0975. The regression estimate of *Age* is considerably greater for the NLSY97 cohort. This conclusion is consistent with the results from interpreting Figure 1. The marginal effect of age squared is positive for both cohorts and greater for the younger cohort. The coefficients of the *Age* variable are statistically significant at the 0.001 level for both specifications. The between-cohort difference in these coefficients is significant at the 0.01 level for the second specification but only at the 0.1 level for the first specification.

Including three potentially endogenous variables in the model has had the opposite impact on regression estimates for two cohorts. It can be noted from Table 1.5 that after adding new variables, the estimated coefficients of almost all variables in the model for the NLSY79 cohort essentially changed. Only for two variables - *Age* and Age^2 - the changes are not very significant. However, for the second cohort, there is almost no effect from appending new variables. All independent variables in the model (including the *Age* variable) had very small and insignificant changes in estimated coefficients.

According to the results for Specification 1, the between-cohort difference in estimated coefficients is not significant for almost all regressors. The estimates of the $Midwest$ variable increased, and this increase is significant at the 0.05 level. Also, there are between-cohort changes for Age^2, $Female$, and $West$ variables that are significant at the 0.1 level.

The estimates of some variables of the second specification are considerably different for the two cohorts. For instance, there is a between-cohort increase in the coefficients of Age^2, $Female$, $Nonwhite$, $Famsize$, and $LogWage$. However, in all these cases, the second (the NLSY97) coefficient is statistically insignificant. The estimates of the *Educated* variable decreased, and the first (the NLSY79) coefficient was not significant. The estimated coefficients of three other variables are statistically significant for both cohorts. For two of them ($JobTenure$ and $HoursPerWeekWorked$), estimates increased, while for the $Married$ variable, there is a between-cohort decrease in coefficients. The changes in all variables above, except Age^2, $Nonwhite$, and $FamSize$, are statistically significant at the 0.001 level.

The difference between the mean values of the probability of a job change for two cohorts is 0.3421 - 0.2872 = 0.0549 (Table 1.1). Using the Oaxaca decomposition, I found that the overall cohort difference in the probability of a job change is attributable only to the cohort differences in observable characteristics of explanatory variables included in the model (specification 1). The total share of differential magnitudes of regression coefficients in the overall cohort difference is very small. The results of this decomposition analysis are presented in Table 1.6. The results of a similar analysis for the second specification are essentially the same.

As can be seen from this table, the differential magnitudes of regression coefficients significantly vary across variables. Particularly, the combined share of a negative effect of unexplained differences in the probability of a job change attributable to differences between coefficients of the Age and Age^2 variables (age effect) for two cohorts is extremely big (about 780%). Nevertheless, this negative effect is canceled out by the overall positive effect of other variables in the model, and the total share of unexplained differences is close to zero. However, this finding suggests that the regression coefficient of Age is essentially smaller for the NLSY97 cohort, and hence, it is consistent with conclusions from interpreting Figure 1 and Table 5.

The next step in the analysis involves examining which socio-demographic categories are most affected by the increase in the negative regression coefficient estimate of the Age variable. This analysis is done by running separate regressions of equation (2) for different socio-demographic groups of participants.[5] First, I run linear probability regressions for male and female respondents. The results presented in Table 1.7 show that the estimated coefficients of the *Age* variable for men vary considerably across the two cohorts (-0.0537 and -0.1245). In contrast, the difference for women is less pronounced (-0.0559 and -0.0637).

Table 1.8 demonstrates regression estimates by race groups. As it can be seen from this table, the between-cohort difference in regression coefficients of the *Age* variable is significantly greater for white participants (-0.0574 and -0.1289), compared with the results for nonwhite respondents (-0.0510 and -0.0611).

The coefficient estimates of regressions by marital status groups are shown in Table 1.9. The arithmetic difference between estimated coefficients of *Age* among two cohorts for unmarried participants (-0.0368 and -0.1078) is almost twice as large as the difference for married respondents (-0.0774 and -0.1155).

Finally, Table 1.10 presents regression estimates by education groups. According to this table, there is a significant decline in regression coefficients of the *Age* variable for less educated participants (-0.0521 and -0.1083). The results for more educated respondents on this measure are more consistent across two cohorts (-0.0597 and -0.0765).

This analysis indicates that the impact of aging on the probability of job transitions varies across different socio-demographic groups of workers. The between-cohort change in the marginal effect of age on the probability of a job change is mostly driven by changes in the effect of age for the following specific groups of respondents: male, white, unmarried, and less educated participants.[6]

[5] Regressions for different socio-demographic groups vary by excluded predictor variables. For example, separate regressions for males and females, for obvious reasons, do not contain the *Female* variable; regressions for white and nonwhite respondents do not include the *Nonwhite* variable; and so on.

[6] As a robustness exercise I have also used the first specification' equation to run separate regressions for different groups. The results are very similar to the results presented in this subsection. For each pair of regressions, the difference between cohorts is smaller and less significant, but it is clearly distinguishable

1.5.2 Occupational Group Changes Models

In this subsection, the focus is on estimating the marginal effects of various directions of job transitions on the probability of an occupational group change while controlling for key socio-demographic factors and variables related to occupational group characteristics. Table 1.11 presents the regression estimates of equations (3) and (4) for two cohorts. The results of the model for the first specification demonstrate that only the estimated coefficients of the $Female$ variable are statistically significant at the 0.001 level for both cohorts. Both regressions exhibit very low R-squared values.

The second specification includes occupational group-related factors and the upward and downward job mobility dummy variables (horizontal (lateral) job mobility is omitted due to collinearity). A comparison of the regression analyses for the two cohorts reveals some important findings. The coefficients of the $DownwardJM$ and $UpwardJM$ variables shown in this table represent the change in the probability as these independent binary variables go from zero to one. The OLS results of the second specification indicate that the marginal effect of upward job mobility on the probability of an occupational group change is 0.0322 and 0.1816 for the NLSY79 and NLSY97, respectively. Downward job mobility increases the probability of an occupational group change by 0.0871 and 0.1818 for the NLSY79 and NLSY97, respectively. There is a significant between-cohort increase in the marginal effects of both non-horizontal directions of job transitions. The results of this analysis underline the strong positive association between two directions for job transitions and occupational mobility for both cohorts.

Only two other predictors have statistically significant coefficients at the 0.001 level for both cohorts. One of them is the $Female$ variable. According to Table 1.11, the marginal effect of this variable does not noticeably vary across cohorts (-0.0416 and -0.0477). The

that changes in the marginal effect of age are due to changes in the same groups of participants.

negative impact of another variable, $OGTenure$, is significantly greater for the older cohort (-0.0044 and -0.0017). In addition, the marginal effects of $Nonwhite$ and $FamSize$ variables are positive for the NLSY79 and negative for the NLSY97 (0.0162 and -0.0183, 0.0071 and -0.0052).

Since Table 1.1 shows that the difference between the mean values of the probability of an occupational group change for two cohorts is not significant (0.6098 - 0.6031 = 0.0067), I do not perform the Oaxaca decomposition to explain this difference.

1.5.3 Short-Term Wage Growth Analysis

This subsection examines the effects of job and occupational group changes on wage differences (the difference between natural logarithms of a current wage and a previous survey wage). Using OLS regression analysis for both cohorts, the wage difference serves as the dependent variable, with job change as the key regressor, while controlling for primary socio-demographic and geographic factors. The OLS results of equation (5) for Sample 1 in Table 1.12 indicate that respondents who changed jobs increased their wage difference by 0.0575 for the NLSY79 cohort and by 0.1222 for the NLSY97 cohort, with both coefficients being highly statistically significant. Aside from the $JobChange$ variable, only the *Educated* variable shows statistically significant coefficients for both cohorts. This suggests that the positive impact of job changes on wage differences is more than twice as pronounced for the younger cohort.

Finally, OLS regressions of equation (6) were conducted for two cohorts, treating the wage difference as the dependent variable and including occupational group change, main socio-demographic factors, and geographic variables as explanatory variables. The results from Table 1.12 for Sample 2 indicate that an occupational group change is significantly associated with the wage difference in one sample but not in the other. Specifically, the marginal effect of an occupational group shift on the wage difference is found to be insignificant and close to zero (0.0029) for the NLSY79 cohort, while it is 0.0370 for the NLSY97 cohort, which is statistically significant at the 0.001 level. Thus, the impact of an occupational group change on short-term wage growth appears to be more substantial for the NLSY97 cohort.

1.5.4 Robustness Check

In this subsection, I examine the robustness of the most important findings of this paper. First, I conducted several robustness checks to verify the finding that the negative effect of age on the probability of a job change is significantly greater for the NLSY97 cohort. As the first robustness check of the baseline regression equation (2), I exclude observations where hours worked per week at the current and previous survey jobs were below 40. In other words, observations of part-time workers are omitted (Model 2 in Table 1.13). With this sample exclusion, the coefficient estimates of the *Age* variable decrease in absolute value for both cohorts compared to the estimates of the baseline model, but the difference in coefficients remains noticeable.

In two additional robustness checks, the baseline equation (2) was re-estimated using fixed-effects models and Hausman-Taylor models (Models 3 and 4 in Table 1.13). The fixed-effects model helps to control for potential average differences across respondents in observable or unobservable predictors. The Hausman-Taylor model addresses the potential correlation between the error term and included variables that may affect random-effects estimation. In both cases, the differences between cohorts in the estimates of *Age* are smaller and less significant than in the baseline model, yet they remain considerable.

The next step involves assessing the robustness of the conclusions regarding the strong positive association between job transition directions and occupational mobility for both cohorts, as well as the finding that the marginal effects of upward and downward job transitions are significantly greater for the NLSY97 cohort. The first two robustness exercises mirror those from the previous tests: samples limited to full-time workers only and the use of fixed-effects models (Models 2 and 3 in Table 1.14).

In another robustness check, I re-estimate the baseline equation (4) employing Heckman's two-step sample selection correction (Model 4 in Table 1.14). This method addresses potential self-selection bias, considering that occupational group shifts occur only among employees who have changed jobs. Table 1.14 indicates that the conclusions drawn from the baseline models hold true across all three robustness checks.

1.6 Conclusion

Several important conclusions can be drawn from the results. First, it can be concluded that the negative impact of age on the probability of a job change is significantly greater for the NLSY97 cohort. The effect size for the younger cohort is nearly twice as large as the estimated coefficient of the *Age* variable for the NLSY79 cohort. This shift could be theoretically explained by changes in young people's social relationships, needs, and emotional experiences driven by economic, socio-cultural, technological, and political changes between the 1979-2000 and 1997-2017 periods. Changes in age discrimination in the labor market may also contribute to this shift in job mobility.

The second major finding is that the relationship between age and job turnover varies noticeably across sample characteristics. Particularly, the significant between-cohort shift is attributed to changes in the impact of age within specific socio-demographic groups such as male, white, unmarried, and less educated workers. Consequently, it suggests that these personal characteristics - gender, race, marital status, and education - should be taken into account alongside age when assessing job mobility. This finding aligns partially with conclusions from Ng and Feldman [82] that the relationship between age and job mobility is stronger among respondents with lower educational levels and more racial minorities in the sample. While my results confirm the first part of this conclusion, they do not support the second part.

The Oaxaca decomposition revealed that the increase in the probability of a job change between cohorts can be attributed to differences in observable characteristics related to job mobility determinants. A comparison between cohorts in the mean values of these determinants indicates significant changes in some sample characteristics. For instance, the proportion of nonwhite, unmarried, and more educated individuals is notably higher in the younger cohort, while the average job tenure is substantially shorter. These differences in observable employee characteristics between cohorts could explain the observed shift in the probability of a job change.

Another important conclusion of the present study is the strong association between directions of job transitions and occupational mobility. While there is almost no difference between cohorts in the probability of an occupational group change, the marginal effects of certain predictors on this probability differ significantly between the two cohorts. Both upward and downward job mobility show positive estimated coefficients for both cohorts, but these coefficients are notably larger for the NLSY97 cohort. Changes in the behavior of young workers in the labor market have led to a stronger positive relationship between both upward and downward job changes and shifts in occupational groups for the NLSY97 cohort. Participants in the younger cohort have a higher probability of shifting their occupational groups when moving to jobs with either higher or lower wages compared to their previous jobs.

Finally, the results of this paper demonstrate a positive association between job mobility and short-term wage growth. After accounting for socio-demographic and geographic factors, workers who changed their jobs had significantly greater differences in natural logarithms of wages compared to those who stayed with the same employer. This marginal effect is approximately twice as large for respondents in the NLSY97 cohort. Similarly, analysis using occupational group changes as predictors of wage differences indicates a positive and significant association with wage growth for NLSY97 respondents, whereas the estimated coefficient for NLSY79 participants is close to zero. These findings are consistent with recent literature suggesting a close relationship between job and occupational mobility and wage inequality (see Fuller [47], Kambourov and Manovskii [65] among others).

There are several limitations of the study. Firstly, annual observations may not accurately capture all job transitions. Some respondents may change jobs more than once between surveys, and these intermediate transitions are not accounted for. Secondly, comparing coefficients from linear probability models between groups may be misleading because differences can arise from the distributional shapes of predictors (Holm et al. [57]). Additionally, the causal relationship between job transition directions and occupational mobility is not clearly established. Finally, drawing conclusions about the relationship between job and occupational mobility and wage growth based on regressions where short-term wage differences are the outcome variable may not fully capture long-term perspectives.

Further empirical research in this field is clearly warranted to continue examining the differences between the two cohorts. The forthcoming data on the NLSY97 cohort will enable comparisons of labor market decisions among middle-aged employees. Additionally, ongoing data collection for the NLSY79 Child and Young Adult cohort will facilitate comparisons of job and occupational mobility dynamics across the NLSY79 and NLSY97 cohorts, along with the youngest cohort, providing further insights into these trends.

One direction for further research could explore the impact of constraining factors on job and occupational mobility. For instance, examining how levels of occupational group skill demand and licensure vary across different cohorts due to recent technological and socio-economic changes could be insightful. Furthermore, understanding how these factors influence job and occupational mobility may vary over time among various socio-demographic groups of workers demands further investigation.

Another potential direction is to investigate between-cohort differences in the occupational mobility of young workers within the context of employment polarization. Autor et al. [11] observed that low-skill workers shifted their employment toward service occupations due to the expansion of computer technology. Comparing the labor market behavior of the youngest and least educated individuals across the two cohorts could provide insights into shifts in the occupational specialization of young workers over recent decades.

1.7 Figures and Tables

Figure 1.1: Probability of Job and Occupational Group Changes by Age [cited on page 13]

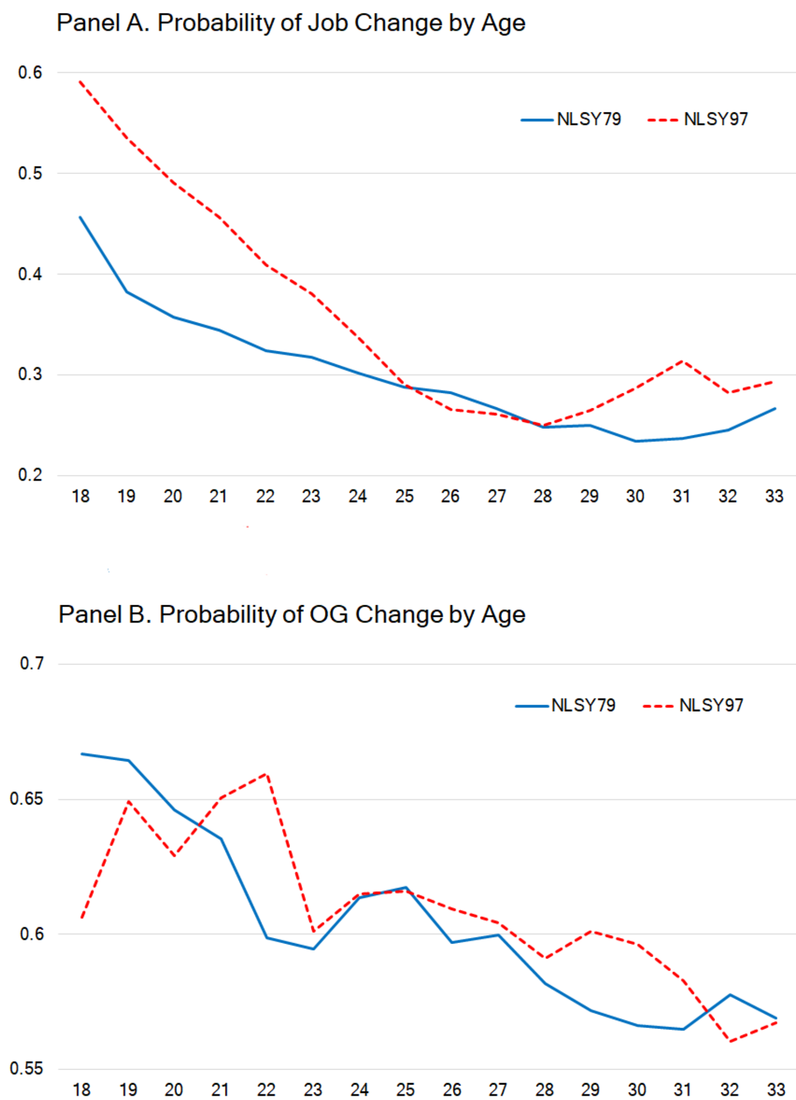

Table 1.1: **Descriptive Statistics of Dependent Variables** [cited on pages 11, 12, 18, 23, and 26]

	NLSY79		NLSY97		Total Sample	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Job Change	0.2872	0.4524	0.3421	0.4744	0.3048	0.4603
N of respondents	11,049		6,923		17,972	
N of observations	77,135		36,581		113,716	
OG Change	0.6031	0.4893	0.6098	0.4878	0.6057	0.4887
N of respondents	7,685		4,782		12,467	
N of observations	17,247		10,693		27,940	

Table 1.2: List of Occupational Groups [cited on page 12]

Group	Occupational Group Description	Occ Codes
1	Management occupations	0010-0430
2	Business and financial operations occupations	0500-0950
3	Computer and mathematical science occupations	1000-1240
4	Architecture and engineering occupations	1300-1560
5	Life, physical, and social science occupations	1600-1965
6	Community and social service occupation	2000-2060
7	Legal occupations	2100-2160
8	Education, training, and library occupations	2200-2550
9	Arts, design, entertainment, sports, and media occupations	2600-2960
10	Healthcare practitioner and technical occupations	3000-3540
11	Healthcare support occupations	3600-3655
12	Protective service occupations	3700-3955
13	Food preparation and serving related occupations	4000-4160
14	Building and grounds cleaning and maintenance occupations	4200-4250
15	Personal care and service occupations	4300-4650
16	Sales and related occupations	4700-4965
17	Office and administrative support occupations	5000-5940
18	Farming, fishing, and forestry occupations	6000-6130
19	Construction and extraction occupations	6200-6940
20	Installation, maintenance, and repair occupations	7000-7630
21	Production occupations	7700-8965
22	Transportation and material moving occupations	9000-9750

Note: the last column represents 2010 Census codes of occupations.

Table 1.3: Descriptive Statistics of Independent Variables (Sample 1) [cited on page 15]

	NLSY79		NLSY97		Total Sample	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	26.17	4.05	25.35	3.88	25.91	4.02
Age Squared	701.4	211.3	657.5	198.5	687.3	208.3
Gender (ref: Male)						
Female	0.451	0.498	0.458	0.498	0.453	0.498
Race (ref: White)						
Nonwhite	0.420	0.494	0.486	0.500	0.441	0.497
Marital Status (ref: Unmarried)						
Married	0.444	0.497	0.272	0.445	0.389	0.487
Education (ref: 12 years and less)						
More than 12 years	0.346	0.476	0.431	0.495	0.374	0.484
Region (ref: Northeast)						
Midwest	0.232	0.422	0.211	0.408	0.225	0.418
South	0.397	0.489	0.402	0.490	0.399	0.490
West	0.191	0.393	0.229	0.420	0.203	0.402
Family Size	3.105	1.780	3.331	1.682	3.178	1.752
Job Tenure	184.9	156.1	78.3	79.0	150.6	145.0
Hours per Week Worked	41.61	8.68	36.72	9.23	40.04	9.15
LogWage	6.589	0.592	6.917	0.528	6.695	0.593
Survey dummies	-	-	-	-	-	-
N of respondents	11,049		6,923		17,972	
N of observations	77,135		36,581		113,716	

Table 1.4: Descriptive Statistics of Independent Variables (Sample 2) [cited on page 16]

	NLSY79		NLSY97		Total Sample	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	25.47	4.11	24.23	3.99	24.99	4.11
Age Squared	665.4	212.1	603.0	199.9	641.5	209.7
Gender (ref: Male)						
Female	0.441	0.497	0.455	0.498	0.446	0.497
Race (ref: White)						
Nonwhite	0.444	0.497	0.504	0.500	0.467	0.499
Marital Status (ref: Unmarried)						
Married	0.370	0.483	0.207	0.405	0.308	0.462
Education (ref: 12 years and less)						
More than 12 years	0.298	0.458	0.335	0.472	0.313	0.464
Region (ref: Northeast)						
Midwest	0.210	0.408	0.209	0.407	0.210	0.407
South	0.421	0.494	0.432	0.495	0.425	0.494
West	0.201	0.401	0.213	0.409	0.206	0.404
Family Size	3.162	1.870	3.443	1.723	3.270	1.820
OG Tenure	13.40	19.47	19.42	23.30	15.70	21.22
OG Unemployment Rate	0.077	0.045	0.072	0.035	0.075	0.041
Proportion of Workers licensed	0.149	0.204	0.185	0.209	0.163	0.206
Proportion of Occupations licensed	0.119	0.141	0.171	0.164	0.139	0.152
JM Direction (ref: Horizontal)						
Upward	0.523	0.499	0.486	0.500	0.509	0.500
Downward	0.255	0.436	0.242	0.428	0.250	0.433
Survey dummies	-	-	-	-	-	-
N of respondents	7,685		4,782		12,467	
N of observations	17,247		10,693		27,940	

Table 1.5: Job Change Regressions Estimates [cited on page 21]

Explanatory	Specification 1			Specification 2		
Variables	NLSY79	NLSY97	P-value	NLSY79	NLSY97	P-value
Age	-0.0635***	-0.0940***	0.0669*	-0.0543***	-0.0975***	0.0085**
	(0.0073)	(0.0150)		(0.0066)	(0.0150)	
Age^2	0.0009***	0.0014***	0.0988*	0.0010***	0.0015***	0.1292
	(0.0001)	(0.0003)		(0.0001)	(0.0003)	
Female	-0.0270***	-0.0131*	0.0818*	-0.0664***	-0.0101	0.0000***
	(0.0046)	(0.0065)		(0.0035)	(0.0065)	
Nonwhite	0.0057	-0.0061	0.1628	-0.0157***	-0.0078	0.3000
	(0.0051)	(0.0068)		(0.0036)	(0.0068)	
Married	-0.0665***	-0.0538***	0.1122	-0.0238***	-0.0527***	0.0001***
	(0.0043)	(0.0067)		(0.0034)	(0.0067)	
Educated	-0.0325***	-0.0434***	0.1918	0.0018	-0.0424***	0.0000***
	(0.0048)	(0.0068)		(0.0036)	(0.0069)	
Midwest	-0.0068	0.0214*	0.0251*	-0.0252***	0.0214*	0.0000***
	(0.0069)	(0.0105)		(0.0049)	(0.0104)	
South	0.0409***	0.0493***	0.4576	0.0057	0.0479***	0.0000***
	(0.0064)	(0.0093)		(0.0046)	(0.0092)	
West	0.0385***	0.0167	0.0837*	0.0185***	0.0170*	0.8982
	(0.0073)	(0.0102)		(0.0053)	(0.0102)	
Family Size	0.0016	0.0014	0.9265	-0.0024*	0.0013	0.0645*
	(0.0012)	(0.0018)		(0.0010)	(0.0018)	
Job Tenure				-0.0009***	-0.0003***	0.0000***
				(0.0000)	(0.0000)	
Hours Worked				-0.0013***	0.0015***	0.0000***
				(0.0002)	(0.0003)	
LogWage				0.1360***	0.0071	0.0000***
				(0.0040)	(0.0062)	
Constant	1.5390***	1.8844***	0.1153	2.3983***	1.8396***	0.0100*
	(0.1002)	(0.1952)		(0.0908)	(0.1969)	
R Squared	0.0311	0.0513		0.1542	0.0545	
Observations	77,135	36,581		77,135	36,581	
Respondents	11,049	6,923		11,049	6,923	

Notes: Regressions include year dummy variables. Cluster-robust standard errors in parentheses.
The "P-value" column presents p-values of the chi-squared statistic of the test that two coefficients are equal.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 1.6: DECOMPOSITION ANALYSIS OF PROBABILITY OF JOB CHANGE [cited on page 23]

Sources of difference in probability of a job change	Change in probability	Contribution to total change (%)
Observed total change	0.0549	100.0 %
Due to characteristics effects	0.0552	100.6 %
Age	0.0136	24.8 %
Gender	−0.0002	−0.3 %
Race	0.0002	0.3%
Marital status	0.0108	19.7 %
Education	−0.0030	−5.5 %
Region	0.0013	2.4%
Family Size	0.0003	0.6%
Time	0.0323	58.7 %
Due to coefficients effects	−0.0003	−0.6 %
Constant	0.3453	628.7 %
Age	−0.4288	−780.6 %
Gender	0.0063	11.5 %
Race	−0.0055	−10.1 %
Marital status	0.0041	7.4%
Education	−0.0044	−8.0 %
Region	0.0048	8.7%
Family Size	−0.0006	−1.1 %
Time	0.0785	142.8 %

Table 1.7: **Job Change Regressions Estimates by Gender Groups** [cited on page 24]

Explanatory Variables	Male NLSY79	Male NLSY97	Male P-value	Female NLSY79	Female NLSY97	Female P-value
Age	-0.0537***	-0.1245***	0.0015**	-0.0559***	-0.0637**	0.7487
	(0.0091)	(0.0203)		(0.0096)	(0.0223)	
Age^2	0.0011***	0.0020***	0.0250*	0.0010***	0.0009*	0.7622
	(0.0002)	(0.0004)		(0.0002)	(0.0004)	
Nonwhite	-0.0158**	-0.0029	0.2323	-0.0186***	-0.0134	0.6330
	(0.0050)	(0.0095)		(0.0052)	(0.0096)	
Married	-0.0177***	-0.0555***	0.0005***	-0.0283***	-0.0504***	0.0327*
	(0.0048)	(0.0097)		(0.0048)	(0.0092)	
Educated	-0.0142**	-0.0623***	0.0000***	0.0194***	-0.0191*	0.0006***
	(0.0051)	(0.0094)		(0.0051)	(0.0100)	
Midwest	-0.0254***	0.0320*	0.0003***	-0.0247***	0.0084	0.0451*
	(0.0068)	(0.0143)		(0.0069)	(0.0150)	
South	0.0106	0.0570***	0.0012**	-0.0005	0.0357**	0.0133*
	(0.0065)	(0.0128)		(0.0064)	(0.0132)	
West	0.0199**	0.0314*	0.4735	0.0188*	0.0004	0.2538
	(0.0072)	(0.0144)		(0.0076)	(0.0142)	
Family Size	-0.0004	0.0026	0.2943	-0.0050**	0.0005	0.0626*
	(0.0013)	(0.0025)		(0.0015)	(0.0026)	
Job Tenure	-0.0010***	-0.0003***	0.0000***	-0.0009***	-0.0003***	0.0000***
	(0.0000)	(0.0000)		(0.0000)	(0.0001)	
Hours Worked	-0.0014***	0.0013**	0.0000***	-0.0014***	0.0016***	0.0000***
	(0.0003)	(0.0005)		(0.0003)	(0.0005)	
LogWage	-0.1408***	0.0109	0.0000***	-0.1339***	-0.0008	0.0000***
	(0.0055)	(0.0081)		(0.0057)	(0.0094)	
Constant	2.3841***	2.0198***	0.1898	2.3843***	1.5537***	0.0065**
	(0.1248)	(0.2484)		(0.1326)	(0.2749)	
R Squared	0.1650	0.0562		0.1403	0.0541	
Observations	42,367	19,815		34,768	16,766	
Respondents	5,685	3,552		5,364	3,371	

Notes: Regressions include year dummy variables. Cluster-robust standard errors in parentheses.
The ”P-value” column presents p-values of the chi-squared statistic of the test that two coefficients are equal.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 1.8: Job Change Regressions Estimates by Race Groups [cited on page 24]

Explanatory Variables	White NLSY79	White NLSY97	White P-value	Nonwhite NLSY79	Nonwhite NLSY97	Nonwhite P-value
Age	-0.0574***	-0.1289***	0.0016**	-0.0510***	-0.0611**	0.6727
	(0.0085)	(0.0211)		(0.0106)	(0.0214)	
Age^2	0.0011***	0.0022***	0.0125*	0.0009***	0.0007*	0.6419
	(0.0002)	(0.0004)		(0.0002)	(0.0004)	
Female	-0.0605***	-0.0003	0.0000***	-0.0739***	-0.0204*	0.0000***
	(0.0046)	(0.0091)		(0.0053)	(0.0092)	
Married	-0.0297***	-0.0598***	0.0029**	-0.0160**	-0.0450***	0.0091**
	(0.0045)	(0.0091)		(0.0052)	(0.0098)	
Educated	-0.0035	-0.0598***	0.0000***	0.0097*	-0.0248*	0.0020**
	(0.0047)	(0.0097)		(0.0056)	(0.0097)	
Midwest	-0.0258***	0.0240*	0.0005***	-0.0180*	0.0252	0.0294*
	(0.0057)	(0.0130)		(0.0094)	(0.0175)	
South	0.0121*	0.0592***	0.0007***	-0.0014	0.0317*	0.0329*
	(0.0059)	(0.0126)		(0.0074)	(0.0137)	
West	0.0243**	0.0505***	0.0998*	0.0107	-0.0166	0.1029
	(0.0071)	(0.0143)		(0.0080)	(0.0147)	
Family Size	-0.0027*	0.0060*	0.0061**	-0.0022*	-0.0011	0.6818
	(0.0015)	(0.0028)		(0.0013)	(0.0023)	
Job Tenure	-0.0009***	-0.0003***	0.0000***	-0.0009***	-0.0003***	0.0000***
	(0.0000)	(0.0000)		(0.0000)	(0.0001)	
Hours Worked	-0.0012***	0.0014**	0.0000***	-0.0015***	0.0015**	0.0000***
	(0.0003)	(0.0004)		(0.0003)	(0.0005)	
LogWage	-0.1360***	0.0013	0.0000***	-0.1357***	0.0138	0.0000***
	(0.0051)	(0.0087)		(0.0064)	(0.0088)	
Constant	2.0510***	2.1822***	0.6402	2.0104***	1.3615***	0.0285*
	(0.1096)	(0.2585)		(0.1364)	(0.2633)	
R Squared	0.1507	0.0564		0.1589	0.0564	
Observations	44,747	18,819		32,388	17,762	
Respondents	6,544	3,522		4,505	3,401	

Notes: Regressions include year dummy variables. Cluster-robust standard errors in parentheses.
The "P-value" column presents p-values of the chi-squared statistic of the test that two coefficients are equal.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 1.9: **Job Change Regressions Estimates by Marital Status Groups** [cited on page 24]

Explanatory		Unmarried			Married	
Variables	NLSY79	NLSY97	P-value	NLSY79	NLSY97	P-value
Age	-0.0368***	-0.1078***	0.0003***	-0.0774***	-0.1155**	0.2895
	(0.0085)	(0.0178)		(0.0111)	(0.0343)	
Age^2	0.0007***	0.0018***	0.0068**	0.0014***	0.0017**	0.6614
	(0.0002)	(0.0004)		(0.0002)	(0.0006)	
Female	-0.0618***	-0.0114	0.0000***	-0.0617***	-0.0079	0.0000***
	(0.0045)	(0.0075)		(0.0052)	(0.0110)	
Nonwhite	-0.0209***	-0.0065	0.1134	-0.0107*	-0.0152	0.7250
	(0.0048)	(0.0078)		(0.0052)	(0.0115)	
Educated	-0.0005	-0.0430***	0.0000***	0.0046	-0.0341**	0.0024**
	(0.0049)	(0.0080)		(0.0052)	(0.0117)	
Midwest	-0.0361***	0.0224*	0.0000***	-0.0126*	0.0179	0.1245
	(0.0066)	(0.0119)		(0.0069)	(0.0186)	
South	0.0030	0.0486***	0.0001***	0.0119*	0.0460**	0.0636*
	(0.0060)	(0.0103)		(0.0067)	(0.0172)	
West	0.0171*	0.0103	0.6094	0.0211**	0.0321*	0.5871
	(0.0069)	(0.0114)		(0.0076)	(0.0187)	
Family Size	-0.0047***	-0.0001	0.0527*	0.0040*	0.0076*	0.3765
	(0.0012)	(0.0021)		(0.0020)	(0.0036)	
Job Tenure	-0.0011***	-0.0003***	0.0000***	-0.0008***	-0.0003***	0.0000***
	(0.0000)	(0.0000)		(0.0000)	(0.0001)	
Hours Worked	-0.0019***	0.0010*	0.0000***	-0.0006*	0.0026***	0.0000***
	(0.0003)	(0.0004)		(0.0003)	(0.0006)	
LogWage	-0.1425***	0.0123*	0.0000***	-0.1274***	-0.0065	0.0000***
	(0.0056)	(0.0072)		(0.0054)	(0.0110)	
Constant	1.9103***	1.9101***	0.9994	2.1809***	2.0927***	0.8464
	(0.1085)	(0.2247)		(0.1465)	(0.4321)	
R Squared	0.1556	0.0488		0.1433	0.0439	
Observations	42,886	26,623		34,249	9,958	
Respondents	9,235	6,151		7,164	2,828	

Notes: Regressions include year dummy variables. Cluster-robust standard errors in parentheses.
The "P-value" column presents p-values of the chi-squared statistic of the test that two coefficients are equal.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 1.10: **Job Change Regressions Estimates by Education Groups** [cited on page 24]

Explanatory Variables	12 years of Education and less NLSY79	NLSY97	P-value	More than 12 years of Education NLSY79	NLSY97	P-value
Age	-0.0521***	-0.1083***	0.0070**	-0.0597***	-0.0765**	0.5819
	(0.0079)	(0.0193)		(0.0141)	(0.0270)	
Age^2	0.0010***	0.0017***	0.0744*	0.0011***	0.0011*	0.9644
	(0.0002)	(0.0004)		(0.0003)	(0.0005)	
Female	-0.0767***	-0.0241**	0.0000***	-0.0479***	0.0100	0.0000***
	(0.0044)	(0.0092)		(0.0056)	(0.0088)	
Nonwhite	-0.0208***	-0.0205*	0.9768	-0.0107*	0.0080	0.0848*
	(0.0046)	(0.0095)		(0.0058)	(0.0092)	
Married	-0.0231***	-0.0489***	0.0154*	-0.0259***	-0.0540***	0.0084**
	(0.0042)	(0.0098)		(0.0057)	(0.0090)	
Midwest	-0.0277***	0.0134	0.0114*	-0.0195*	0.0311*	0.0013**
	(0.0062)	(0.0150)		(0.0078)	(0.0138)	
South	0.0118*	0.0466***	0.0150*	-0.0060	0.0474***	0.0002***
	(0.0059)	(0.0131)		(0.0071)	(0.0126)	
West	0.0276***	0.0085	0.2305	0.0032	0.0288*	0.1131
	(0.0067)	(0.0144)		(0.0084)	(0.0139)	
Family Size	-0.0029*	0.0018	0.0674*	-0.0020	-0.0001	0.5744
	(0.0012)	(0.0023)		(0.0018)	(0.0027)	
Job Tenure	-0.0010***	-0.0005***	0.0000***	-0.0008***	-0.0002***	0.0000***
	(0.0000)	(0.0001)		(0.0000)	(0.0000)	
Hours Worked	-0.0008**	0.0022***	0.0000***	-0.0024***	0.0009*	0.0000***
	(0.0003)	(0.0005)		(0.0003)	(0.0004)	
LogWage	-0.1334***	0.0143	0.0000***	-0.1398***	0.0007	0.0000***
	(0.0051)	(0.0090)		(0.0063)	(0.0085)	
Constant	2.3293***	1.9370***	0.1352	2.5314***	1.5424***	0.0130*
	(0.1075)	(0.2398)		(0.1947)	(0.3479)	
R Squared	0.1606	0.0534		0.1363	0.0337	
Observations	50,427	20,801		26,708	15,780	
Respondents	7,415	4,098		4,364	3,541	

Notes: Regressions include year dummy variables. Cluster-robust standard errors in parentheses.
The ”P-value” column presents p-values of the chi-squared statistic of the test that two coefficients are equal.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 1.11: **OG Change Regressions Estimates** [cited on page 25]

Explanatory	Specification 1			Specification 2		
Variables	NLSY79	NLSY97	P-value	NLSY79	NLSY97	P-value
Age	-0.0356*	0.0119	0.1142	-0.0282*	0.0164	0.1258
	(0.0158)	(0.0257)		(0.0150)	(0.0251)	
Age^2	0.0007*	-0.0001	0.1841	0.0006*	-0.0002	0.2156
	(0.0003)	(0.0005)		(0.0003)	(0.0005)	
Female	-0.0594***	-0.0538***	0.6776	-0.0416***	-0.0477***	0.6649
	(0.0087)	(0.0104)		(0.0089)	(0.0112)	
Nonwhite	0.0192*	-0.0170	0.0095**	0.0162*	-0.0183*	0.0092**
	(0.0091)	(0.0106)		(0.0084)	(0.0102)	
Married	-0.0212*	-0.0082	0.4139	-0.0098	-0.0050	0.7543
	(0.0088)	(0.0133)		(0.0083)	(0.0129)	
Educated	-0.0095	0.0147	0.1091	-0.0159*	0.0116	0.0647*
	(0.0095)	(0.0117)		(0.0093)	(0.0116)	
Midwest	0.0254*	0.0306*	0.8165	0.0160	0.0389*	0.2841
	(0.0139)	(0.0175)		(0.0130)	(0.0170)	
South	0.0216*	0.0131	0.6745	0.0192*	0.0217	0.8956
	(0.0124)	(0.0160)		(0.0116)	(0.0155)	
West	0.0047	0.0251	0.3668	-0.0056	0.0279	0.1200
	(0.0142)	(0.0176)		(0.0133)	(0.0170)	
Family Size	0.0081***	-0.0052*	0.0004***	0.0071**	-0.0052*	0.0007***
	(0.0023)	(0.0030)		(0.0022)	(0.0029)	
Downward JM				0.0874***	0.1815***	0.0000***
				(0.0108)	(0.0136)	
Upward JM				0.0319**	0.1820***	0.0000***
				(0.0094)	(0.0114)	
OG Tenure				-0.0044***	-0.0017***	0.0000***
				(0.0002)	(0.0002)	
OG Unempl Rate				-0.4417*	-0.1595	0.4316
				(0.2018)	(0.2976)	
Prop Work Licensed				-0.4013***	-0.3089**	0.5259
				(0.0949)	(0.1109)	
Prop Occ Licensed				0.1994*	0.0861	0.4180
				(0.0908)	(0.1068)	
Constant	1.0018***	0.5880*	0.2511	0.8577***	0.7214*	0.7061
	(0.1999)	(0.3005)		(0.1986)	(0.3026)	
R Squared	0.0107	0.0088		0.0719	0.0509	
Observations	17,247	10,693		17,247	10,693	
Respondents	7,685	4,782		7,685	4,782	

Notes: Regressions include year dummy variables. Cluster-robust standard errors in parentheses.
The ”P-value” column presents p-values of the chi-squared statistic of the test that two coefficients are equal.
Significance levels: *** p $<$ 0.001, ** p $<$ 0.01, * p $<$ 0.1.

Table 1.12: LogWage Difference Regressions Estimates [cited on pages 26 and 26]

Explanatory Variables	Sample 1 NLSY79	NLSY97	P-value	Sample 2 NLSY79	NLSY97	P-value
JobChange/	0.0575***	0.1222***	0.0000***	0.0029	0.0370***	0.0035**
OGChange	(0.0036)	(0.0044)		(0.0072)	(0.0092)	
Age	-0.0147**	-0.0035	0.2698	-0.0447**	-0.0161	0.2966
	(0.0050)	(0.0088)		(0.0142)	(0.0236)	
Age^2	0.0002*	0.0000	0.4109	0.0007*	0.0002	0.3697
	(0.0001)	(0.0002)		(0.0003)	(0.0005)	
Female	-0.0029	-0.0094**	0.0632*	-0.0030	-0.0281**	0.0191*
	(0.0021)	(0.0028)		(0.0066)	(0.0084)	
Nonwhite	-0.0026	-0.0063*	0.3148	0.0062	-0.0197*	0.0172*
	(0.0022)	(0.0029)		(0.0066)	(0.0086)	
Married	0.0019	0.0093**	0.0717*	0.0016	0.0353**	0.0129*
	(0.0024)	(0.0033)		(0.0071)	(0.0115)	
Educated	0.0261***	0.0194***	0.0717*	0.0405***	0.0675***	0.0256*
	(0.0023)	(0.0029)		(0.0073)	(0.0096)	
Midwest	-0.0036	-0.0090*	0.3232	-0.0061	-0.0361*	0.0909*
	(0.0033)	(0.0044)		(0.0108)	(0.0141)	
South	-0.0113***	-0.0072*	0.4208	-0.0235*	-0.0222*	0.9313
	(0.0031)	(0.0040)		(0.0095)	(0.0124)	
West	-0.0117**	-0.0048	0.2492	-0.0258*	-0.0193	0.7258
	(0.0038)	(0.0046)		(0.0113)	(0.0145)	
Constant	0.3054***	0.0888	0.1041	0.8590***	0.4319	0.1926
	(0.0742)	(0.1108)		(0.1755)	(0.2772)	
R Squared	0.0085	0.0353		0.0096	0.0117	
Observations	73,882	35,985		20,044	11,815	
Respondents	10,926	6,860		8,093	5,089	

Notes: Regressions include year dummy variables. Cluster-robust standard errors in parentheses.
The "P-value" column presents p-values of the chi-squared statistic of the test that two coefficients are equal.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 1.13: **Job Change Models Robustness Testing** [cited on page 27]

Explanatory	Model 1		Model 2		Model 3		Model 4	
Variables	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
Age	-0.0543***	-0.0975***	-0.0311***	-0.0762***	-0.0452***	-0.0680***	-0.0435***	-0.0736***
	(0.0066)	(0.0150)	(0.0074)	(0.0206)	(0.0092)	(0.0189)	(0.0066)	(0.0148)
Age^2	0.0010***	0.0015***	0.0006***	0.0012**	0.0006***	0.0008*	0.0007***	0.0010***
	(0.0001)	(0.0003)	(0.0001)	(0.0004)	(0.0001)	(0.0003)	(0.0001)	(0.0003)
R Squared	0.1542	0.0545	0.1394	0.0428	0.0990	0.0329		
Observations	77,135	36,581	58,176	20,007	77,135	36,581	77,135	36,581
Respondents	11,049	6,923	9,979	4,901	11,049	6,923	11,049	6,923

Notes: Model 1: baseline (linear probability) models,
Model 2: linear probability models with hours restrictions [40,90] - only full-time workers,
Model 3: fixed-effects linear probability models,
Model 4: Hausman-Taylor models to control potential endogeneity.
Regressions include $Female, Nonwhite, Married, Educated, FamilySize, JobTenure, HoursPerWeekWorked, LogWage$ variables, region and year dummy variables.
Cluster-robust standard errors in parentheses.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 1.14: OCCUPATIONAL GROUPS CHANGE MODELS ROBUSTNESS TESTING [cited on page 28]

Explanatory	Model 1		Model 2		Model 3		Model 4	
Variables	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97
DownwardJM	0.0874***	0.1815***	0.0800***	0.1796***	0.0495***	0.1850***	0.0894***	0.1758***
	(0.0108)	(0.0136)	(0.0136)	(0.0210)	(0.0135)	(0.0177)	(0.0105)	(0.0129)
UpwardJM	0.0319**	0.1820***	0.0316**	0.1526***	0.0371**	0.1640***	0.0291**	0.1836***
	(0.0094)	(0.0114)	(0.0116)	(0.0180)	(0.0117)	(0.0147)	(0.0092)	(0.0112)
R Squared	0.0719	0.0509	0.0722	0.0591	0.0353	0.0204		
Observations	17,247	10,693	11,059	4,565	17,247	10,693	17,247	10,693
Respondents	7,685	4,782	5,765	2,704	7,685	4,782	7,685	4,782

Notes: Model 1: baseline (linear probability) models,
Model 2: linear probability models with hours restrictions [40,90] - only full-time workers,
Model 3: fixed-effects linear probability models,
Model 4: Heckman's two-step model to control potential self-selection issues.
Regressions include $Age, Age^2, Female, Nonwhite, Married, Educated, FamilySize, OGTenure, OGUnempRate, OGLicensure$ variables, region, skill demand, and year dummy variables.
Cluster-robust standard errors in parentheses.
Significance levels: *** p $<$ 0.001, ** p $<$ 0.01, * p $<$ 0.1.

Chapter 2

Gender Differences in Robotization Effects: Cross-Sectional Analysis

2.1 Introduction

The term ”robot” is relatively recent, originating from the creative works of Czech author and playwright Karel Čapek (1880-1938) in his 1920 science-fiction masterpiece, ”R.U.R.” or ”Rossum's Universal Robots.”[1] This neologism finds its roots in the Czech word ”robota,” signifying servitude or involuntary labor. Its linguistic counterparts can be observed in various European languages, including German, Polish, and Russian. Within the narrative of ”R.U.R.,” a fictional factory employs principles of biochemistry and physiology to engage in the mass production of a novel type of laborer who possesses every attribute except for a soul.

In the opening scenes of the play, Harry Domin, the general manager of Rossum's Universal Robots, recounts the company's historical background and explains the pivotal role of robots in driving down labor costs across the world. By the time the events of the play unfold, situated approximately in the year 2000, the use of robot laborers is already both economical and readily available. Domin anticipates a future where, within a mere decade, everything will be done by robots worldwide (Čapek [109]). Automation will permeate every facet of

[1] first premiered on January 2, 1921 in Hradec Králové, Czechoslovakia, https://www.uhk.cz/cs/pedagogicka-fakulta/pdf/aktualne/svetova-premiera-r.u.r.-byla-pred-100-lety-v-hradci-kralove

global productivity, and robots will produce ”so much of everything that nothing will cost anything,” bringing the human need to work to a close. As a result, people will not work; they ”will do only the things they want to do.” But the narrative takes a twist as the robots rebel against their creators, embarking on a campaign to exterminate humanity, thereby thwarting the realization of Domin’s vision. However, evaluating the accuracy of the robot creator’s predictions through the lens of contemporary labor economics is thought-provoking. In the current era, approximately a century after the coining of the term ”robot,” our world is witnessing a groundbreaking shift in the realm of employment driven by technological progress. This transformation is reshaping the labor landscape, diminishing the need for certain occupations while expanding the demand for others. Among the pioneering domains of technology underpinning these changes, robotics stands as a formidable force. The International Federation of Robotics (IFR) provides a succinct definition of an industrial robot as ”an automatically controlled, reprogrammable, and multipurpose machine.” These machines exhibit the capacity to supplant human labor across a diverse array of tasks. Although there are several other types of robots (androids, telechir robots, smart robots, etc.), the primary focus of this study centers on industrial robots, and the terms ”robots” and ”industrial robots” will be used interchangeably.

According to the IFR’s definition, industrial robots are entirely autonomous machines programmed to execute manual, repetitive tasks without the necessity of human intervention (Acemoglu and Restrepo [2]). Given their capacity to operate independently of direct people’s participation in the production process, robots may be categorized as a form of physical capital. Analogous to other forms of physical capital, such as tools and equipment utilized in the production of goods and services, industrial robots can effectively serve as replacements for human labor. However, the adoption of these highly efficient manufacturing tools is likely to result in increased output, thereby leading to a heightened demand for labor. While labor demand for certain routine occupations may decline due to the substitution by robots, there emerges a complementary demand for other occupations, primarily those necessitating higher skill levels. Thus, industrial robots act as substitutes for particular manual routine occupations and complements to other, often more skill-intensive, roles (albeit not necessarily in a direct manner). In addition, this supplanting by robots for routine work may contribute to employment polarization, whereby lower-skilled labor is redirected toward service sectors characterized by lower income and slower career advancement (Autor and Dorn [10], Dauth et al. [36]). Consequently, the effect of robotization on employment can extend to directly unaffected industries.

Presently, the appeal of industrial robots as replacements for human labor continues to intensify due to the compelling cost-effectiveness they offer to manufacturers in automating routine tasks. Over the recent decades, the field of robotics has experienced rapid technological advancement, resulting in a notable upswing in the prevalence of robots in the United States and Western Europe. Figure 2.1 underscores this trend, illustrating a more than fourfold increase in the number of industrial robots in the USA from 1995 to 2017.

The growing robotics technology significantly impacts our society, including the labor market. A series of papers have linked the rise of robots to essential effects on overall employment, manufacturing employment, earnings, and migration (Acemoglu and Restrepo [2], Faber et al. [40], Graetz and Michaels [50], Grigoli et al. [53]). It has been ascertained that exposure to industrial robots amplifies both productivity and wages but concurrently diminishes employment opportunities for low-skill workers. However, this impact does not affect overall employment in the USA, South Korea, Australia, and 14 European countries (Graetz and Michaels [50]). Other studies assert that the adoption of robots leads to reduced employment and wages for American workers (Acemoglu and Restrepo [2]). Within German local labor markets that specialize in industries characterized by extensive robot usage, the introduction of robots does not exhibit an unfavorable effect on total employment, as the gains experienced within the business service sector offset the job losses in manufacturing

(Dauth et al. [36]).

Artificial Intelligence (AI) has the potential to impact labor markets in a manner akin to industrial robots, replacing certain occupations and complementing others. Recent studies highlight the differential influence of AI on various skill groups within the workforce. According to Webb [104], high-skilled workers constitute the most vulnerable segment of the labor force to artificial intelligence. In stark contrast to robots, AI tends to exert a more pronounced effect on highly educated and older workers. This divergence is attributed to the nature of artificial intelligence, which entails the development of algorithms and computer programs capable of learning to perform tasks traditionally reliant on human intelligence, whereas industrial robots primarily adhere to instructions provided by humans.

The negative impact of robotization on employment displays relatively limited variation across different skill groups. Industrial robots similarly reduce high-skilled (some college or more) and low-skilled (less than college) employment (Acemoglu and Restrepo [2], Faber et al. [40]). An unexpected and, to some extent, intriguing observation is the absence of a positive effect on workers holding master's or doctoral degrees, which might be elucidated by reduced demand for highly educated workers within the non-tradable sector. Another conceivable explanation is that industrial robots do not directly complement high-skilled workers, in contrast to other computer-assisted technologies such as AI.

Given that industrial robots act as substitutes for labor in some occupational categories and complements in others, and considering the foreseeable differences in the socio-demographic characteristics of these occupations, the impact of robot penetration on key labor market outcomes may exhibit discrepancies among specific socio-demographic groups within local labor markets. Historically, following the Industrial Revolution, roles in manufacturing that required physical strength tended to offer higher wages and became more appealing to men. For that reason, many sectors associated with strenuous manual labor are characterized by a male-dominated workforce. Owing to this substantial diversity in the gender composition of industries, one can anticipate differing gender-related effects of robotization. Nevertheless, recent literature has yet to empirically explore the distinctions in the consequences of robot adoption on employment and migration for female and male workers. The ultimate goal of this paper is to fill this gap in the existing research.

One of the primary outcomes of robot exposure in local labor markets is the job transitions undergone by workers replaced by robots. Typically, patterns of job mobility exhibit gender-based variations. An earlier study by Viscusi [103] identified that women tend to resign from their positions more frequently than men, although this observation lacks informativeness due to the inherent heterogeneity of worker characteristics, job attributes, and regional economic conditions. Royalty [94] suggests that disparities between the job mobility of men and women are primarily rooted in the turnover behavior of less educated women. Their job mobility diverges from that of more educated women and both educational strata of men, with more educated women closely resembling men in their turnover behavior. In addition to this, research by Cotton and Tuttle [34] reveals that unmarried workers of both genders exhibit a higher likelihood of leaving their jobs in comparison to their married counterparts. The potential responses of workers who are forced out of the labor market due to robots can be twofold. Some individuals who have lost their jobs might opt to relocate to local labor markets with lower exposure to robots, seeking opportunities in the same occupations. Overall, robots have been linked to a notable reduction in the population size of local labor markets (Faber et al. [40]). Alternatively, another response pertains to occupational mobility, where unemployed workers may decide to change their occupations while remaining within the same local labor markets. Empirical evidence concerning gender as a determinant of occupational mobility is varied. While some studies have reported that men exhibit a greater tendency to change occupations than women (Blau [20], Felmlee [43], Markham et al. [71]), other researchers have implied little difference in overall occupational mobility between males and females (Gabriel [48], Rosenfeld and Sorensen [93]), or have posited that women are more likely than men to switch occupations (Ranson [89]). Additionally, it was found that female workers face a significantly higher risk of displacement due to automation[2] compared to their male counterparts (Brussevich et al. [26]).

A similar scenario of automating specific occupations to substitute human labor transpired about a century ago. During the first half of the previous centenary, automation led to the elimination of an essential number of manual telephone operation roles, a field primarily occupied by young American women. However, this transformation did not impact the overall employment prospects of future cohorts, as the decline in operators was offset by a resurgence in demand for middle-skill clerical positions and lower-skill service jobs (Feigenbaum and Gross [42]). In the contemporary context, industrial robots are capable of executing physical tasks, thereby supplanting "brawn" skills traditionally associated with male-dominated industries. As a result, the comparative advantage held by low-skilled male workers in contrast to their female counterparts may be diminished (Rendall [91]).

Empirical findings in recent literature concerning the effect of robotization on the gender wage gap present a mixed picture. It has been observed that exposure to industrial robots tends to reduce the gender wage gap in the USA but increases it in European countries. In the United States, the negative impact of robots on male wages substantially exceeds that on female wages, thus diminishing the gender income disparity (Anelli et al. [7], Ge and Zhou [49]). However, across 20 European nations, the adoption of industrial robots results in higher earnings for both men and women while simultaneously widening the gender pay gap (Aksoy et al. [4]). This stark difference in outcomes is predominantly influenced by Eastern European countries characterized by significant initial gender inequality. Besides, the productivity effect allows male middle-skill and high-skill workers in Europe to disproportionately benefit

[2] Although the terms "automation" and "robotics" are occasionally used interchangeably and can yield comparable effects on labor market outcomes, there exists a conceptual distinction between them. Automation refers to the utilization of technology to execute a range of human tasks, whereas robotics pertains to the creation and deployment of robots (including industrial robots) designed to perform only specific functions.

from upscaled robot penetration. These divergent results imply that the influence of robot exposure on local labor markets may be context-specific.

There are general predictions indicating that the impact of automation and robotics on Americans will be uneven. Given that occupations principally held by male workers often involve more manual tasks that are relatively easier to be substituted by industrial robots, men are at a higher risk of experiencing job displacement due to robotization (Muro et al. [80]). In recent decades, male workers have been mainly concentrated in occupations related to construction, production, and transportation – occupational groups characterized by tasks that are relatively more exposed to automation and robotization.

On the other hand, women are disproportionately represented in occupations that revolve around human interaction, including education, healthcare, and social work – roles that are considerably reliant on human labor (Ngai and Petrongolo [83]). Furthermore, women are currently more likely to achieve higher education degrees than men. Consequently, female workers' occupations may be somewhat more resilient to displacement by automation tools, including industrial robots. In line with these assertions, the effect of robot adoption is anticipated to be relatively more advantageous for female workers.

Nonetheless, it is likely that skilled men stand to gain more from the productivity enhancements driven by robots (Aksoy et al. [4]). This conclusion is primarily attributed to the overrepresentation of male workers in higher positions within the occupational hierarchy of companies. In addition, men are disproportionately prevalent in STEM (science, technology, engineering, mathematics) occupations that hold relevance in this context. For these reasons, the foreseeable influence of robotization is expected to exhibit variations across skill-based occupational groups for both genders.

The main objective of this paper is to examine potential discrepancies in the consequences of robot exposure on various aspects of the local labor markets in the USA, such as migration, labor force participation, total employment, private employment, and public employment, focusing on diverse socio-demographic groups categorized by gender.

To delve deeper into the distinctions in the impact of robot penetration and provide a comprehensive explanation, the supplementary analysis within gender groups is extended to different socio-demographic subgroups, including those distinguished by marital status, broad industry categories, and occupational groups. Moreover, this study explores the intricacies of intra-household adjustments in response to robotization. A similar analysis in recent literature uncovers that heightened competition from Chinese imports, representing another potent and localized shock to American local labor markets, led to an increase in married female labor force participation (Besedeš et al. [18]).

This paper makes contributions to various strands of literature. It endeavors to investigate gender discrepancies in the consequences of exposure to industrial robots. The empirical findings indicate that, on the whole, the negative effects of robot adoption on the working-age population and total employment are more pronounced for females. However, the impact of robot penetration on private employment tends to have a more negative effect on the male population. Notably, the influence of robot exposure is comparatively less negative for married workers of both genders.

Within the context of three broad industry categories, the unfavorable impact of robotization is found to be more substantial within low-skilled non-manufacturing industries, regardless of gender. In line with the predictions, the influence of robot adoption in manufacturing industries is negative for the male population and conducive for females. This positive impact is mostly attributed to married female workers and women in cognitive routine manufacturing occupations. In addition, robot penetration exerts a positive effect on labor force participation and the proportion of family income among married women.

The rest of the paper is organized as follows. Section 2 demonstrates the data and descriptive statistics. Section 3 describes the empirical framework. The results are presented in Section 4. Finally, Section 5 concludes.

2.2 Data and Descriptive Statistics

This section of the paper introduces the data sources utilized in constructing the commuting zone's level of robotization variable, several outcome variables, and the covariates. In addition to this, it provides essential descriptive statistics for rendering an initial overview.

2.2.1 Robot Adoption

In alignment with Acemoglu and Restrepo [2], this study draws upon data encompassing the United States and five European countries (Denmark, Finland, France, Italy, and Sweden) sourced from the International Federation of Robotics (IFR). The dataset provided by the IFR includes counts of the operational stock of industrial robots categorized by industry, country, and year within the time frame of 1993 to 2017. Additionally, data related to employment and output growth rates in industries are extracted from the EU KLEMS database. Consistent with recent literature, robot capital is quantified as the number of robots per thousand workers.

This paper relies on robot data spanning 15 industries. Within these, nine belong to the manufacturing sector, which includes food and beverages; textiles (including apparel); wood, furniture, paper, and printing; plastic, chemicals, glass, and non-metals; basic metals and metal products; electronics; industrial machinery; automotive, shipbuilding, and aerospace; and miscellaneous manufacturing. Outside of the manufacturing domain, the dataset consists six broad industries, namely agriculture, forestry, and fishing; mining; construction; utilities; education, research, and development; and services.

The data regarding the numbers of robots per thousand workers across IFR industries in the United States for the years 1997, 2007, and 2017 are provided in Table 2.1. It is evident that the distribution of robots across these industries is not uniform. Specifically, the automotive, shipbuilding, and aerospace sectors exhibited the highest numbers of robots per thousand workers in 1997, 2007, and 2017, while all other industries displayed considerably lower figures.

One limitation of the IFR data is that industry-specific data for the USA is reported only after 2004. To address this, the distribution across industries in 2004 is employed to allocate the total number of the operational stock of robots in preceding years to the IFR industries. Moreover, the IFR categorizes some robot stocks as ”unspecified” when the number of suppliers to a particular industry is less than four. To assign these unspecified robots to each industry, the proportions across industries in the specified data from 2017 are used as weighting factors.

2.2.2 Dependent Variables

In line with recent literature, this study adopts commuting zones (CZs) as the unit of observation. CZs are characterized as clusters of counties exhibiting strong commuting connections within the zone but weak commuting ties across different CZs (Autor and Dorn [10]). Unlike other definitions of local labor markets, such as metropolitan areas, states, or counties, CZs are economically meaningful boundaries that encompass both urban and rural regions of the country.

It is assumed that individuals residing in a particular CZ are highly likely to work within the same CZ. The dataset contains 722 commuting zones, providing comprehensive coverage of the entire continental United States (Tolbert and Sizer [100]).

The dependent variables in this paper include migration, employment, private employment, and public employment. The examination of two distinct employment types is conducted separately, as women are more inclined to work in the public sector (Lewis and Frank [67]). The first outcome variable, migration, is defined as the change in the logarithm of the number of working-age individuals (aged 15-64) residing in CZ c between periods t and $t + 1$ within the subgroup Y:

$$\Delta lnY_{c,t:t+1} = lnY_{c,t+1} - lnY_{c,t} \tag{2.1}$$

The remaining three similar outcome variables represent the changes in the logarithm of the count of the employed population and the employed population in the private and public sectors, respectively.

This study also employs labor force participation and employment rate changes as dependent variables. The total, private, and public employment rates of various socio-demographic subgroups of the population are determined as the proportion of the population within these subgroups that are employed, employed in the private sector, and employed in the public sector, respectively. The labor force participation rate denotes the proportion of the population engaged in the labor force.

The dependent variables are constructed using census samples of Integrated Public Use Microdata Series (IPUMS) for 1970, 1990, and 2000, and the American Community Survey (ACS) data for 2007 and 2017 (Flood et al. [44]). The sample size is 1% for 1970 and 5% for the other samples. To enhance the sample size, following Autor et al. [11], the outcomes for 2007 and 2017 are measured using the ACS data for 2005–2009 and 2015-2019.

For intra-household analysis, the IPUMS and ACS samples are limited to households containing married or cohabiting working-age couples who are not on active military duty. Households with more than one married couple and households with same-sex married couples are excluded from the dataset used for the intra-household analysis.

Descriptive statistics for the dependent variables are detailed in Table 2.2. The table presents unweighted means of these variables across all 722 CZs over the period from 1990 to 2017 and three subperiods (1990-2000, 2000-2007, and 2007-2017). Consistent with the approach of Acemoglu and Restrepo [2] and Autor et al. [11], changes in the second period in this paper are adjusted to 10-year equivalents. This adjustment is achieved by dividing shifts in the dependent and explanatory variables over the 2000-2007 subperiod by 0.7, effectively rescaling the seven-year changes to the ten-year period for comparability.

This table demonstrates notable disparities in changes for certain dependent variables between men and women. These distinctions are most pronounced when examining changes in the labor force participation rate, total employment rate, and the logs of total and public employment. The primary source of these gender differences is the first subperiod (1990-2000), while gender discrepancies in the two subsequent subperiods are less perceptible.

The preliminary step of this study involves a visual inspection of the correlation between robotization and the dependent variables. Figures 2.2 and 2.3 reveal that robot exposure is primarily concentrated in the Eastern part of the US, particularly within the Rust Belt region. The second panels of these figures depict that the Eastern part of the country in general, and the Rust Belt in particular, experienced relatively low increases in population and total, private, and public employment. In contrast, the western part of the country exhibits lower levels of the adoption of robots but relatively high changes in all four dependent variables. Therefore, it is anticipated that there is a negative correlation between robot penetration and the dependent variables. However, Figures 2.4-2.7 do not illustrate significant visual dissimilarities in changes in the dependent variables between men (panel C) and women (panel D). The geographic distribution of all four outcome variables for both gender groups closely resembles the overall distribution among CZs (panel B).

2.2.3 Covariates

The first covariate employed in this paper is the exposure to Chinese imports per worker, which is constructed following the method of Autor et al. [11]. This covariate is included to control for potentially confounding changes in trade patterns. Recent literature has highlighted the significant impact of Chinese import competition on local labor markets. The substantial growth in Chinese exports to the USA and other Western countries was particularly consolidated in labor-intensive industries within the manufacturing sector, such as electronics and electrical, industrial machinery, and textiles and apparel (Faber et al. [40]). This crucial covariate is computed using data from two sources: industry-specific data on Chinese import values per year and destination country, sourced from the UN Comtrade database, alongside data on industry employment proportions by commuting zone derived from IPUMS samples. The variable is created utilizing crosswalks from Autor et al. [11] and Autor et al. [12].

Other covariates in the model consist of the following baseline CZ characteristics. Dummy variables for census divisions are included to account for the general geographic characteristics of commuting zones. Changes in the outcome variables between 1970 and 1990 are included to account for potential confounding factors, such as long-term trends in the labor market that could influence the results. In order to control for the initial (before exposure to industrial robots) characteristics of commuting zones, the model contains different demographic characteristics and employment proportions in major (broad) industries in 1990. These variables are constructed from the IPUMS samples. Finally, the introductory proportions of the average offshorability index (the share of tasks in an industry that can be offshored) and routine jobs in 1990 serve as indicators for contemporaneous changes in skill demand that might potentially impact the results as confounding factors. In alignment with Autor and Dorn [10], these two variables are included in the model to control the potential susceptibility of a CZ's routine-intensive occupations to the substitution of routine tasks by technology or task offshoring to cheaper labor markets.

2.3 Empirical Framework

The effect of robot adoption on outcome variables (changes in population size, labor force participation rate, different employment rates, and various types of employment) within the subgroup Y can be written as follows:

$$\begin{aligned}\Delta Y_{c,t:t+1} =& \beta_0 + \beta_1 \text{US Robot Adoption}_{c,t:t+1} + \beta_2 \text{US Exposure to Chinese Imports}_{c,t:t+1} + \\ & X'_{c,1990}\gamma_{t:t+1} + \varepsilon_{c,t:t+1},\end{aligned} \tag{2.2}$$

where $\Delta Y_{c,t:t+1}$ represents the change in the logarithm of the population count, employed population, and employed population in the private and public sector in the local labor market c between periods t and $t+1$, multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. $\Delta Y_{c,t:t+1}$ also denotes the change in the labor participation rate, total employment rate, private employment rate, and public employment rate within commuting zone c between two periods.

US Exposure to Chinese Imports$_{c,t:t+1}$ in this estimation equation is the change in the values of Chinese imports to the US in commuting zone c between periods t and $t+1$ (Autor et al. [11]). $X'_{c,1990}\gamma_{t:t+1}$ represents a vector of interactions between baseline CZ characteristics ($X'_{c,1990}$) and period dummies ($\gamma_{t:t+1}$), and $\varepsilon_{c,t:t+1}$ is a random error.

The US robot exposure variable for a commuting zone is constructed following the method employed by Acemoglu and Restrepo [2]. It is a Bartik-style measure that is based on the change in robot density within each industry in the US between t and $t+1$, as well as the baseline industry employment proportions within CZ c in 1990:

$$\text{US Robot Adoption}_{c,t:t+1} \equiv \sum\nolimits_{i \in I} l_{ci,1990} \left(\frac{R^{US}_{i,t+1} - R^{US}_{i,t}}{L^{US}_{i,1990}} - g^{US}_{i,t:t+1} \frac{R^{US}_{i,t}}{L^{US}_{i,1990}} \right), \tag{2.3}$$

where, $L^{US}_{i,t}$ and $R^{US}_{i,t}$ indicate the number of employed individuals (in thousands of workers) and robots in industry i at time t, $g^{US}_{i,t:t+1}$ denotes the output growth rate of industry i in the US between time t and $t+1$, and $l_{ci,1990}$ represents the employment share of industry i within CZ c in 1990.

The dependent variables, including changes in population size and employment, can directly influence manufacturers' decisions within local labor markets, conceivably affecting robot adoption choices. To address this anticipated endogeneity issue, the measure of US robot penetration is instrumented, replacing the robotization of American industries with average robotization in five European countries that were ahead of the USA in this regard (Acemoglu and Restrepo [2]). To mitigate any potential correlation related to robot exposure before the 1990s, the employment shares in 1990 are replaced with those from 1970:

$$\text{EU Robot Adoption}_{c,t:t+1} \equiv \sum\nolimits_{i\in I} l_{ci,1970} \frac{1}{5} \sum\nolimits_{j\in EU5} \left(\frac{R^j_{i,t+1} - R^j_{i,t}}{L^j_{i,1990}} - g^j_{i,t:t+1} \frac{R^j_{i,t}}{L^j_{i,1990}} \right), \quad (2.4)$$

where j represents the five European countries: Denmark, Finland, France, Italy, and Sweden.

Europe indeed provides a valuable context for this analysis due to the notable divergence in the adoption of industrial robots in comparison to the USA, experiencing a 19% higher exposure in 2016 (Chiacchio et al. [30]). Besides, an examination of Figure 2.1 reveals a convergence in the average growth trends of the industrial robot stock in Denmark, Finland, France, Italy, and Sweden with the patterns observed in the United States, particularly evident in the period preceding 2010.

In line with the methodology outlined in recent literature, the exposure to Chinese imports is instrumented by substituting imports to the USA with imports to eight affluent countries to alleviate the analogous endogeneity concerns related to consequent shifts in US demand. (Autor et al. [11]). Both the robot penetration variable and this instrument are standardized, yielding a mean of 0 and a standard deviation of 1.

In this study, the 27-year timeframe spanning from 1990 to 2017 is divided into three distinct periods: 1990-2000, 2000-2007, and 2007-2017. It is important to point out that all regression models employ weighting, with the weights assigned based on a commuting zone's national share of the outcome group as of 1990. The standard errors are robust against heteroskedasticity and correlation within US states.

2.4 Results

2.4.1 General Effects of Robotization

The general findings of this paper align with existing literature. Table 2.3 presents the results, indicating an overall negative relationship between a commuting zone's exposure to industrial robots and population size (-0.48), labor force participation rate (-0.06), total employment rate (-0.14), and private employment rate (-0.26). However, there is a positive overall impact on public employment (0.14). The statistical significance of these coefficients varies, with all being significant at conventional levels except for the labor force participation rate. The study reveals that the negative effects of robotization on population size and the public employment rate are more pronounced for women (-0.55 compared to -0.42 and -0.68 compared to -0.05, respectively). In contrast, for the other three dependent variables, the negative impact is more substantial among male respondents (-0.15 vs. zero, -0.94 vs. -0.85, and -1.24 vs. -1.07). It is also worth noting that the adoption of robots has a more prominent negative effect on all dependent variables for the unmarried population, for instance, on the labor force participation rate (-0.19 compared to 0.03) and the total employment rate (-1.23 compared to -0.86).

The table additionally illustrates the differential impact of robot penetration on the labor force participation rate across various demographic groups. The findings display a negative and statistically significant effect on male labor force participation (-0.15), whereas there is no impact on women. This effect on male respondents has similar magnitudes for unmarried and married men (-0.19 and -0.14, respectively). The negative and statistically significant impact of robot adoption is nearly identical for both genders within the unmarried population (-0.19 for men and -0.20 for women). All the coefficients mentioned above are statistically significant.

One may find that the effect of robot exposure on the alteration in female labor force participation significantly depends on marital status. The impact of robotization is negative for unmarried females (-0.20) and positive for women in married or cohabiting households (0.14). Both coefficients are statistically significant. This discrepancy might be attributed to the hypothesis that married women might enter the labor force to compensate for the income lost when their husbands withdraw from the labor force. If this assumption holds, the observed increase in labor force participation among married women may lead to a more conspicuous contribution of wives to household income in married couples. The analysis of the effect of robots on intra-household work dynamics in the fourth section of this chapter will further investigate this proposition.

Given that the robot penetration variable is constructed as a Bartik-style measure, the interpretation of the regression coefficient for the effect of industrial robotization on the labor force participation rate of married women requires a nuanced understanding. For example, an increase of 50,000 industrial robots in the automotive, shipbuilding, and aerospace industry from 2007 to 2017 (the actual increase, calculated assigning unspecified robots, is 46,531) leads to a robot density rise. This density is adjusted by the output growth rate and divided by the 1990 employment level in this IFR industry, resulting in an increase of 14.8 units. In a commuting zone with a relatively sizeable arbitrary share of this industry in 1990 equal to 0.094[3], this adjustment translates to an increase of 1.398 in the robot adoption variable,

[3] The average share of this industry across 722 CZs in 1990 is 0.0086 and the maximum share is 0.2395.

which standardizes to 1 unit. This one standardized unit increase in the robot exposure variable correlates with a 0.14 increase in the change in the labor force participation rate of married women within that commuting zone.

Lastly, upon scrutinizing the statistically significant coefficients related to changes in population size and employment rates, an essential pattern emerges: the influence of robot penetration appears to be least negative for married women, with coefficients of -0.46 for migration, -0.54 for total employment, and -0.73 for private employment. Conversely, this unfavorable impact is notably more pronounced for other demographic groups.

The further analysis is expanded by estimating a relationship between a commuting zone's exposure to industrial robots and its labor market outcomes within three broad industry groups: manufacturing industries (including construction and mining) and two groups encompassing non-manufacturing industries[4]. Since these industry groups are contingent on employment, the dependent variables are solely the changes in different employment categories. The effect of robot adoption on the working-age population is not assessed for these subgroups of workers, as it is assumed that only employed respondents provide information about their respective industries and occupations.

Table 2.4 discloses compelling evidence that robotization reduces total employment, private employment, and public employment, as reflected in the respective changes in log counts. The coefficients associated with the robot penetration variable demonstrate the extent of this impact, revealing values of -0.71, -0.96, and -0.35, respectively. All of them, except the coefficient on public employment, are statistically significant. It is noteworthy that this negative effect on two variables is more distinct for females, where the coefficients for total employment (-0.85 compared to -0.67) and public employment (-0.58 compared to -0.11) exhibit greater magnitudes. On the other hand, male workers experience a more substantial

[4]High-skilled non-manufacturing industries include Finance and Insurance, and Real Estate; Professional, Scientific, and Technical Services; Management of companies and enterprises; Educational and Health Care Services; Public Administration. Other non-manufacturing industries are considered as low-skilled.

negative impact on private employment (-1.05 against -0.96). All coefficients, except the one pertaining to public employment for men, indicate statistical significance at conventional levels.

The negative effect of robot exposure on all three dependent variables is notably more prominent among unmarried respondents. The estimated coefficients for total and private employment are -1.16, contrasting with -0.51, and -1.37, contrasting with -0.72, respectively. Both coefficients on public employment are statistically insignificant.

The findings outlined in this table suggest that robotization diminishes total employment, private employment, and public employment in both categories of non-manufacturing industries. This negative influence is stronger for low-skilled non-manufacturing industries. Remarkably, the impact of robot adoption on all three dependent variables within manufacturing industries is nearly zero and lacks statistical significance.

2.4.2 Gender Effects of Robotization on Industry Groups

To investigate further the gender-specific impact of robotization, the analysis is extended to diverse socio-demographic subgroups. The results in Table 2.5 reveal that the negative effect of robot penetration on total employment, private employment, and public employment is particularly more pronounced in low-skilled non-manufacturing industries, while it is comparatively weaker in manufacturing industries, irrespective of gender. One exception worth noting is the impact of robot exposure on male public employment, which is more negative in high-skilled non-manufacturing industries. The most noteworthy discovery from this table is that among the female population, robot adoption has a positive and statistically significant effect on all three outcome variables within manufacturing industries. The estimated coefficients stand at 1.66 for total employment, 1.65 for private employment, and 2.31 for public employment. In comparison, the coefficients for males are negative, measuring at

-0.57, -0.61, and -0.27, respectively.

It is also noticeable that within low-skilled non-manufacturing industries, the negative impact of the primary variable of interest on all three outcome variables is more conspicuous among female workers. However, in the case of high-skilled non-manufacturing industries, the unfavorable effect on two of the response variables, namely private and public employment, is more discernible among male employees.

Table 2.6 illustrates that the negative impact of exposure to robots on the three dependent variables is notably more distinct among unmarried male workers. All coefficients in this table, except for two, exhibit greater negativity for unmarried men. The first deviation pertains to the influence of robotization on private employment in low-skilled non-manufacturing industries, where married male workers experience a more negative effect of robot penetration (-1.72 compared to -1.58 for unmarried men). The second exception is seen in the coefficient related to public employment in manufacturing industries. In this instance, the impact on unmarried men is not only less negative compared to their married counterparts but even turns positive (1.18). However, it is important to note that neither of the coefficients in this comparison is statistically significant.

The examination of female workers in manufacturing industries indicates that the positive relationship between robot adoption and both total and private employment primarily stems from married females. Table 2.7 displays that the coefficients of the predictor variable for married women are 2.23 and 2.31, both of which are statistically significant. On the contrary, for unmarried female workers, these coefficients are 0.75 and 0.66, respectively, and both are statistically insignificant. The results are inverted for public employment. The effect of robotization on unmarried women is positive and statistically significant (3.22). In contrast, the same coefficient for married females is also positive but considerably smaller and statistically insignificant. The negative impact of robot exposure on all three response variables for female workers in both non-manufacturing industry groups is more prominent for unmarried women.

The analysis of gender disparities in the impact of robotization is further expanded by considering a breakdown of workers into various broad occupational groups. These occupational groups represent detailed occupation recodes based on census occupation codes, resulting in a total of 22 distinct categories (as depicted in Table 2.8). Following recent literature [10, 32], these occupational groups are categorized into four broader groups: cognitive non-routine, cognitive routine, manual routine, and manual non-routine occupations.

According to the results presented in Table 2.9, the effect of robot penetration on the four broad occupational groups is predominantly unfavorable for both male and female workers. An exception to this pattern is observed in the case of male employees engaged in cognitive routine occupations, where the adoption of robots has a positive and statistically significant impact on public employment (1.41). However, the effect of robot exposure on private employment in this particular occupational group is more negative for male workers (-0.98, contrasting with -0.60). All three of these coefficients attain statistical significance.

In cognitive non-routine occupations, the negative influence of robotization on total employment and public employment is more pronounced for women (-1.16 compared to -0.92 and -0.73 compared to -0.18, respectively) and on private employment is stronger for men (-1.72 compared to -1.63). For male workers in manual routine occupations, the impact of robot penetration on total and private employment is noticeably more negative (-0.91 and -1.04) than for women, where both effects are close to zero. Finally, in manual non-routine occupations, the negative impact of robot adoption on total and private employment is more substantial for female workers (-1.42, contrasting with -0.95 and -1.64, contrasting with -1.31, respectively) and on public employment for their male colleagues (-1.05, contrasting with -0.94). All these coefficients, except the one concerning public employment for men in cognitive non-routine occupations, are statistically significant at conventional levels.

2.4.3 Gender Effects of Robotization in Manufacturing Industries

The subsequent phase of this study involves an examination of four broad occupational groups within manufacturing industries. Table 2.10 demonstrates the impact of robot penetration on these occupational groups for both male and female workers. This table reveals that the most conspicuous negative effects on total and private employment are observed among male employees engaged in manual non-routine occupations (-3.09 and -3.03). Although the unfavorable influence on these two dependent variables is somewhat less discernible, it remains statistically significant for males in manual routine occupations as well (-1.08 and -1.16).

Among women, robot exposure effects are statistically significant only for cognitive routine workers, indicating a positive impact on total employment, private employment, and public employment (1.26, 1.20, and 3.31, respectively). None of the other coefficients attain statistical significance. It is also worth noting that the adoption of robots has a negative impact only on manual, non-routine female workers.

To advance the analysis of robotization within manufacturing industries, the robot penetration effect on different occupational groups is explored separately. In Appendix B, one can find the average numbers of total employment, private employment, and public employment within manufacturing industries for male and female workers in 1990, 2000, 2007, and 2017 (Tables B.1, B.4, and B.7, respectively). For a more comprehensive view of the workforce composition, Tables B.2, B.5, and B.8 illustrate the distribution of workers across occupational groups by gender and Tables B.3, B.6, and B.9 display workers' shares of occupational groups.

The data presented in Tables B.1 and B.2 depict perceptible shifts in the gender composition of the workforce in manufacturing industries over the years. The average number of women in total manufacturing employment declined from 10,298 in 1990 to 7,457 in 2017, corresponding to an overall reduction in the average share of women from 24.6% in 1990 to 19.1% in 2017. Remarkably, there is a distinct increase in both the average numbers and percentages of female workers in specific occupational groups. For instance, business and financial operations occupations witnessed an uptick from 443 workers and a 43% share in 1990 to 618 workers and 51.9% in 2017, while legal occupations experienced a rise from 12 workers and 35.1% in 1990 to 26 workers and 53.1% in 2017.

In some other occupational groups, such as farming, fishing, and forestry occupations; life, physical, and social science occupations; and protective service occupations, the expansion in the share of women can be attributed to a significant reduction in the average number of male workers. Conversely, a substantial increase in the average numbers and proportions of men was observed in the two most populous occupational groups – construction and extraction occupations, which increased from 7,212 and 96.9% in 1990 to 9,276 and 97.2% in 2017, and production occupations, which changed from 8,067 and 67.2% in 1990 to 6,286 and 75.6% in 2017. These tables point to an essential growth in the average number of male workers in the first case and a prominent augmentation in their proportion in the second.

Table B.3 demonstrates that the two most prevalent occupational groups for men remained consistent over time – construction and extraction occupations (29.9% in 1990 and 34.7% in 2017) and production occupations (28.8% in 1990 and 25.3% in 2017). However, the fraction of the third group, transportation and material moving occupations, decreased from 11.8% in 1990 to 9.4% in 2017, which is lower than the 10.6% share held by management occupations in 2017 (increased from 7.3% in 1990).

A similar pattern can be observed among female workers. The two most prevailing groups are the same – production occupations (43.6% in 1990 and 34.6% in 2017) and office and administrative support occupations (26.3% in 1990 and 25.0% in 2017). These occupational groups remained relatively stable in terms of their proportions. Notably, there was a substantial increase in the percentage of women in management occupations, rising from 4.9%

in 1990 to 9.4% in 2017. The share of the third group in 1990, transportation and material moving occupations, increased from 6.7% to 6.9%.

Table 2.11 illustrates the impact of exposure to robots on three types of employment in manufacturing industries, considering gender and 22 occupational groups. The consequences of robotization on total and private employment are mostly similar for male manufacturing workers. This effect is negative in the majority of occupational groups, including the two most populous groups such as construction and extraction occupations (-1.54 and -1.74) and production occupations (-0.83 and -0.93), as well as installation, maintenance, and repair occupations (-3.09 and -3.18) and business and financial operations occupations (-2.71 and -2.76). However, robot adoption has a positive impact on arts, design, entertainment, sports, and media occupations (2.42 and 1.82). Results diverge in the case of male public employment. Robot penetration exhibits a positive influence on certain occupational groups, such as business and financial operations (12.68), computer and mathematical science (14.38), arts, design, entertainment, sports, and media (20.49), and food preparation and serving-related occupations (27.18). The effect of industrial robots on public employment is only negative for healthcare practitioners and technical occupations (-13.06). All these coefficients are statistically significant.

The relationship between robot exposure and employment indicates variation among female manufacturing workers. The impact of robotization is favorable for total employment within specific occupational groups, namely arts, design, entertainment, sports, and media (4.55); healthcare support (17.27); personal care and service (19.36); production (2.05); and transportation and material moving occupations (2.05). There is a positive influence of robot adoption on private employment in another set of occupational groups, including legal (8.35); education, training, and library (9.62); healthcare support (22.55); production (1.96); and transportation and material moving occupations (2.13). In terms of public employment, the robot penetration effect is positive for certain occupational groups like management (12.08);

life, physical, and social science (12.50); protective service (12.40); installation, maintenance, and repair (24.71); and production occupations (4.35), but negative for others such as legal (-17.82) and farming, fishing, and forestry occupations (-6.33). All coefficients mentioned in this paragraph attain statistical significance at conventional levels.

2.4.4 Effects of Robotization on Intra-household Work Dynamics

The final segment of this study delves into the impact of industrial robot adoption on intra-household employment dynamics. It is observed that the robotization effect on the labor force participation rate is negative for unmarried females and positive for women in married households, as depicted in Table 2.3. This divergence in outcomes may be elucidated by the assumption that married women, when faced with their husbands exiting the labor force due to the influence of robot penetration, are motivated to enter the labor force themselves to compensate for the lost household income.

The negative consequences of exposure to robots are mostly concentrated within male-dominated manufacturing industries characterized by heavy manual labor and repetitive routine tasks. The displaced male workers have the option of relocating to other commuting zones or shifting to different occupations within the same geographic areas. However, for married men, particularly those with children, the prospect of migrating to a different local labor market poses substantial challenges. The logistical complexities and social considerations associated with relocating an entire family can be formidable. Consequently, this group of men affected by robotic technology will probably tend to remain within the same commuting zones in their efforts to secure new employment opportunities.

Given that not all of these unemployed men will immediately find success in the labor market, their wives are likely compelled to join the labor force. This response on the part of married women serves as a pragmatic measure to ameliorate the economic deficits that result from husbands departing the labor force due to robotization. In this context, the entrance of married women into the labor force can be viewed as a strategy to offset the negative economic consequences of husbands' unemployment stemming from the changing employment landscape induced by robotics.

The results in Table 2.12 provide confirmation for this hypothesis. The effect of robot adoption on the change in the proportion of households with only the husband engaged in the labor force is observed to be negative and statistically significant (-0.12). The impact on the other three dependent variables (both spouses, only the wife, and neither of the spouses entering the labor force) is positive but statistically significant solely for the third coefficient, where both spouses are not participating in the labor force (0.05).

The effect of robot penetration on the composition of households in terms of employment is also noteworthy. Specifically, there is a positive and statistically significant influence on the shares of married households where only the wife is employed (0.07) and those where neither of the spouses is employed (0.09). The impact on the change in the fractions of households with both spouses employed and with only the husband employed is negative, although these effects are not statistically significant. Furthermore, it is evident that in commuting zones characterized by higher levels of robotization, there is an increase in the female share of family income in married or cohabiting households (0.14), and this coefficient holds statistical significance.

As a result, it might be concluded that potentially lower labor market opportunities associated with the significantly growing robotics technology have contributed to a reduction in gender inequality among married workers. Nevertheless, this notable upswing in the role of wives in income-earning within married households could also be attributed to other factors, including declining fertility rates or structural shifts in available employment opportunities that favor women.

2.4.5 Robustness Checks

This section outlines various robustness checks. Tables 2.13 and 2.14 present a series of robustness checks for the general robot adoption impact and the effects of robotization in manufacturing industries. In both tables, Column 2 demonstrates the coefficients of the robot exposure variable in 2SLS models weighted by population.

To address a potential concern that robot adoption effects may be primarily driven by commuting zones with the highest levels of robotization, the sample omits the top one percent of CZs with the greatest robot penetration. The estimates of the robot exposure coefficients for these models are illustrated in Column 3 of both tables.

Additionally, the robotization effect for both gender groups is assessed, excluding the post-2007 time period. This methodology permits researchers to account for the potential influence of variations in the macroeconomic landscape following the Great Recession, which could have a significant impact on the effects of robot penetration. The results of this exercise are indicated in Column 4 of both tables.

Tables 13 and 14 highlight that when utilizing 2SLS models weighted by the national population share of commuting zones in 1990, rather than the share of the outcome variable (total employment, etc.), the estimation results closely resemble those of the baseline specification. The disparities in estimated effects of robot exposure on male and female workers largely remain robust after omitting the top 1% of CZs with the highest levels of robot penetration and eliminating the third period from the analysis. However, it is worth noting that the impact of robotization on private employment becomes more negative for women than men when the commuting zones with the most substantial robot adoption levels are excluded.

2.5 Conclusion

This study reveals that the negative influence of robot adoption on the working-age population, total employment, and public employment is more pronounced for women, while the impact of robot penetration on private employment is more negative among men. This observation underscores the differential responses of the two gender groups to the adverse economic shock. In addition to this, the negative effect of exposure to robots is found to be more conspicuous for the unmarried population, irrespective of gender.

Furthermore, there is a negative effect of robotization on the labor force participation rate of both unmarried and married men. Conversely, for female respondents, robot penetration has a positive impact on married women and a negative influence on unmarried females. This conclusion suggests that married women might be compelled to enter the labor force to compensate for any potential decline in household income caused by their husbands leaving the labor force. Supporting this substitution assumption, the intra-household analysis implies that robot exposure negatively affects the percentage of households where only the husband is in the labor force or employed while positively impacting the proportion of households with only the wife participating in the labor force or being employed. Additionally, robot adoption has a positive effect on the proportion of household income contributed by females in married couples.

According to the findings presented in this paper, the introduction of industrial robots leads to a reduction in all outcome variables within both categories of non-manufacturing industries. This negative effect is notably more discernible in low-skilled industries of the non-manufacturing sector, and it persists irrespective of gender. In low-skilled industries, the negative impact of robotization is particularly heightened for female workers. Oppositely, in non-manufacturing industries with high-skilled workers, the negative effect on private and public employment is more prominently amplified among male employees.

Nevertheless, within manufacturing industries, the influence of robot penetration exhibits a conducive trend among female participants but conversely impacts their male colleagues in a negative way. This observation could be elucidated by the divergence in the automation potential of jobs typically held by men and women. Professions traditionally associated with men tend to have a significantly higher susceptibility to automation and robotization, implying that a larger proportion of these positions could be automated using current technological capabilities (Muro et al. [80]). The positive relationship between robot exposure and employment among women in manufacturing industries is determined to predominantly result from the married segment of female employees.

Further analysis of manufacturing industries demonstrates that the positive influence of robotization on three types of employment for women can be primarily attributed to workers in cognitive routine manufacturing occupations. The impact of robot penetration on total and private employment tends to be negative for men employed in manual routine and non-routine occupational groups. Moreover, it is noteworthy that the effect of robot adoption on employment within one of the most extensive occupational groups in manufacturing industries, namely production occupations, is distinct for males and females. Specifically, it is unfavorable for male workers but advantageous for women.

Some recent studies have aimed to discern the gender-specific ramifications of automation by linking occupation-specific assessments of automation probability with data on job task compositions. As noted by Brussevich et al. [26], female employees across 30 countries, including 28 OECD member states, Cyprus, and Singapore, face a remarkably upscaled risk of displacement by automation technologies compared to their male counterparts, albeit with noticeable cross-country variations. This conclusion is primarily rooted in the observation that ”female workers engage in fewer tasks that require analytical and interpersonal skills or physical labor and more tasks characterized by routine attributes, limited job flexibility, minimal on-the-job learning, and heightened repetitiveness” (Brussevich et al. [25]). The probability of replacement by automation is ascertained to be lower for younger female workers and women in managerial roles.

On the other hand, employers in manufacturing industries are increasingly seeking workers with the expertise to efficiently operate tools and equipment in highly automated environments. Data from the Census Bureau, as well as trends within the manufacturing sector, suggest that these changes could present essential opportunities for females. This shift may allow them to reduce the underrepresentation of women, which has long been a considerable problem in the manufacturing sector.

Besides this, as more women gain access to education and skills training, their presence in the industry has significantly expanded over the past few decades. Women now occupy various roles within manufacturing organizations, spanning from executive positions to production roles and everything in between. According to Benjamin Wann, an expert in manufacturing product costs, the top typical positions women hold within the manufacturing sector include such roles as designers, engineers, operators, quality control specialists, and logistics professionals[5]. The majority of these key positions are not easily replaceable by robots. The findings presented in this paper align with this side of the discussion.

One of the limitations of this study pertains to the use of cross-sectional data, which may not definitively establish cause-and-effect relationships between robotization and labor market outcomes. Another concern is that this paper's aggregate findings at the commuting zone level may be driven by unobservable individual-level factors. Consequently, there is a clear need for additional empirical research in this field to explore the impact of robot adoption on outcomes of interest at the individual level. A promising approach for gaining a more nuanced understanding of the effects of robot penetration regarding gender and marital status differences involves utilizing longitudinal data on migration and job mobility, such as the National Longitudinal Survey of Youth 1997 (NLSY97).

[5]https://benjaminwann.com/blog/the-impact-and-role-of-women-in-manufacturing-what-can-they-do

Using this dataset would complement the aggregate results by examining the relationship between local labor markets' exposure to industrial robots and the propensity of young adults to move and change occupations in response to the adverse shock employing panel microdata from the BLS. The NLSY97 data would allow for tracking migration and employment behavior among young millennials while controlling for a broad range of individual-level characteristics. The aforementioned method would presumably mitigate concerns related to the aggregate-level findings of this paper.

2.6 Figures and Tables

Figure 2.1:
Industrial robots per thousand workers in USA and Europe [cited on pages 49 and 61]

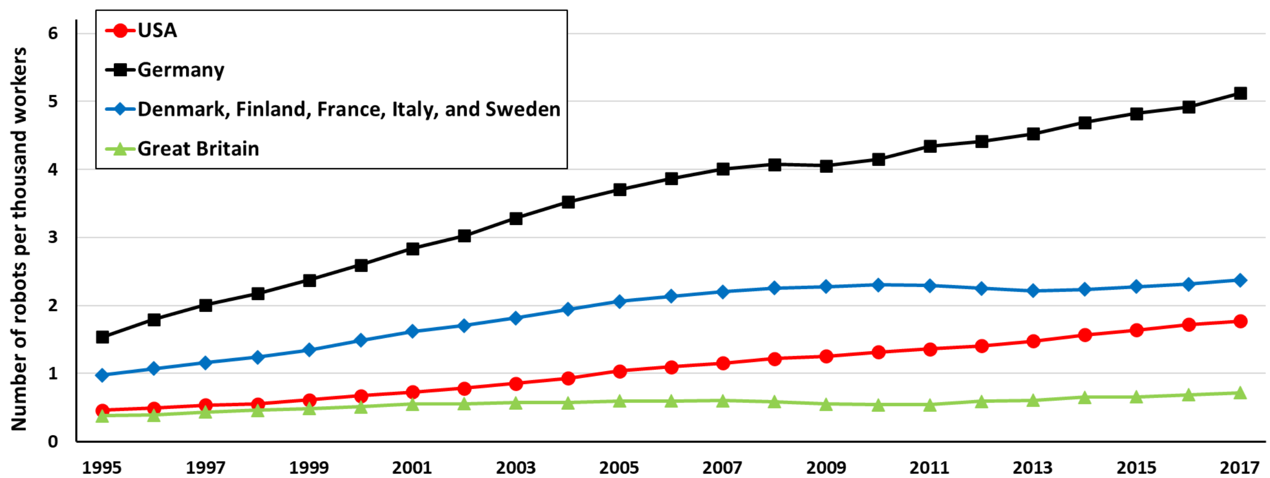

Table 2.1: **Robot Capital (the Number of Robots (Operational Stock) per Thousand Employees) by Industries in the USA** [cited on page 55]

Industries	1997	2007	2017
Manufacturing industries			
Food and beverages	0.1861	1.5892	5.8512
Textiles (including apparel)	0.0000	0.0031	0.4270
Wood, furniture, paper, and printing	0.0000	0.0048	0.4616
Plastic, chemicals, glass, and non-metals	0.2350	2.6568	10.0728
Basic metals and metal products	0.3120	3.0568	9.7648
Electrical/electronics	0.2915	5.7418	32.6076
Industrial machinery	0.0000	0.0008	3.0704
Automotive, shipbuilding, and aerospace	2.2772	22.4319	73.1389
Miscellaneous manufacturing	0.0000	0.3636	10.7061
Non-manufacturing industries			
Agriculture, forestry, and fishing	0.0000	0.0009	0.0366
Mining	0.0000	0.0029	0.0642
Construction	0.0000	0.0021	0.0185
Utilities	0.0000	0.0000	0.0921
Education, research, and development	0.0000	0.0210	0.2553
Services	0.0000	0.0000	0.0031

Notes: Robot capital is measured by the number of industrial robots per thousand workers. The numbers of industrial robots in industries come from the IFR, and the numbers of workers come from the EU KLEMS.

Table 2.2: Descriptive Statistics [cited on page 57]

	1990-2017		1990-2000		2000-2007		2007-2017	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Robot Adoption	2.05	(1.54)	0.58	(0.46)	0.85	(0.70)	0.94	(0.59)
Change in Log Working-Age Population								
All	17.62	(20.01)	11.35	(11.15)	6.19	(9.04)	1.93	(7.42)
Men	19.43	(19.61)	12.49	(11.41)	6.75	(8.87)	2.22	(7.65)
Women	15.76	(20.67)	10.20	(11.24)	5.61	(9.51)	1.63	(7.49)
Change in Labor Force Participation Rate								
All	-1.06	(3.09)	-0.65	(2.67)	0.92	(2.63)	-1.05	(1.81)
Men	-5.64	(3.88)	-4.05	(3.43)	-0.02	(3.18)	-1.58	(2.41)
Women	3.39	(3.39)	2.67	(3.01)	1.83	(2.86)	-0.56	(1.88)
Change in Total Working-Age Employment Rate								
All	-0.03	(3.48)	-0.10	(2.88)	-0.08	(3.51)	0.12	(1.92)
Men	-4.42	(4.23)	-3.31	(3.56)	-1.12	(4.21)	-0.33	(2.53)
Women	4.23	(3.67)	3.03	(3.17)	0.94	(3.48)	0.54	(1.94)
Change in Private Working-Age Employment Rate								
All	2.20	(4.45)	0.76	(3.26)	-0.20	(3.54)	1.58	(2.11)
Men	1.02	(5.79)	-0.30	(4.08)	-0.63	(4.57)	1.76	(2.99)
Women	3.18	(3.96)	1.71	(3.22)	0.15	(3.26)	1.36	(2.05)
Change in Public Working-Age Employment Rate								
All	-0.20	(2.33)	-0.21	(1.92)	0.57	(1.44)	-0.39	(1.42)
Men	-1.95	(3.12)	-1.73	(2.77)	0.23	(1.68)	-0.38	(1.80)
Women	1.69	(2.15)	1.40	(1.70)	0.97	(1.88)	-0.40	(1.61)
Change in Log Total Working-Age Employment								
All	17.46	(20.37)	11.13	(11.55)	6.07	(9.78)	2.08	(8.43)
Men	13.04	(21.34)	7.82	(12.60)	5.08	(10.29)	1.67	(9.06)
Women	22.72	(19.73)	15.15	(10.97)	7.21	(10.15)	2.51	(8.35)
Change in Log Private Working-Age Employment								
All	23.14	(22.11)	13.24	(13.09)	6.03	(11.29)	5.68	(10.22)
Men	21.95	(23.74)	11.93	(14.47)	5.78	(12.26)	5.97	(11.52)
Women	24.78	(21.19)	15.04	(12.46)	6.32	(12.13)	5.32	(9.92)
Change in Log Public Working-Age Employment								
All	17.16	(21.14)	10.69	(13.89)	9.81	(11.08)	-0.39	(10.38)
Men	7.25	(24.68)	1.37	(17.99)	8.87	(14.10)	-0.32	(13.67)
Women	24.98	(20.23)	18.02	(13.07)	10.62	(12.05)	-0.47	(10.28)

Notes: This table presents unweighted averages and standard deviations of several variables across 722 commuting zones. The changes in the logarithm of the working-age population, total employment, private employment, and public employment are multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$.

Figure 2.2: Geographic Distribution of Exposure to Robots and Changes in Population [cited on page 58]

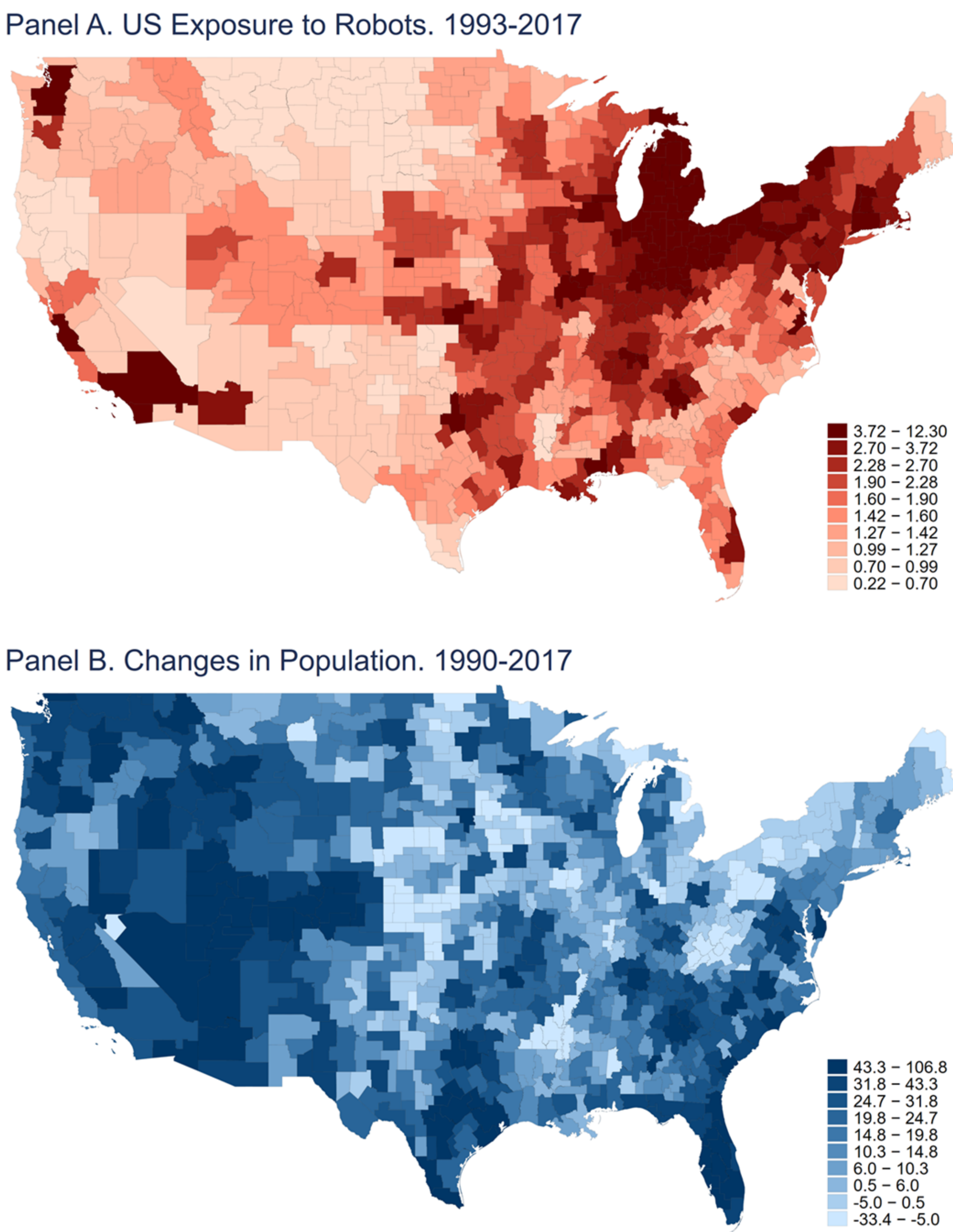

Figure 2.3: Geographic Distribution of Exposure to Robots and Changes in Employment [cited on page 58]

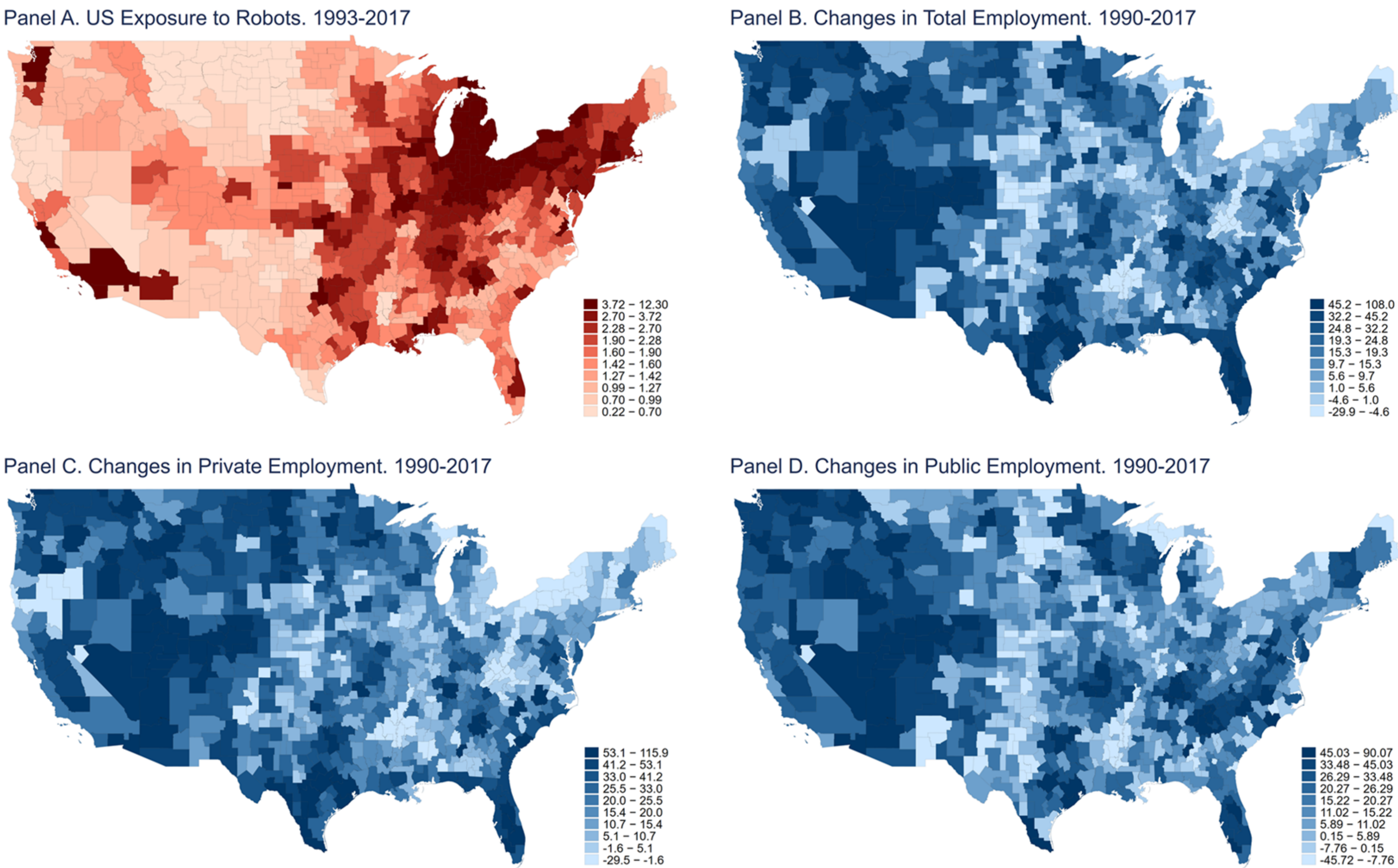

Figure 2.4: Geographic Distribution of Exposure to Robots and Changes in Population by Gender [cited on page 58]

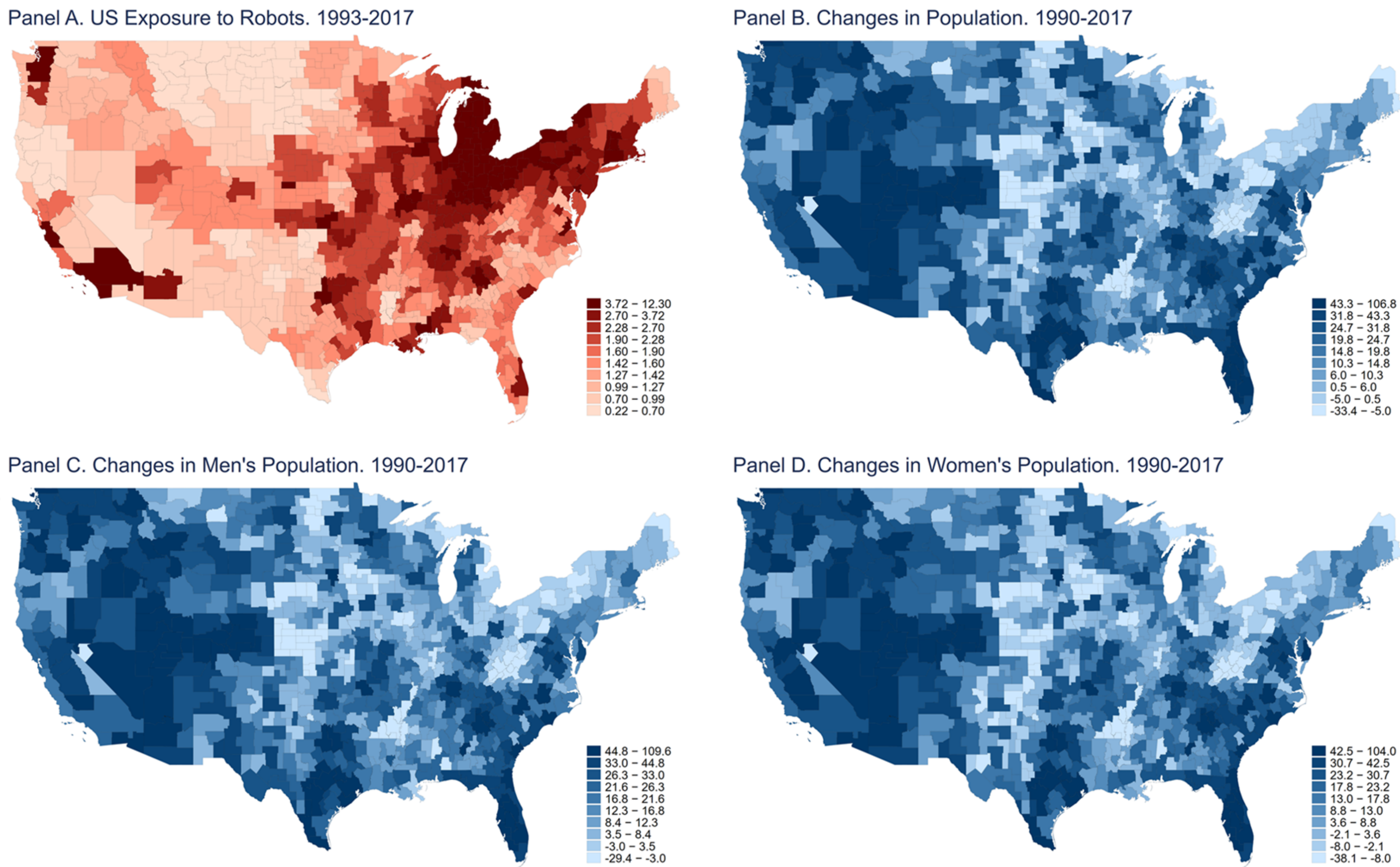

Figure 2.5: Geographic Distribution of Exposure to Robots and Changes in Total Employment by Gender [cited on page 58]

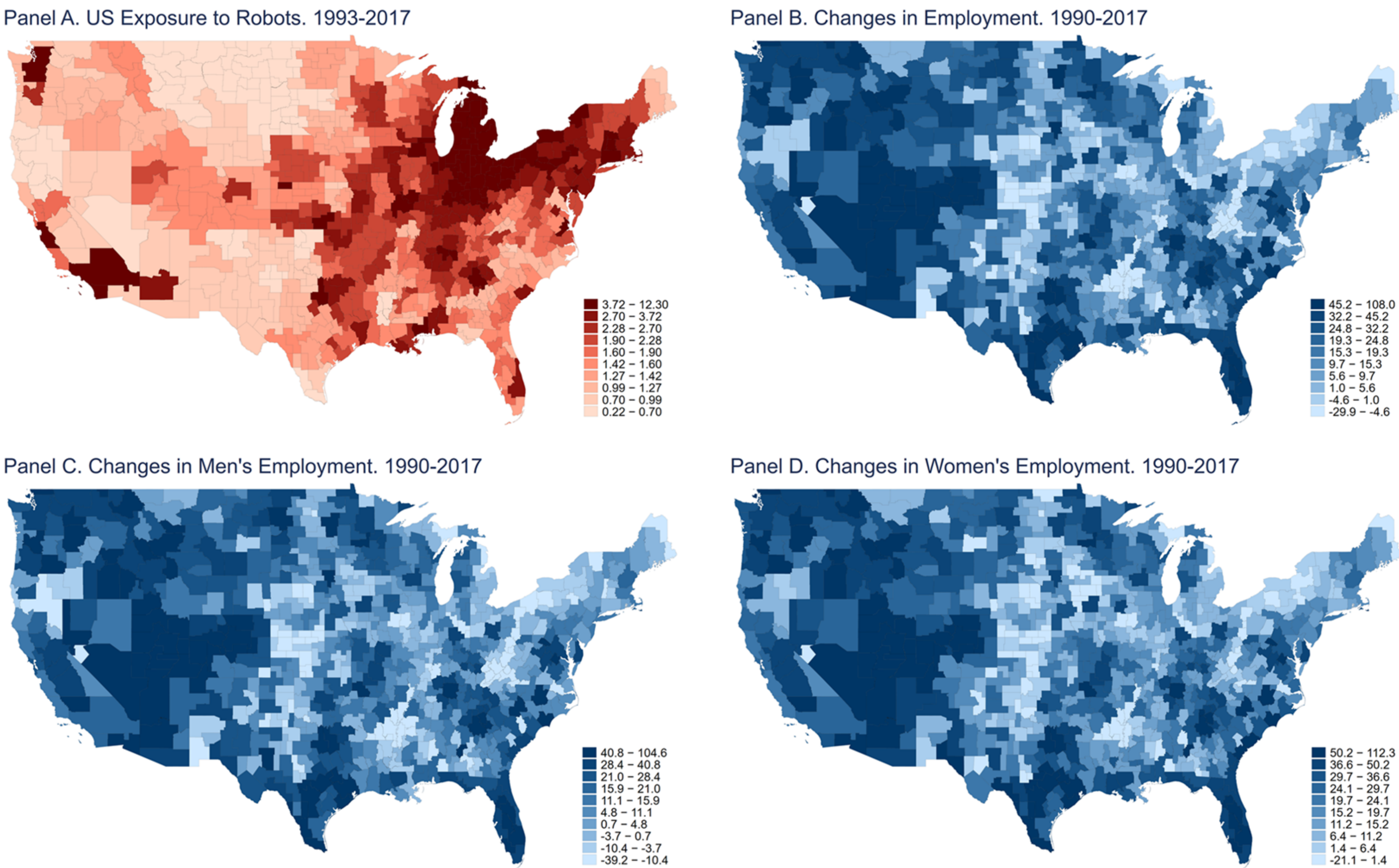

Figure 2.6: Geographic Distribution
of Exposure to Robots and Changes in Private Employment by Gender [cited on page 58]

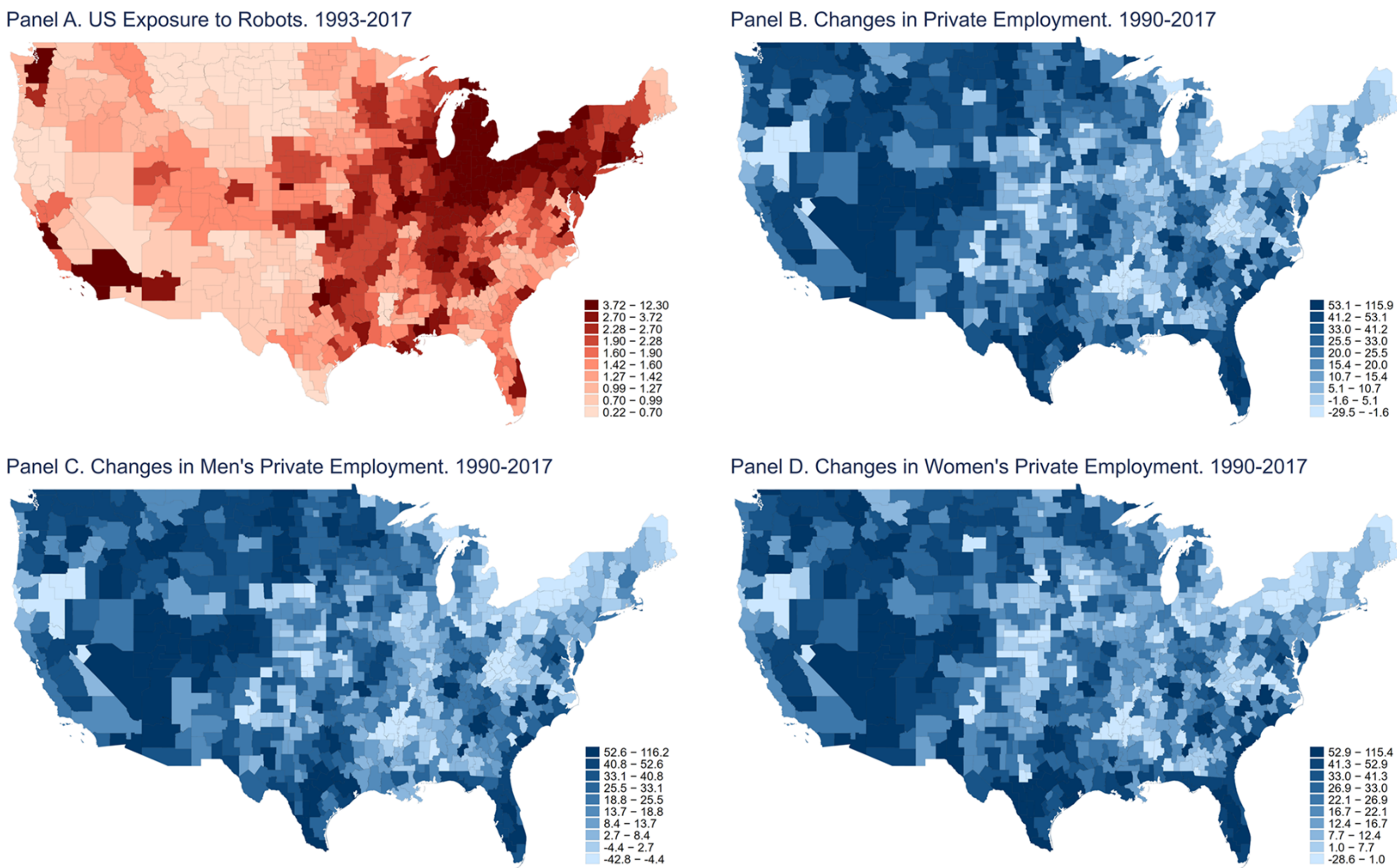

Figure 2.7: Geographic Distribution of Exposure to Robots and Changes in Public Employment by Gender [cited on page 58]

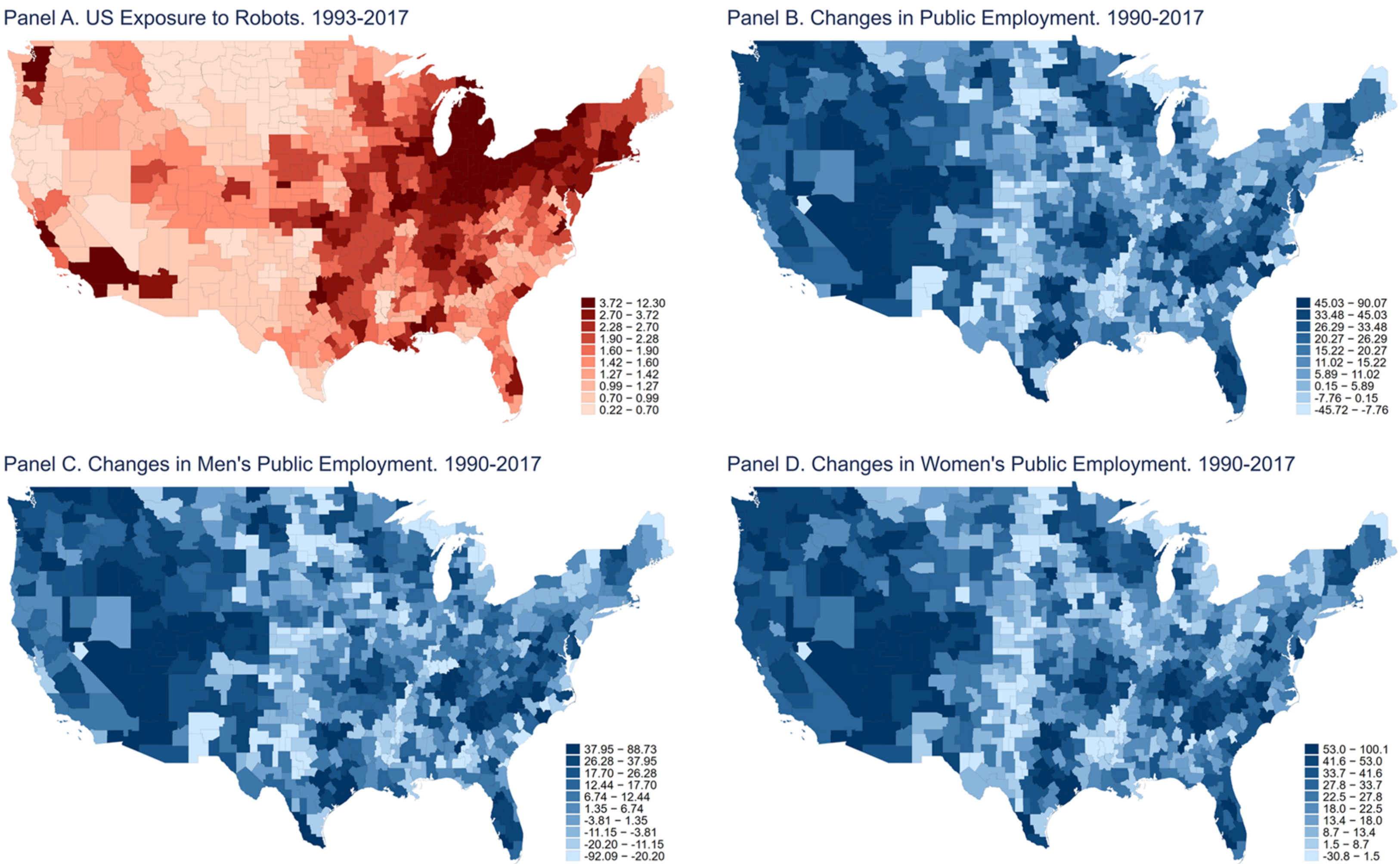

Table 2.3: General Robot Adoption Effects (2SLS) [cited on pages 62 and 71]

	(1)	(2)	(3)	(4)	(5)
	Dependent Variables				
Samples	Population	Labor Force Participation Rate	Total Employment Rate	Private Employment Rate	Public Employment Rate
Total sample	-0.48*	-0.06	-0.14*	-0.26***	0.14**
	(0.21)	(0.05)	(0.06)	(0.04)	(0.05)
Male respondents	-0.42*	-0.15**	-0.94**	-1.24***	-0.05
	(0.20)	(0.05)	(0.30)	(0.30)	(0.36)
Female respondents	-0.55*	0.00	-0.85**	-1.07**	-0.68
	(0.22)	(0.06)	(0.31)	(0.32)	(0.42)
Unmarried respondents	-0.76**	-0.19**	-1.23**	-1.50***	-0.44
	(0.25)	(0.06)	(0.36)	(0.36)	(0.45)
Married respondents	-0.40*	0.03	-0.86**	-1.05**	-0.05
	(0.24)	(0.05)	(0.31)	(0.32)	(0.35)
Unmarried male respondents	-0.68**	-0.19*	-1.13**	-1.54***	-0.19
	(0.23)	(0.08)	(0.39)	(0.38)	(0.49)
Married male respondents	-0.33	-0.14*	-0.86**	-1.11***	0.08
	(0.24)	(0.06)	(0.29)	(0.29)	(0.35)
Unmarried female respondents	-0.85**	-0.20**	-1.34***	-1.51***	-0.96*
	(0.29)	(0.06)	(0.36)	(0.36)	(0.47)
Married female respondents	-0.46*	0.14*	-0.54*	-0.73*	-0.49
	(0.23)	(0.06)	(0.31)	(0.36)	(0.38)

Notes: The dependent variables in columns (1)-(5) are the changes in the log count of the working-age population, multiplied by a factor of 100, in the labor force participation rate, in total employment, private employment, and public employment rates, respectively. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the population (columns 1-2), total employment (3), private employment (4), and public employment (5) in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 2.4: GENERAL ROBOT ADOPTION EFFECTS (2SLS) [cited on page 64]

	(1)	(2)	(3)
	Dependent Variables		
Samples	Total Employment	Private Employment	Public Employment
Total sample	-0.71***	-0.96***	-0.35
	(0.24)	(0.25)	(0.28)
Male respondents	-0.67**	-1.05***	-0.11
	(0.25)	(0.27)	(0.33)
Female respondents	-0.85**	-0.96***	-0.58*
	(0.25)	(0.26)	(0.29)
Unmarried respondents	-1.16***	-1.37***	-0.53
	(0.30)	(0.32)	(0.41)
Married respondents	-0.51*	-0.72**	-0.20
	(0.23)	(0.24)	(0.27)
Manufacturing industries	0.05	0.07	0.36
	(0.33)	(0.35)	(0.81)
High-skilled non-manufacturing	-0.95**	-1.40***	-0.63*
industries	(0.28)	(0.37)	(0.30)
Low-skilled non-manufacturing	-1.62***	-1.86***	-0.84*
industries	(0.33)	(0.37)	(0.33)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the outcome group in 1990

Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 2.5: Robot Adoption Effects on Industry Groups (2SLS) [cited on page 65]

	(1)	(2)	(3)
	Dependent Variables		
Samples	Total Employment	Private Employment	Public Employment
	Male respondents		
All industries	-0.67**	-1.05***	-0.11
	(0.25)	(0.27)	(0.33)
Manufacturing industries	-0.57*	-0.61*	-0.27
	(0.32)	(0.34)	(0.92)
High-skilled non-manufacturing industries	-0.85**	-1.50***	-0.63*
	(0.27)	(0.33)	(0.31)
Low-skilled non-manufacturing industries	-1.34***	-1.65***	-0.45
	(0.34)	(0.37)	(0.49)
	Female respondents		
All industries	-0.85**	-0.96***	-0.58*
	(0.25)	(0.26)	(0.29)
Manufacturing industries	1.66**	1.65**	2.31*
	(0.50)	(0.53)	(1.16)
High-skilled non-manufacturing industries	-0.95**	-1.32***	-0.57*
	(0.31)	(0.41)	(0.34)
Low-skilled non-manufacturing industries	-1.80***	-2.03***	-1.24***
	(0.35)	(0.40)	(0.29)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the outcome group in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 2.6: ROBOT ADOPTION EFFECTS ON MALE SOCIO-DEMOGRAPHIC GROUPS (2SLS) [cited on page 66]

	(1)	(2)	(3)
	Dependent Variables		
Samples	Total Employment	Private Employment	Public Employment
	Unmarried male respondents		
All industries	-1.07**	-1.34***	-0.20
	(0.33)	(0.36)	(0.50)
Manufacturing industries	-0.82*	-0.98*	1.18
	(0.49)	(0.54)	(1.36)
High-skilled non-manufacturing industries	-1.40***	-2.34***	-0.83*
	(0.34)	(0.44)	(0.40)
Low-skilled non-manufacturing industries	-1.56***	-1.58***	-1.24*
	(0.38)	(0.39)	(0.68)
	Married male respondents		
All industries	-0.51*	-0.95***	0.01
	(0.24)	(0.26)	(0.30)
Manufacturing industries	-0.55*	-0.54*	-0.92
	(0.29)	(0.31)	(1.00)
High-skilled non-manufacturing industries	-0.55*	-0.92*	-0.57*
	(0.30)	(0.41)	(0.33)
Low-skilled non-manufacturing industries	-1.18**	-1.72***	-0.00
	(0.38)	(0.47)	(0.49)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the outcome group in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 2.7: **Robot Adoption Effects on Female Socio-Demographic Groups (2SLS)** [cited on page 66]

	(1)	(2)	(3)
	Dependent Variables		
	Total	Private	Public
Samples	Employment	Employment	Employment
	Unmarried female respondents		
All industries	-1.25***	-1.43***	-0.85*
	(0.30)	(0.31)	(0.39)
Manufacturing industries	0.75	0.66	3.22*
	(0.58)	(0.61)	(1.29)
High-skilled non-manufacturing	-1.24**	-1.51**	-0.96*
industries	(0.39)	(0.55)	(0.43)
Low-skilled non-manufacturing	-2.18***	-2.36***	-1.38***
industries	(0.37)	(0.40)	(0.38)
	Married female respondents		
All industries	-0.60*	-0.61*	-0.46
	(0.25)	(0.27)	(0.31)
Manufacturing industries	2.23***	2.31***	1.34
	(0.48)	(0.49)	(2.45)
High-skilled non-manufacturing	-0.87**	-1.37***	-0.36
industries	(0.32)	(0.38)	(0.35)
Low-skilled non-manufacturing	-1.52**	-1.65**	-1.27**
industries	(0.44)	(0.52)	(0.39)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the outcome group in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 2.8: List of Occupational Groups [cited on page 67]

Occupational Group Description	Occ Codes	Cognitive or Manual	Routine or Non-routine
Management occupations	0010-0430	C	NR
Business and financial operations occupations	0500-0950	C	NR
Computer and mathematical science occupations	1000-1240	C	NR
Architecture and engineering occupations	1300-1560	C	NR
Life, physical, and social science occupations	1600-1965	C	NR
Community and social service occupation	2000-2060	C	NR
Legal occupations	2100-2160	C	NR
Education, training, and library occupations	2200-2550	C	NR
Arts, design, entertainment, sports, and media occupations	2600-2960	C	NR
Healthcare practitioner and technical occupations	3000-3540	C	NR
Healthcare support occupations	3600-3655	C	NR
Protective service occupations	3700-3955	C	NR
Food preparation and serving related occupations	4000-4160	M	NR
Building and grounds cleaning and maintenance occupations	4200-4250	M	NR
Personal care and service occupations	4300-4650	M	NR
Sales and related occupations	4700-4965	C	R
Office and administrative support occupations	5000-5940	C	R
Farming, fishing, and forestry occupations	6000-6130	M	R
Construction and extraction occupations	6200-6940	M	R
Installation, maintenance, and repair occupations	7000-7630	C	R
Production occupations	7700-8965	C	R
Transportation and material moving occupations	9000-9750	M	R

Note: the second column represents 2010 Census codes of occupations.

Table 2.9: **Robot Adoption Effects on Broad Occupational Groups (2SLS)** [cited on page 67]

	(1)	(2)	(3)
	Dependent Variables		
	Total	Private	Public
Samples	Employment	Employment	Employment
	Male respondents		
Cognitive Non-routine	-0.92**	-1.72***	-0.18
occupations	(0.30)	(0.44)	(0.36)
Cognitive Routine	-0.37	-0.98**	1.41*
occupations	(0.43)	(0.38)	(0.62)
Manual Routine	-0.91*	-1.04*	-0.85
occupations	(0.51)	(0.55)	(0.76)
Manual Non-routine	-0.95*	-1.31*	-1.05*
occupations	(0.48)	(0.52)	(0.54)
	Female respondents		
Cognitive Non-routine	-1.16***	-1.63***	-0.73*
occupations	(0.29)	(0.37)	(0.34)
Cognitive Routine	-0.48	-0.60*	0.02
occupations	(0.32)	(0.31)	(0.43)
Manual Routine	-0.12	0.07	-1.62
occupations	(0.53)	(0.58)	(1.10)
Manual Non-routine	-1.42**	-1.64**	-0.94*
occupations	(0.47)	(0.52)	(0.52)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the outcome group in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 2.10: Robot Adoption Effects on Broad Occupational Groups in Manufacturing Industries (2SLS) [cited on page 68]

	(1)	(2)	(3)
	Dependent Variables		
Samples	Total Employment	Private Employment	Public Employment
	Male respondents		
Cognitive Non-routine	-0.04	0.08	0.36
occupations	(0.75)	(0.84)	(1.35)
Cognitive Routine	-0.75	-0.85	0.14
occupations	(0.54)	(0.56)	(1.98)
Manual Routine	-1.08*	-1.16*	-0.91
occupations	(0.53)	(0.63)	(0.95)
Manual Non-routine	-3.09**	-3.03**	8.01
occupations	(1.03)	(1.08)	(6.25)
	Female respondents		
Cognitive Non-routine	1.09	1.15	2.11
occupations	(0.84)	(0.87)	(2.10)
Cognitive Routine	1.26*	1.20*	3.31*
occupations	(0.61)	(0.64)	(1.46)
Manual Routine	1.35	1.69	-1.59
occupations	(1.11)	(1.19)	(5.32)
Manual Non-routine	-2.06	-2.10	-9.63
occupations	(1.72)	(1.87)	(10.26)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the outcome group in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 2.11: **Robot Adoption Effects on Occupational Groups in Manufacturing Industries (2SLS)** [cited on page 70]

	Total Employment				Private Employment				Public Employment			
Occupational groups	Male		Female		Male		Female		Male		Female	
Management	-0.27	(0.57)	0.88	(0.90)	-0.33	(0.67)	0.92	(0.92)	-0.09	(2.39)	12.08*	(5.50)
Business and financial operations	-2.71*	(1.30)	0.08	(1.05)	-2.76*	(1.36)	0.29	(1.11)	12.68*	(6.96)	-0.23	(6.10)
Computer and mathematical science	1.52	(1.96)	-0.06	(1.67)	1.81	(2.00)	-0.40	(1.72)	14.38*	(8.03)	10.74	(10.50)
Architecture and engineering	-0.46	(1.20)	1.23	(1.49)	-0.33	(1.28)	1.50	(1.61)	0.12	(2.09)	-1.57	(6.61)
Life, physical, and social science	0.47	(1.82)	-1.00	(1.84)	0.61	(1.84)	-0.86	(2.00)	-9.24	(8.99)	12.50*	(7.36)
Community and social service occupations	-13.84*	(7.03)	4.71	(9.96)	-7.10	(8.51)	-5.83	(10.09)	2.71	(3.19)	5.28	(6.21)
Legal	-4.37	(4.17)	3.13	(4.86)	-4.73	(4.30)	8.35*	(4.68)	-9.99	(6.40)	-17.82**	(5.21)
Education, training, and library	6.43	(5.24)	9.23	(5.87)	5.16	(5.70)	9.62*	(5.82)	-0.88	(6.01)	-7.53	(10.18)
Arts, design, entertainment, sports, and media	2.42*	(1.04)	4.55**	(1.75)	1.82*	(1.05)	2.80	(1.78)	20.49*	(8.58)	3.51	(10.28)
Healthcare practitioner and technical	-2.46	(3.55)	-0.59	(4.68)	-1.49	(3.56)	-1.65	(5.16)	-13.06*	(5.28)	-3.14	(4.76)
Healthcare support	-13.49*	(7.95)	17.27*	(8.96)	-4.50	(9.12)	22.55*	(11.55)	1.85	(2.65)	-1.76	(2.49)
Protective service	-5.70**	(1.71)	6.42	(5.01)	-4.06*	(1.83)	9.13	(5.66)	-6.46	(9.58)	12.40*	(7.36)
Food preparation and serving related occupations	0.39	(5.96)	-5.79	(4.28)	1.89	(5.91)	-4.84	(4.76)	27.18***	(6.51)	6.76	(6.57)
Building and grounds cleaning and maintenance	-3.36***	(0.92)	-2.80	(2.00)	-3.61***	(0.95)	-1.66	(2.24)	10.04	(6.28)	11.25	(7.72)
Personal care and service	-4.13	(8.74)	19.36***	(5.36)	-5.34	(8.93)	6.99	(6.16)	3.29	(4.98)	1.31	(4.53)
Sales and related occupations	0.31	(0.59)	0.23	(1.02)	0.19	(0.54)	0.30	(1.09)	11.89	(7.89)	14.08	(9.31)
Office and administrative support	-0.70	(0.78)	-0.66	(0.55)	-0.67	(0.83)	-0.81	(0.63)	2.78	(3.98)	4.82	(4.30)
Farming, fishing, and forestry	-7.17	(7.07)	8.73	(12.85)	-8.23	(7.31)	19.87	(19.57)	-2.02	(8.43)	-6.33*	(2.84)
Construction and extraction	-1.54**	(0.54)	-1.00	(1.51)	-1.74*	(0.69)	-0.02	(1.75)	-1.37	(1.04)	2.48	(8.87)
Installation, maintenance, and repair	-3.09**	(0.91)	-0.32	(2.02)	-3.18**	(0.97)	-1.30	(2.19)	-3.85	(2.67)	24.71**	(8.30)
Production	-0.83*	(0.49)	2.05*	(0.87)	-0.93*	(0.53)	1.96*	(0.94)	0.82	(2.69)	4.35*	(2.46)
Transportation and material moving	-0.47	(0.67)	2.05*	(1.04)	-0.57	(0.67)	2.13*	(1.06)	1.94	(2.05)	11.49	(9.11)

Notes: The dependent variables in columns (1)-(3) are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the outcome group in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 2.12: ROBOT ADOPTION EFFECTS ON INTRA-HOUSEHOLD WORKING OUTCOMES (2SLS) [cited on page 72]

	(1)	(2)	(3)
	Dependent Variables		
Samples	Fraction of Households	Fraction of Households	Share of Income in Household Income
Both spouses are in the labor force	0.08		
	(0.06)		
Only husband is in the labor force	-0.12*		
	(0.05)		
Only wife is in the labor force	0.05		
	(0.03)		
Both spouses are not in the labor force	0.05*		
	(0.03)		
Both spouses are employed		-0.02	
		(0.08)	
Only husband is employed		-0.08	
		(0.05)	
Only wife is employed		0.07*	
		(0.03)	
Both spouses are not employed		0.09**	
		(0.04)	
Share of female income			0.14***
			(0.04)

Notes: The dependent variables in columns (1)-(3) are the changes in the fraction of households with both spouses or just one spouse (either husband or wife) or neither of spouses in the labor force (1) or employed (2) and in the share of income earned by women in married or cohabiting households. The number of observations is 2,166 (722 commuting zones in each of the three time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the population in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 2.13: Robustness Checks of General Robot Adoption Effects (2SLS) [cited on page 73]

	(1)	(2)	(3)	(4)
	Specifications			
Dependent Variables	Baseline Specification	Weighted by Population	Without 1% Top Robot Adoption CZs	Without 2007-2017
	Male respondents			
Population	-0.42*	-0.42*	-0.53	-0.29
	(0.20)	(0.20)	(0.41)	(0.26)
Total Employment	-0.67**	-0.69**	-0.60	-0.81*
	(0.25)	(0.25)	(0.44)	(0.34)
Private Employment	-1.05***	-1.07***	-1.15*	-1.32**
	(0.27)	(0.28)	(0.51)	(0.42)
Public Employment	-0.11	-0.04	0.03	0.05
	(0.33)	(0.33)	(0.58)	(0.40)
	Female respondents			
Population	-0.55*	-0.55*	-0.61	-0.53*
	(0.22)	(0.22)	(0.44)	(0.24)
Total Employment	-0.85**	-0.85**	-1.01*	-0.92**
	(0.25)	(0.25)	(0.46)	(0.28)
Private Employment	-0.96***	-0.97***	-1.25*	-1.20***
	(0.26)	(0.26)	(0.49)	(0.32)
Public Employment	-0.58*	-0.58*	-0.70	-0.31
	(0.29)	(0.29)	(0.53)	(0.31)
Observations	2,166	2,166	2,145	1,444

Notes: The dependent variables are the change in the log count of the working-age population, total employment, private employment, and public employment, respectively, multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. Regressions in columns 1, 3, and 4 are weighted by a commuting zone's national share of the outcome group in 1990; in column 2, they are weighted by a commuting zone's national share of the population in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 2.14: **ROBUSTNESS CHECKS OF ROBOT ADOPTION EFFECTS IN MANUFACTURING INDUSTRIES (2SLS)** [cited on page 73]

	(1)	(2)	(3)	(4)
	Specifications			
Dependent Variables	Baseline Specification	Weighted by Population	Without 1% Top Robot Adoption CZs	Without 2007-2017
	Male respondents			
Total Employment	-0.57*	-0.59*	-0.43	-0.83
	(0.32)	(0.32)	(0.62)	(0.54)
Private Employment	-0.61*	-0.63*	-0.56	-0.91
	(0.34)	(0.35)	(0.66)	(0.60)
Public Employment	-0.27	0.76	-1.80	0.70
	(0.92)	(0.81)	(1.27)	(1.13)
	Female respondents			
Total Employment	1.66**	1.68**	2.54**	1.17
	(0.50)	(0.51)	(0.77)	(0.72)
Private Employment	1.65**	1.69**	2.53**	1.11
	(0.53)	(0.54)	(0.81)	(0.76)
Public Employment	2.31*	2.56*	2.75	3.22*
	(1.16)	(1.22)	(1.76)	(1.91)
Observations	2,166	2,166	2,145	1,444

Notes: The dependent variables are the change in the log count of total employment, private employment, and public employment, respectively, multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$. The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. Regressions in columns 1, 3, and 4 are weighted by a commuting zone's national share of the outcome group in 1990; in column 2, they are weighted by a commuting zone's national share of the population in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Chapter 3

Gender Differences in Robotization Effects: Panel Data Analysis

3.1 Introduction

The last chapter of the dissertation aims to broaden the cross-sectional examination of gender disparities in the effects of robotization at the individual level by employing panel data from the National Longitudinal Survey of Youth 1997 (NLSY97). Given that the NLSY97 encompasses a dataset of young individuals, providing extensive information about their lives from adolescence to early adulthood, the primary objective of this chapter is to investigate the impacts of robot exposure on young adults.

As extensively noted in the existing literature (see McHenry [73], Greenland et al. [52] among others), young adults display a heightened sensitivity to local economic conditions. This demographic's responsiveness to economic fluctuations renders the data especially pertinent for this study. The ability of young adults to quickly adapt to and be influenced by changes in their economic environment makes them an ideal focus group for analyzing the effects of local economic factors. Consequently, the utilization of the NLSY97 is particularly advantageous for this paper, enabling a more nuanced understanding of the economic impacts of robotization on this responsive age group.

Generally, the local labor market outcomes (mostly employment outcomes) for young people can differ significantly from those experienced by the entire population. These differences arise due to various factors related to young people's unique position in the labor market and their life stage.

One primary reason for the different employment outcomes is the varying levels of experience and skill. Young people typically have less work experience than older workers, making them more vulnerable to job loss and less competitive in the job market. As they are still developing essential skills, changes in demand for certain skills can impact them more severely.

Education and training play a crucial role in shaping labor market outcomes for young people. Many young individuals are still in school or pursuing higher education, which limits their availability for full-time work and influences their employment patterns. They are also more likely to be employed in internships, part-time jobs, or entry-level positions, which tend to be less stable and more susceptible to economic fluctuations.

The challenges associated with entering the labor market for the first time also contribute to the different employment outcomes for young people. Young individuals face unique hurdles during their initial entry into the workforce, particularly during economic downturns when companies are less inclined to hire new employees. Additionally, they often lack the networks and job search skills that older workers have developed, making it harder for them to find employment.

Economic vulnerability is another factor that disproportionately affects young people. Historically, youth unemployment rates are higher than those for the overall population due to factors like less job security, fewer connections, and higher competition for entry-level jobs. Young people are often more impacted by economic downturns as they are more likely to be in precarious employment situations.

Sectoral differences in employment also contribute to the distinct effects on young workers. Young individuals are often concentrated in sectors such as retail, hospitality, and food services, which can be more volatile and sensitive to economic changes compared to sectors where older, more experienced workers are employed. Moreover, young workers are more likely to be involved in gig economy jobs or part-time work, which may not offer the same stability and benefits as full-time employment.

Employment policies and programs often target youth differently, which can lead to different labor market outcomes. Programs such as apprenticeships, internships, and educational initiatives are specifically designed for young people, providing them with unique opportunities and challenges. Additionally, changes in minimum wage laws can disproportionately affect young workers, who are more likely to earn entry-level wages.

Young people's life stage and financial responsibilities also influence their employment outcomes. Compared to older workers, they often have fewer financial responsibilities, such as mortgages or supporting a family. This can affect their employment choices and resilience to job loss. Additionally, young individuals may have more flexibility to explore different career paths and job opportunities without the constraints that older workers might face.

In summary, the effects of robotization on young people might differ from those on the entire population due to factors such as their experience, education, sectoral employment, and economic vulnerability.

According to the results of the cross-sectional analysis at the commuting zone level, the effects of robot adoption are more negatively pronounced on the younger segment of the population compared to a similar cross-sectional analysis on the overall population in the previous chapter.

The results of panel data analysis at the individual level reveal a negative impact of robot penetration on migration, whereas the effect on labor force participation and employment is found to be positive. Utilizing the fixed-effects method yields a partial effect for this study. The overall impact of robot exposure remains unexpectedly negative on migration and positive on labor force participation. However, the effect of robotization on employment is mostly negative.

The final stage of the analysis incorporates an alternative definition of the robot adoption variable. The robot intensity variable signifies the extent of robotization within the industry. Unlike the Bartik-style variable utilized in the previous chapter, it is not associated with the individual's geographic location. Implementing this alternative variable in fixed-effects models yields more substantive and less counterintuitive results, such as a more negative overall effect of robot penetration on employment.

The existing body of literature on the impact of robot exposure on labor market outcomes predominantly comprises cross-sectional and case-specific studies. However, comprehensive analyses utilizing panel data remain relatively scarce.

Using panel data for manufacturing employees in Germany, Dauth et al. [36] discovered that robotization did not elevate the risk of displacement for incumbent workers. Although numerous workers transitioned to different occupations, they remained at their initial workplace. The decrease in manufacturing employment is entirely ascribed to the reduction in the creation of new positions for young entrants into the labor force.

Fossen and Sorgner [45] document the substantial effects of AI at the individual level. Utilizing comprehensive panel data from the matched monthly Current Population Survey, their study provides evidence that an increased risk of digitalization within an individual's current occupation is associated with a higher likelihood of transitioning to a different occupation or experiencing unemployment.

Aghion et al. [3] employ French plant-level and firm-level panel data. This study underscores that the influence of Artificial intelligence and automation on employment is contingent upon education level, with individuals possessing lower levels of education experiencing more pronounced negative effects. Additionally, the research offers initial insights indicating that automation may augment employment at the plant level in the long run, particularly benefiting individuals with intermediate to high levels of skills.

Aydin [13] investigates the association between robot adoption and employment across various age groups and utilizes a dynamic panel dataset encompassing 28 countries spanning from 2004 to 2016. The results suggest that robot exposure exerts a negative influence on young laborers while yielding positive effects on their older counterparts. Furthermore, the prevalence of young workers in the labor force is identified as a driving force behind the penetration of industrial robots.

The paucity of panel individual-level data studies highlights a gap in the empirical research, underscoring the need for further longitudinal investigations to capture the dynamic interactions between automation and robotics technologies and labor market outcomes over time. This paper aims to fill this gap by focusing on gender differences in robotization effects.

The rest of the paper is organized as follows. Section 2 elucidates the impacts of robot penetration on young people at the commuting zone level. Section 3 delineates the outcomes of the panel data analysis. Alternative modeling approaches are showcased in Section 4. Lastly, Section 5 concludes deliberating on the potential rationales behind the disparities in results between the two chapters.

3.2 Robotization Effects on Young Population at Commuting Zone Level

3.2.1 Data and Descriptive Statistics

Similarly to the previous chapter, the cross-sectional analysis of the effects of robot adoption on young individuals at the commuting zone level uses data from the International Federation of Robotics (IFR), the IPUMS census samples, and the American Community Survey (Flood et al. [44]). In order to be concordant with the panel data analysis based on the NLSY97, the samples are restricted to the young segment of the working-age population (18-36 years), which is consistent with the sample used in the panel data analysis. For the same reason, this analysis uses only two time periods: 2000-2007 and 2007-2017.

The dependent variables are migration (change in the population), changes in the labor force participation rate, and employment for the young segment of the working-age population (18-36 years). Changes in population and employment are defined as the change in the logarithm of the number of young individuals (employed individuals in the case of employment variable) residing in CZ c between periods t and $t+1$ within the subgroup Y:

$$\Delta lnY_{c,t:t+1} = lnY_{c,t+1} - lnY_{c,t} \tag{3.1}$$

The change in the labor force participation rate is defined as the change in the proportion of the population in the labor force.

This analysis does not investigate different employment types because the proportion of the population working in the public sector is expected to be lower among the younger workers. Young people tend to have lower rates of employment in the public sector due to factors like entry-level positions being more common in the private sector and longer tenure requirements for many public sector jobs.

Unweighted means of dependent variables across all 722 CZs over two subperiods (2000-2007 and 2007-2017) are presented in Table 3.1. For a more detailed explanation of the empirical framework, data sources, robot adoption variables, and covariates included in the models, refer to corresponding sections of the second chapter of the dissertation: Chapter 2. Data and Descriptive Statistics and Chapter 2. Empirical Framework.

3.2.2 Effects of Robotization

Table 3.2 illustrates the impact of robot adoption on migration, labor force participation rate, and employment of the young population. The overall impact of robot exposure on migration is negative (-0.66), and this coefficient is deemed statistically significant. This negative effect of robotization appears to be more pronounced for females (-0.84 compared to -0.49). Across the entire young population, the impact of robot penetration tends to exhibit greater negativity among unmarried segments of both sexes. All coefficients are found to attain statistical significance.

The overall impact of robot adoption on the labor force participation rate is negative. This negative effect is stronger for young men (-0.29 and -0.11, lacking statistical significance for women). As depicted in Table 3.2, the impact of robot exposure on male labor force participation is negative, irrespective of marital status. Regarding the female population, the direction of the robotization effect diverges between unmarried and married women. It is negative for young unmarried women (-0.27) yet positive for married females (0.07). While the regression coefficients achieve statistical significance for unmarried men and women, they are deemed insignificant for the married population of both genders.

The overall robotization impact on the employment of the young population is determined to be negative (-1.23). This effect is negative and possesses statistical significance for both male (-1.15) and female (-1.38) workers. As can be seen from this table, the negative effect on employment is only marginally more pronounced among young women, and it exhibits heightened intensity among unmarried workers, regardless of gender.

According to Table 3.3, the overall negative (albeit lacking statistical significance) impact of robot adoption on employment in manufacturing industries varies between male and female workers. The effect of robot exposure is found to be negative for men (-1.31) and positive, however statistically insignificant, for women (1.02). Regarding the two non-manufacturing industry categories, the findings outlined in this table indicate that the negative effect in high-skilled non-manufacturing industries is slightly more pronounced for male employees, whereas it is stronger for female workers in low-skilled industries.

Finally, Table 3.4 illustrates that the overall negative effect of robot penetration on employment is more amplified for unmarried respondents, encompassing both male (-1.42 for unmarried and -1.01 for the married employees) and female workers (-1.72 and -1.30, respectively). The same conclusion is valid regarding non-manufacturing industry categories, with the exception of low-skilled non-manufacturing industries for male workers.

The negative effect of robot adoption on male employment in manufacturing industries is markedly more pronounced for unmarried workers (-2.00 compared to -0.77). The positive correlation between robot exposure and employment among young women in manufacturing sectors is largely attributed to the married segment of female workers (1.98 versus -0.11 for unmarried women).

In general, the impacts of robotization on the young segment of the population exhibit heightened negativity in comparison to the effects observed on the entire population (Chapter 2. Results). Hence, it is anticipated that the panel data analysis may yield disparate outcomes when juxtaposed with the cross-sectional analysis conducted for the entire working-age population.

3.3 Panel Data Analysis of Robotization Effects

3.3.1 Data and Empirical Specification

This segment of the paper utilizes the National Longitudinal Survey of Youth 1997 (NLSY97), a longitudinal study tracking a cohort of American youth born between 1980 and 1984. Since the IFR data is available from 1993 to 2017, the last wave of the NLSY97 used for this paper is 2017. Additionally, the NLSY97 Geocode dataset furnishes geographical data concerning the respondents' locations over time. This dataset is restricted due to privacy concerns and requires special access.[1] The Geocode dataset represents a powerful resource for researchers investigating the geographical facets of social and economic outcomes.

[1] This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here do not necessarily reflect the views of the BLS.

Despite the complexities associated with obtaining and utilizing this data, its potential to illuminate how local contexts shape individual trajectories renders it highly advantageous for a wide range of studies.

The sample is constrained by age, with participants required to be a minimum of 18 years old. Additionally, it excludes respondents who are pursuing further education, as indicated by the continuous annual increase in the highest grade completed. Table 3.5 showcases the descriptive statistics of the dataset, comprising 108,825 annual data points corresponding to 8,530 individuals spanning the years 2000 to 2017. In particular, this table displays the average, minimum, and maximum values of basic demographic variables and the number of children.

The robot adoption variable is constructed using the NLSY97 Geocode dataset. Utilizing commuting zones recorded in each survey wave, the variable is characterized by the level of robotization within the commuting zone of each respondent. However, a limitation of this dataset emerges post-2011, as the NLSY97 has transitioned to a biennial survey schedule. Consequently, commuting zone designations for 2012, 2014, and 2016 remain unchanged from those of 2011, 2013, and 2015, respectively.

The binary migration variable is formulated only for individuals who have provided information regarding their geographical whereabouts in two successive survey iterations. This variable is assigned a value of one if the commuting zones between the two surveys differ and zero otherwise.

The labor force participation and employment variables are derived from the NLSY97 weekly employment history dataset, which provides detailed insights into respondents' employment engagements on a weekly basis. For each annual period, one can compute the frequency of weeks during which survey participants were actively engaged in the labor force, were employed, or were employed within one of the broad industry classifications. There are three types of binary dummy variables. The first variable (representing >0% of weeks) assumes a value of one if the respondent was part of the labor force or employed for at least one week within a specific calendar year and zero otherwise. The second and third variables (representing 25% and 50% of weeks, respectively) are assigned a value of one if the respondent's labor force participation or employment exceeded 25% or 50% of the weeks in the calendar year, respectively.

Lastly, the Log of employment hours variable is formulated by applying the natural logarithm function to the annual number of reported employment hours. This variable does not have a value if a respondent has reported zero employment hours within a particular calendar year.

The effect of robot exposure on individual outcome variables Y (migration, labor force participation, and employment-related variables) can be written as follows:

$$Y_{i,c,t} = \beta_0 + \beta_1 \text{US Robot Adoption}_{c,t-1} + X'_{i,t-1} + Z'_{c,t-1} + \varepsilon_{i,t}, \tag{3.2}$$

where $X'_{i,t-1}$ is a vector of individual characteristics (age, gender, race, marital status, education, geographic division, and the number of children) and $Z'_{c,t-1}$ represents a vector of baseline 1990 characteristics of a CZ c[2] in which individual i lived in time $t-1$.

3.3.2 Effects of Robotization on Migration and Labor Force Participation

Table 3.6 illustrates the impacts of robot penetration on both migration and labor force participation. Notably, the first column of the table unveils a somewhat unexpected and counterintuitive finding: the effect of robot adoption on migration manifests as a negative (-0.007). This implies that individuals residing in commuting zones characterized by ele-

[2] This specification uses the same commuting zone characteristics that were employed in the previous chapter; namely, the log of population, fraction of population aged 65 and above, fraction of population without a college degree, fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics, shares of employment in major industries, the average offshorability index, and the proportion of routine jobs.

vated levels of industrial robotization during time period t-1 exhibit a reduced propensity to relocate to different commuting zones during time period t.

This unanticipated negative impact is consistent across genders (-0.008 for male respondents and -0.007 for female respondents). Nevertheless, among male participants, this impact is more pronounced for those who are married (-0.012 compared to -0.006), whereas for female participants, it is conversely more robust among those who are unmarried (-0.010 compared to -0.004).

The overall impacts of robot exposure on the three labor force participation variables (columns 2-4) exhibit congruence. Each of these impacts is positive and attains statistical significance. Analogous to migration, discernible gender differentials are scarce, with coefficients for both males and females demonstrating proximity. This positive impact is marginally amplified among unmarried male respondents compared to their married counterparts. Conversely, among women, the positive effect is considerably more prominent among married participants.

3.3.3 Effects of Robotization on Employment

The next table delineates the impacts of robot penetration on employment variables. Across all three binary employment indicators in Table 3.7, this impact is identified as a positive. Nevertheless, only one of these indicators, specifically the >25% employment variable, exhibits a statistically significant coefficient (0.005).

This positive impact of robot adoption on binary employment variables exhibits greater strength among female workers. Notably, for two variables (>25% and >50%), the coefficient for women attains statistical significance (0.007 compared to 0.003 for men). Additionally, it is pertinent to observe that the positive effect is found to be more pronounced for married participants, irrespective of gender. However, the disparity between coefficients for unmarried and married men is not substantial.

The impact of incorporating robots into the workforce on employment hours exhibits a positive trend yet lacks statistical significance. This favorable trend is notably more pronounced among female laborers (0.012 compared to 0.003). However, none of the coefficients presented in column 4 attain statistical significance.

As depicted in Table 3.8, all regression coefficients assessing the impacts of exposure to robots on employment across three overarching industrial categories are likewise deemed statistically insignificant. Hence, the directional trends observed, such as the positive coefficients for males in manufacturing industries and females in high-skilled non-manufacturing industries, as well as the negative coefficients for men in high-skilled non-manufacturing industries and women in low-skilled non-manufacturing industries, bear limited importance.

The impact of robotization on employment hours is positive but lacks statistical significance across all broad industry categories, with the exception of high-skilled non-manufacturing industries for female workers.

The influence of robot adoption demonstrates a negative impact on migration but a positive effect on labor force participation and employment, as indicated by the findings in Tables 3.6-3.8. These outcomes, largely counterintuitive, diverge from prevalent conclusions in recent literature and contradict findings from the cross-sectional analysis in the previous chapter. Consequently, the subsequent examination is broadened through the utilization of fixed-effects models and an alternative characterization of the main variable of interest.

3.4 Alternative Approaches

3.4.1 Fixed-Effects Models

The initial progression in advancing the panel data analysis involves the utilization of fixed-effects models. These models account for the inherent characteristics of the entities (in this case, the NLSY97 participants) that persist over time, which might otherwise introduce biases into the findings. By focusing on within-entity fluctuations, fixed-effects models control for all latent factors that remain constant over time. They achieve this by differencing out time-invariant variables, thereby facilitating a more transparent examination of the influence of variables that exhibit temporal variations. Furthermore, fixed-effects models exhibit resilience against the misspecification of individual effects, as they do not presuppose any specific distribution for these effects. The outcomes of fixed-effects 2SLS regression models are presented in Tables 3.9-3.11.

Table 3.9 illustrates the impact of robot penetration on migration and labor force participation. The overall effect on migration, while positive, lacks statistical significance. Notably, column 1 reveals discernible gender disparities: the effect of robot adoption for male respondents is negative and statistically significant (-0.012), while for female respondents, it is positive but lacks statistical significance (0.003). Additionally, it is noteworthy that the effect is more negative for married participants, irrespective of gender.

The overall impact of robotization on binary labor force participation variables reveals a positive yet statistically significant outcome only for the >50% variable (0.005). Notably, this positive outcome is primarily attributable to female respondents (0.009 versus zero for men). Furthermore, this positive effect among women is largely influenced by their married counterparts (0.010 versus 0.002 for unmarried women). Conversely, among the male population, the positive effect is more pronounced among unmarried men.

As per the findings presented in Table 3.10, the impact of robot exposure on binary employment variables is notably negative and statistically significant. Across the three delineated variables (>0%, >25%, and >50% employment), discernible gender disparities emerge in a progressive fashion. The disparity is most modest for the >0% employment variable (-0.007 for men and -0.005 for women), whereas it reaches its peak for the >50% employment variable (-0.010 and zero, respectively). Among male workers, the negative effect is notably amplified for married individuals across all three variables. Conversely, among female workers, the effect of robot adoption is more negative for unmarried individuals for the >25% and >50% employment variables while exhibiting a contrasting trend for married women concerning the >0% employment variable.

The overall impact of robot penetration on employment hours is observed to be negative yet statistically insignificant. Notably, column 4 of this table illuminates a significant gender dichotomy. Specifically, the effect of robotization is negative (-0.016) for male workers, contrasting with a positive impact (0.004, albeit statistically insignificant) for female workers. This negative effect among male workers is predominantly attributed to those who are married (-0.048 compared to -0.009 for unmarried males). Among female workers, the effect is negative for unmarried respondents and positive for married participants; however, both coefficients lack statistical significance.

Table 3.11 elucidates notable gender divergences in the impacts of robot exposure on three binary employment variables within various broad industry categories. Within manufacturing industries, this impact is predominantly negative for female workers but largely positive for their male counterparts. Conversely, in high-skilled non-manufacturing industries, the effect of robotization tends to be positive for women but negative for male respondents. Finally, in low-skilled non-manufacturing industries, the influence is negative for females and exhibits a mixed pattern for male employees.

As observed in column 4, the impact of robot penetration on employment hours is negative and lacks statistical significance for men across all three broad industry categories.

Conversely, for female workers, this impact is positive in manufacturing and high-skilled non-manufacturing sectors, albeit statistically significant only in the latter case (0.039). In low-skilled non-manufacturing industries, the effect of robot adoption on female employees is negative but not statistically significant.

The examination of Tables 3.9-3.11, in contrast to Tables 3.6-3.8, reveals that the implementation of fixed-effect models has partially enhanced the analytical outcomes. Regarding migration and labor force participation, there appears to be minimal disparity between the findings delineated in Tables 3.6 and 3.9. The negative robotization impact on migration still persists, counterintuitively, and the influence on binary labor force participation variables remains predominantly positive across most subgroups. These results present challenges in terms of explication and interpretation, diverging from recent scholarly works.

Nonetheless, Tables 3.7-3.8 and 3.10-3.11 yield considerably disparate results. Within the framework of fixed-effects models, a predominant proportion of the subgroups exhibit a negative impact of robot exposure on employment variables, aligning more closely with anticipated trends and corroborating recent scholarly discourse.

3.4.2 Alternative Definition of Robot Adoption

The second alternative methodology involves employing a fundamentally distinct robot adoption variable, departing from the conventional Bartik-style approach. This variable is constructed following Abeliansky et al. [1], and it encapsulates the robot intensity within an industry. It is created by dividing the number of robots by the total employment within the industry and taking the natural logarithm of this fraction:

$$\text{US Robot Intensity}_{s,t} = ln\left(\frac{R^{US}_{s,t}}{L^{US}_{s,t}}\right), \tag{3.3}$$

where $R_{s,t}^{US}$ and $L_{s,t}^{US}$ represent the operational stock of robots and total employment (in thousands of workers) in the industry s in the US at time t.

The instrument variable, the average robot intensity in five European countries, is constructed in a similar way:

$$\text{EU Robot Intensity}_{s,t} = \frac{1}{5}\sum\nolimits_{j \in EU5} ln\left(\frac{R_{s,t}^{j}}{L_{s,t}^{j}}\right), \tag{3.4}$$

where j represents the five European countries: Denmark, Finland, France, Italy, and Sweden.

In contrast to the traditional Bartik-style robot exposure variable utilized in the majority of recent literature concerning robotization, the robot intensity variable is not geographically bound. Instead, it is associated with NLSY97 participants through their respective industries rather than commuting zones. This characteristic enables the inclusion of individuals who may not have reported their locations in specific surveys.

However, this variable exhibits a significant and apparent limitation. Given that the robot intensity variable is associated with individuals through industrial sectors, it necessitates knowledge of the industries in which the survey participants are engaged. This data is accessible and dependable solely for individuals who are employed. Unemployed respondents are only able to provide information regarding the industries of their previous employers, which is presumed to be unrelated to the decision-making process of the NLSY97 participants. Consequently, this variable can only be utilized to analyze variations in employment-related dependent variables. Regression models targeting migration or labor force participation encompass unemployed respondents and, thus, cannot utilize the robot intensity variable as a predictor for panel data analysis[3].

[3] Another disadvantage of this approach is rooted in the reporting frequency of the NLSY97 participants. Specifically, respondents provide information regarding the industries of their current or most recent employers exclusively during survey periods. Since 2011, the NLSY97 has shifted to a biennial schedule, which poses a notable challenge for data continuity. Consequently, it becomes unfeasible to accurately link individuals to

The effect of robot penetration on individual outcome employment-related variables Y can be written as follows:

$$Y_{i,s,t} = \beta_0 + \beta_1 \text{US Robot Intensity}_{s,t-1} + X'_{i,t-1} + I'_{s,t-1} + \varepsilon_{i,t}, \tag{3.5}$$

where $X'_{i,t-1}$ is a vector of individual characteristics, and $I'_{s,t-1}$ represents a vector of covariates related to industry s in which individual i worked in time $t-1$ (IFR industry dummies and national employment shares of industries in 1990).

The industry fixed effects are included in the model to account for unobserved variations that exist at the industry level. Additionally, the initial surge in robot penetration may not have directly impacted the NLSY97 participants causally; rather, the increase in robot installations could reflect ongoing industry-specific trends that predate the observed rise. To mitigate this potential confounding effect and more accurately isolate the impact of robot adoption, it is prudent to incorporate fixed effects for the 15 industries classified by the International Federation of Robotics (IFR). By doing so, the model can control for unobserved heterogeneity and pre-existing trajectories within these industries, ensuring that the results are more robust and reliable.

Table 3.12 presents the overall negative impact of robot adoption on the trio of binary employment variables. These variables, denoting employment rates exceeding 0%, 25%, and 50% of weeks, respectively, unveil a consistent escalation in negative effects (-0.080, -0.135, -0.179, correspondingly). All these coefficients are statistically significant. Notably, the negative influence remains largely consistent across genders for all three variables. Furthermore, this negative effect of robotization is notably amplified among unmarried workers, irrespective of gender, across all employment variables.

the robot intensity variable for the years 2012, 2014, and 2016. As a result, the annual data points for these specific years must be excluded from the dataset, leading to gaps in the longitudinal analysis and potential biases in the research findings due to missing observations.

Column 4 of the table outlines the significant negative impact of robot exposure on employment hours (-0.87). In addition, one can observe an insignificant gender difference. This impact is slightly more pronounced among men (-0.96 compared to -0.78 for female respondents). All aforementioned coefficients demonstrate statistical significance. Analogous to binary employment variables, the negative effect of robot penetration is notably accentuated among unmarried participants.

As depicted in Table 3.13, the significant gender differentiations in the impacts of robot adoption on all binary employment variables across three broad industry categories are lacking. Within manufacturing industries, this impact is predominantly negative for both male and female workers. It is noteworthy that the binary variables manifest increasing gender differentials in a sequential manner. The disparity is minimal for the >0% of weeks variable (-0.274 for men and 0.015 for women), discernible for the >25% variable (-0.439 and -0.053), and most pronounced for the >50% variable (-0.708 and -0.109, respectively). In high-skilled non-manufacturing industries, the effect of robotization is positive for both genders, with a more pronounced effect observed among men. Lastly, in low-skilled non-manufacturing industries, the impact of robot exposure is found to be positive for male participants and mostly negative for women.

Nearly all coefficients delineated in column 4 of this table exhibit statistical significance and do not reveal gender disparities, with the exception of the impact of robot penetration in manufacturing industries. This impact is negative for male workers (-0.96) and positive for their female counterparts (0.74). The negative effect on employment hours for both genders is nearly comparable in high-skilled non-manufacturing industries and completely identical in low-skilled non-manufacturing industries.

The straightforward juxtaposition of Tables 3.7-3.8 and 3.12-3.13 illustrates that utilizing the alternative delineation of robot adoption in fixed-effects models yields more robust and statistically significant outcomes. Additionally, a majority of the subsamples indicate a negative effect of robot penetration on employment variables, aligning with contemporary literature and the previous chapter of this dissertation.

3.5 Conclusion

The findings detailed in Section 2 reveal that robotization's impact on local labor market outcomes for the young population is more negative than the effects on the total population found in the previous chapter of the dissertation.

Utilizing a comprehensive panel data analysis, it has been determined that the adoption of robots exerts a negative influence on migration while concurrently having a positive effect on the labor force participation rate and employment. These results are largely unexpected and stand in stark contrast to the prevailing conclusions of recent scholarly literature on the subject.

One element that may account for potential discrepancies between the findings of the NLSY97 analysis and the cross-sectional models presented in the previous chapter is the conceptual differentiation between cross-sectional data and panel data.

According to the academic literature on econometrics and applied statistics, the results of panel data analysis might differ from those of cross-sectional data analysis due to several key reasons rooted in the structure, methodology, and nature of the data. While cross-sectional analysis focuses on variations across different entities at a single point in time, panel data analysis considers both cross-sectional and time-series dimensions, offering a more comprehensive perspective. Despite their utility, discrepancies in results between these two methodologies are not uncommon, prompting a closer examination of the underlying factors.

In contrast to cross-sectional analysis, panel data analysis involves modeling individual behavior over time, thereby capturing both individual-specific effects and time-specific effects.

Other factors contributing to discrepancies besides temporal dynamics are individual heterogeneity, time-invariant variables, and endogeneity concerns (Baltagi [14], Cameron and Trivedi [29], Greene [51], Wooldridge [107]).

Temporal dynamics play a pivotal role in distinguishing between panel data analysis and cross-sectional data analysis. Panel data analysis, by its nature, incorporates temporal dependencies by examining trends over time and incorporating lagged variables. On the contrary, cross-sectional analysis treats each observation independently, disregarding temporal dynamics. This difference in approach can lead to divergent results, especially in scenarios where temporal evolution is significant.

Individual heterogeneity introduces another dimension of complexity. Panel data analysis allows for the estimation of individual-specific effects, recognizing that entities may exhibit unique characteristics that evolve over time. However, cross-sectional analysis treats all observations equally, failing to account for individual heterogeneity adequately. Consequently, disparities in results may arise due to the neglect of individual-specific dynamics.

The treatment of time-invariant variables differs between panel data analysis and cross-sectional data analysis. Panel data analysis exploits within-individual variations to identify time-invariant variables, thereby mitigating biases associated with omitted variable bias. In contrast, cross-sectional analysis lacks this capability, potentially leading to inflated standard errors and biased estimates. Thus, the failure to account for time-invariant variables adequately can contribute to discrepancies in results between the two methodologies.

Lastly, the endogeneity concerns pose challenges that necessitate careful consideration. Panel data analysis offers greater flexibility in addressing endogeneity concerns through fixed effects or instrumental variable approaches. This flexibility allows researchers to account for dynamic relationships and mitigate biases effectively. In contrast, cross-sectional analysis, constrained by its static nature, may struggle to address endogeneity issues adequately. Consequently, methodological disparities in addressing endogeneity concerns can lead to disparities in results between panel data analysis and cross-sectional data analysis.

These factors collectively underscore the importance of understanding the nuances of panel data analysis and cross-sectional data analysis. These nuances might explain the significant differences between the results in Tables 3.6-3.8 and the results from the previous chapter of this dissertation. The panel data analysis found that the overall effect of robot adoption is surprisingly negative on migration and positive on labor force participation and employment. This contradicts findings from both the preceding chapter and recent literature (Acemoglu and Restrepo [2], Faber et al. [40]).

To address these anomalies, the analysis is further refined by employing fixed-effects models and adopting an alternative definition of the robot penetration variable, thereby ensuring a more robust examination of the observed phenomena. This expanded methodological approach aims to provide a deeper and more accurate understanding of the impact of robot exposure on labor market dynamics.

Utilizing fixed-effects models might effectively overcome the potential adverse impact of these factors. Overall, these models offer several advantages in panel data analysis, including the ability to control for time-invariant heterogeneity, address endogeneity concerns, make efficient use of panel data, and provide robust estimates in the presence of unobserved heterogeneity.

In the context of this paper, employing fixed-effects models yielded at least partially substantive results. When examining migration and labor force participation, the outcomes from both the fixed-effects and initial approaches showed no significant differences. The impact of robotization on migration remained unexpectedly negative, and the influence on binary labor force participation continued to be positive across almost all subsamples. These results present interpretative challenges and stand in opposition to the findings reported in recent academic literature.

However, divergent results were observed in relation to employment. Specifically, within the fixed-effects models, the effect of robot penetration on employment variables was predominantly negative, aligning more closely with the anticipated outcomes and corroborating the conclusions of recent studies. This alignment suggests a nuanced understanding of robot adoption's impact on employment, which the initial models failed to capture.

The primary reason fixed-effects models produce different results from non-fixed-effects models might lie in their handling of unobserved heterogeneity and time-invariant characteristics. Fixed-effects models provide more accurate, robust, and theoretically consistent estimates by focusing on within-entity variation and eliminating biases from unobserved, constant factors. This makes them particularly valuable for longitudinal studies and causal inference, where understanding the dynamics of change within entities over time is crucial.

Ultimately, the implementation of an alternative definition of robot exposure within fixed-effects models has yielded notable advancements. The outcomes have exhibited increased robustness and attained statistical significance. Moreover, a majority of the subsamples have indicated a negative effect of robot penetration on employment variables, which is in alignment with the recent literature as well as the findings presented in the previous chapter of this dissertation. This consistency underscores the reliability and validity of the fixed-effects model approach in capturing the negative impacts of robot adoption on employment, thereby offering a more precise and comprehensive understanding of the subject matter.

Two approaches used in this chapter involve using robotization variables based on geographic areas or industry sectors. While these methods aim to shed light on the same phenomenon, they yield notably different results. This difference between the results of estimating the effect of robot exposure on individuals using different robot penetration variables—the average level of robotization in that individual's local labor market and the level of robotization in that individual's industry—can differ for several reasons.

The first strategy, used in many recent papers, employs what is often referred to as a Bartik-style robot adoption variable. In this setup, the level of robotization for each individual is determined by the average level of robotization within their geographic area. This conceptual approach offers a broad perspective, capturing the overall impact of robot exposure across various industries within a given commuting zone. It's akin to assessing how the overall technological landscape within a community affects individuals, regardless of their specific industry of employment.

Conversely, the second technique utilizes a robot penetration variable that focuses on the individual's industry. Here, the level of robotization is measured within the specific industry in which each individual works. This method allows for a more granular examination, honing in on the unique dynamics of robotization within particular industries. By doing so, it aims to uncover how the technological transformation within an industry directly affects the individuals employed within it.

The divergence in results between these two approaches can be attributed to several factors. Firstly, they capture different dimensions of variation in robotization levels. While the Bartik-style variable offers a spatially aggregated view, the industry-specific variable delves into the nuances of technological adoption within particular sectors. This difference in perspective can lead to varying estimations of the effect of robot adoption.

Moreover, spatial spillover effects may come into play when using the Bartik-style variable. It accounts for the influence of neighboring areas, potentially impacting individuals even if they are not directly employed in highly robotized industries. On the other hand, the industry-specific variable focuses only on the technological landscape within each industry, potentially missing out on broader spatial dynamics.

Additionally, the choice of robot exposure variable can affect the identification strategy and address concerns regarding endogeneity. The Bartik-style variable may better capture exogenous variations in robotization levels across geographic areas, while the industry-specific variable may face challenges related to self-selection biases if individuals choose industries based on preferences or skills correlated with outcomes of interest.

Besides this, the industry-level robot intensity variable is calculated using current employment figures, which could potentially be influenced by the degree of robotization within specific industries. This introduces a concern regarding the endogeneity of the measure, as the employment levels may not be entirely exogenous. In contrast, the Bartik-style variable utilizes employment data from a base year, specifically 1990, thereby addressing some of the endogeneity issues by anchoring the measure to a period before significant robotization trends took hold. This historical baseline helps mitigate the risk that current employment levels are influenced by the level of robotization. However, employing an instrumented variable approach in both cases should provide a more robust solution, ensuring that the relationship between robot penetration and industry employment is accurately captured without bias from contemporary employment dynamics.

In the realm of data analysis, it is discerned that the utilization of Bartik-style variables may find greater applicability in scenarios characterized by cross-sectional data, wherein the regression's units of observations pertain to distinct commuting zones, each characterized by its unique level of robot exposure. This assertion implies that such variables are highly effective in capturing and distinguishing the variability in robotization levels across different geographic regions.

Oppositely, in contexts where the focus shifts to individual-level analysis, the efficacy of Bartik-style variables in elucidating variations in outcome variables might be comparatively diminished. This observation underscores the potential limitations of employing Bartik-style variables in elucidating granular variations at the individual level, wherein the explanatory power of these variables may not be as robust as in the broader spatial contexts.

The inherent complexity arising from the methodological disparities between the two aforementioned approaches might elucidate the notable lack of consistency between the results discerned in the second chapter of this dissertation and those ascertained through the individual-level panel data analysis in the present chapter.

Ultimately, the choice between these two modeling methods necessitates careful consideration of the underlying mechanisms driving robotization and the appropriate level of aggregation for capturing its effects. Both groups of models offer valuable insights into the impact of technological change on individuals within the workforce, but their differing perspectives highlight the complexity intrinsic in studying such phenomena.

3.6 Tables

Table 3.1: DESCRIPTIVE STATISTICS OF CROSS-SECTIONAL DATA [cited on page 104]

	2000-2007				2007-2017			
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
Change in log of population								
Total Population	0.73	11.35	-29.81	39.68	6.13	10.26	-22.79	49.21
Men	2.72	11.44	-23.31	48.27	6.18	11.23	-21.20	56.78
Women	-1.41	12.28	-37.68	36.26	6.11	10.12	-24.74	40.52
Change in Labor Force Participation Rate								
Total Population	0.50	3.70	-11.08	13.98	-0.46	2.88	-12.50	12.59
Men	-0.15	4.64	-18.49	14.39	-1.43	3.69	-18.96	20.14
Women	1.03	4.24	-11.34	14.24	0.51	3.25	-13.80	9.74
Change in Log Employment								
Total Population	-0.76	13.54	-41.03	43.16	7.87	11.06	-28.82	51.50
Men	-0.07	14.57	-41.57	50.86	6.56	12.54	-31.70	61.74
Women	-1.62	14.29	-41.27	40.51	9.38	10.97	-25.15	44.92

Notes: This table presents unweighted averages, standard deviations, and minimum and maximum values of variables across 722 commuting zones. The changes in the logarithm of population and employment are multiplied by a factor of 100: $[ln(Y_{t+1}) - ln(Y_t)] \cdot 100$.

Table 3.2: Robot Adoption Effects on Young Population (2SLS) [cited on page 104]

	(1)	(2)	(3)
	Dependent Variables		
Samples	Population	Labor Force Participation Rate	Employment
Total sample	-0.66**	-0.19**	-1.23**
	(0.25)	(0.07)	(0.39)
Male respondents	-0.49*	-0.29*	-1.15*
	(0.25)	(0.11)	(0.46)
Female respondents	-0.84**	-0.11	-1.38***
	(0.27)	(0.08)	(0.34)
Unmarried respondents	-0.91**	-0.27**	-1.58**
	(0.32)	(0.10)	(0.49)
Married respondents	-0.83*	-0.02	-1.11***
	(0.37)	(0.10)	(0.31)
Unmarried male respondents	-0.69*	-0.29*	-1.42*
	(0.34)	(0.13)	(0.59)
Married male respondents	-0.63*	-0.21	-1.01**
	(0.37)	(0.19)	(0.36)
Unmarried female respondents	-1.12**	-0.27**	-1.72***
	(0.35)	(0.09)	(0.43)
Married female respondents	-1.02**	0.07	-1.30***
	(0.37)	(0.10)	(0.35)

Notes: The dependent variable is the change in the log count of the working-age population multiplied by a factor of 100. The number of observations is 1,444 (722 commuting zones in each of the two time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the population in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 3.3: **Robot Adoption Effects on Young Population Employment by Industry Groups (2SLS)** [cited on page 105]

	(1)	(2)	(3)
	Samples		
Subsamples	All respondents	Male respondents	Female respondents
All industries	-1.23**	-1.15*	-1.38***
	(0.39)	(0.46)	(0.34)
Manufacturing industries	-0.67	-1.31*	1.02
	(0.75)	(0.75)	(0.99)
High-skilled non-manufacturing	-1.68***	-1.81***	-1.61***
industries	(0.32)	(0.39)	(0.38)
Low-skilled non-manufacturing	-1.72***	-1.36***	-1.93***
industries	(0.33)	(0.35)	(0.38)

Notes: The dependent variable is the change in the log count of the total employment multiplied by a factor of 100. The number of observations is 1,444 (722 commuting zones in each of the two time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the total employment in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 3.4: **ROBOT ADOPTION EFFECTS ON YOUNG POPULATION EMPLOYMENT BY INDUSTRY AND SOCIO-DEMOGRAPHIC GROUPS (2SLS)** [cited on page 105]

	(1)	(2)	(3)	(4)
	Samples			
	Male workers		Female workers	
Subsamples	Unmarried	Married	Unmarried	Married
All industries	-1.42*	-1.01**	-1.72***	-1.30***
	(0.59)	(0.36)	(0.43)	(0.35)
Manufacturing industries	-2.00*	-0.77	-0.11	1.98*
	(0.95)	(0.59)	(1.28)	(0.86)
High-skilled non-manufacturing	-1.90***	-1.51**	-1.92***	-1.59***
industries	(0.53)	(0.55)	(0.50)	(0.44)
Low-skilled non-manufacturing	-1.47**	-1.49***	-2.28***	-1.88***
industries	(0.47)	(0.41)	(0.42)	(0.47)

Notes: The dependent variable is the change in the log count of the total employment multiplied by a factor of 100. The number of observations is 1,444 (722 commuting zones in each of the two time periods). The robot adoption variable is standardized to have a mean of 0 and a standard deviation of 1. Following Autor and Dorn [10] and Faber et al. [40], regressions include such covariates as instrumented US exposure to Chinese imports; dummy variables for census divisions interacted with dummies for time periods; the change in the dependent variable from 1970 to 1990; demographic characteristics in 1990 (log of population, the fraction of population aged 65 and above, fraction of population without a college degree, the fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics), interacted with time dummies; shares of employment across major industries in 1990 (manufacturing, construction, mining, agriculture), interacted with time dummies; the average offshorability index and the proportion of routine jobs in 1990, interacted with time dummies. Standard errors in parentheses are heteroskedasticity-robust and permit arbitrary clustering at the state level. All regressions presented in the table are weighted by a commuting zone's national share of the total employment in 1990.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 3.5: DESCRIPTIVE STATISTICS OF NLSY97 PANEL DATA [cited on page 107]

	Obs.	Mean	Std. Dev.	Min	Max
Female	108825	0.5003	0.5000	0	1
Male	108825	0.4997	0.5000	0	1
White	108825	0.4953	0.5000	0	1
Black	108825	0.2791	0.4485	0	1
Hispanic	108825	0.2159	0.4115	0	1
Mixed	108825	0.0097	0.0983	0	1
Age	108825	26.50	4.72	18	36
Number of children	108825	0.63	1.05	0	12
Unmarried	108825	0.56	0.50	0	1
Married	108825	0.44	0.50	0	1
Robot Adoption	108825	1.389	1.375	0.007	9.915
Migration (1 if new CZ)	85932	0.096	0.295	0	1
Labor Force Participation (Weeks)	108825	41.48	18.11	0	53
Labor Force Participation (>0% of weeks)	108825	0.90	0.30	0	1
Labor Force Participation (>25% of weeks)	108825	0.86	0.35	0	1
Labor Force Participation (>50% of weeks)	108825	0.81	0.39	0	1
Employment (Weeks)	108825	37.99	20.01	0	53
Employment (>0% of weeks)	108825	0.85	0.35	0	1
Employment (>25% of weeks)	108825	0.81	0.39	0	1
Employment (>50% of weeks)	108825	0.75	0.44	0	1
Employment in Manuf. Ind. (Weeks)	108825	5.81	15.31	0	53
Employment in Manuf. Ind. (>0% of weeks)	108825	0.15	0.36	0	1
Employment in Manuf. Ind. (>25% of weeks)	108825	0.13	0.34	0	1
Employment in Manuf. Ind. (>50% of weeks)	108825	0.11	0.31	0	1
Employment in High-Skilled Non-Manuf. Ind. (Weeks)	108825	11.73	20.58	0	53
Employment in High-Skilled Non-Manuf. Ind. (>0% of weeks)	108825	0.28	0.45	0	1
Employment in High-Skilled Non-Manuf. Ind. (>25% of weeks)	108825	0.25	0.44	0	1
Employment in High-Skilled Non-Manuf. Ind. (>50% of weeks)	108825	0.22	0.42	0	1
Employment in Low-Skilled Non-Manuf. Ind. (Weeks)	108825	20.08	22.99	0	53
Employment in Low-Skilled Non-Manuf. Ind. (>0% of weeks)	108825	0.51	0.50	0	1
Employment in Low-Skilled Non-Manuf. Ind. (>25% of weeks)	108825	0.45	0.50	0	1
Employment in Low-Skilled Non-Manuf. Ind. (>50% of weeks)	108825	0.39	0.49	0	1
Employment (Log of Hours)	91282	7.29	0.83	0	9.09
Employment in Manuf. Ind. (Log of Hours)	16273	7.15	1.00	0	9.08
Employment in High-Skilled Non-Manuf. Ind. (Log of Hours)	29906	7.19	0.93	0	9.06
Employment in Low-Skilled Non-Manuf. Ind. (Log of Hours)	54333	7.04	1.00	0	9.09

Notes: This table presents numbers of observations, unweighted averages, standard deviations, minimum and maximum values of variables across respondents of the sample.

Table 3.6: **Robot Adoption Effects on Migration and Labor Force Participation (2SLS)**
[cited on page 108]

	(1)	(2)	(3)	(4)
	Dependent Variables			
Samples	Migration	Labor Force Participation (>0%)	Labor Force Participation (>25%)	Labor Force Participation (>50%)
Total sample	-0.007***	0.005*	0.007**	0.007**
	(0.002)	(0.002)	(0.002)	(0.003)
Male respondents	-0.008**	0.005*	0.006*	0.007*
	(0.002)	(0.002)	(0.003)	(0.003)
Female respondents	-0.007**	0.005	0.007*	0.008*
	(0.002)	(0.003)	(0.004)	(0.004)
Unmarried male	-0.006*	0.006*	0.007	0.007
respondents	(0.003)	(0.003)	(0.004)	(0.005)
Married male	-0.012***	0.004	0.005	0.006
respondents	(0.003)	(0.003)	(0.004)	(0.004)
Unmarried female	-0.010**	0.001	0.003	0.001
respondents	(0.003)	(0.004)	(0.005)	(0.005)
Married female	-0.004	0.007	0.010*	0.012*
respondents	(0.003)	(0.005)	(0.005)	(0.006)

Notes: The binary dependent variables are migration (1 if the respondent reported lives in a new commuting zone, and 0 otherwise) and three variables of labor force participation (1 if the respondent was in the labor force more than 0% of weeks, more than 25% of weeks, and more than 50% of weeks in the calendar year, respectively). Regressions include such covariates as individual-level variables (age, gender, race, marital status, education, geographic division, and number of children) and demographic characteristics in 1990 of the respondent's commuting zone (log of population, fraction of population aged 65 and above, fraction of population without a college degree, fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics, shares of employment in broad industries, the share of routine jobs, and the average offshorability index). Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the individual level.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 3.7: ROBOT ADOPTION EFFECTS ON EMPLOYMENT (2SLS) [cited on page 109]

	(1)	(2)	(3)	(4)
	Dependent Variables			
Samples	Employment (>0%)	Employment (>25%)	Employment (>50%)	Employment (Log Hours)
Total sample	0.003	0.005*	0.004	0.006
	(0.002)	(0.003)	(0.003)	(0.005)
Male respondents	0.002	0.003	0.003	0.003
	(0.003)	(0.003)	(0.004)	(0.007)
Female respondents	0.005	0.007*	0.007*	0.012
	(0.004)	(0.004)	(0.004)	(0.007)
Unmarried male respondents	0.002	0.002	0.001	-0.000
	(0.005)	(0.005)	(0.006)	(0.009)
Married male respondents	0.002	0.003	0.003	-0.003
	(0.004)	(0.004)	(0.004)	(0.007)
Unmarried female respondents	0.001	0.002	0.002	0.012
	(0.005)	(0.005)	(0.005)	(0.009)
Married female respondents	0.006	0.009*	0.010*	0.008
	(0.005)	(0.005)	(0.006)	(0.011)

Notes: The binary dependent variables are three variables of employment (1 if the respondent was employed more than 0% of weeks, more than 25% of weeks, and more than 50% of weeks in the calendar year, respectively) and the log count of annual worked hours. Regressions include such covariates as individual-level variables (age, gender, race, marital status, education, geographic division, and number of children) and demographic characteristics in 1990 of the respondent's commuting zone (log of population, fraction of population aged 65 and above, fraction of population without a college degree, fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics, shares of employment in broad industries, the share of routine jobs, and the average offshorability index). Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the individual level.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 3.8: **Robot Adoption Effects on Employment in Industry Groups (2SLS)** [cited on page 110]

	(1)	(2)	(3)	(4)
	Dependent Variables			
Samples	Employment (>0%)	Employment (>25%)	Employment (>50%)	Employment (Log Hours)
	Male respondents			
All industries	0.002	0.003	0.003	0.003
	(0.003)	(0.003)	(0.004)	(0.007)
Manufacturing industries	0.004	0.006	0.004	0.011
	(0.005)	(0.005)	(0.006)	(0.013)
High-skilled non-manufacturing	-0.007	-0.007	-0.006	0.015
industries	(0.005)	(0.005)	(0.005)	(0.013)
Low-skilled non-manufacturing	-0.001	0.000	0.002	0.004
industries	(0.006)	(0.006)	(0.006)	(0.010)
	Female respondents			
All industries	0.005	0.007*	0.007*	0.012
	(0.004)	(0.004)	(0.004)	(0.007)
Manufacturing industries	-0.003	-0.002	-0.001	0.014
	(0.003)	(0.003)	(0.003)	(0.027)
High-skilled non-manufacturing	0.005	0.007	0.009	0.030**
industries	(0.006)	(0.006)	(0.006)	(0.011)
Low-skilled non-manufacturing	-0.007	-0.007	-0.004	0.007
industries	(0.006)	(0.006)	(0.006)	(0.012)

Notes: The binary dependent variables are three variables of employment (1 if the respondent was employed more than 0% of weeks, more than 25% of weeks, and more than 50% of weeks in the calendar year, respectively) and the log count of annual worked hours. Regressions include such covariates as individual-level variables (age, gender, race, marital status, education, geographic division, and number of children) and demographic characteristics in 1990 of the respondent's commuting zone (log of population, fraction of population aged 65 and above, fraction of population without a college degree, fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics, shares of employment in broad industries, the share of routine jobs, and the average offshorability index). Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the individual level. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 3.9: ROBOT ADOPTION EFFECTS ON MIGRATION AND LABOR FORCE PARTICIPATION (FE-2SLS) [cited on page 111]

	(1)	(2)	(3)	(4)
	Dependent Variables			
Samples	Migration	Labor Force Participation (>0%)	Labor Force Participation (>25%)	Labor Force Participation (>50%)
Total sample	-0.005	0.002	0.002	0.005*
	(0.003)	(0.002)	(0.002)	(0.002)
Male respondents	-0.012**	0.001	0.001	-0.000
	(0.005)	(0.002)	(0.003)	(0.003)
Female respondents	0.003	0.003	0.002	0.009*
	(0.005)	(0.003)	(0.003)	(0.003)
Unmarried male	-0.006	0.006*	0.006	0.004
respondents	(0.006)	(0.003)	(0.004)	(0.005)
Married male	-0.038**	0.002	0.000	0.002
respondents	(0.012)	(0.003)	(0.004)	(0.005)
Unmarried female	0.000	0.003	-0.000	0.002
respondents	(0.007)	(0.004)	(0.004)	(0.005)
Married female	-0.003	-0.002	0.001	0.010*
respondents	(0.010)	(0.005)	(0.006)	(0.006)

Notes: The binary dependent variables are migration (1 if the respondent reported lives in a new commuting zone, and 0 otherwise) and three variables of labor force participation (1 if the respondent was in the labor force more than 0% of weeks, more than 25% of weeks, and more than 50% of weeks in the calendar year, respectively). Regressions include such covariates as individual-level variables (age, gender, race, marital status, education, geographic division, and number of children) and demographic characteristics in 1990 of the respondent's commuting zone (log of population, fraction of population aged 65 and above, fraction of population without a college degree, fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics, shares of employment in broad industries, the share of routine jobs, and the average offshorability index). Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the individual level.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 3.10: Robot Adoption Effects on Employment (FE-2SLS) [cited on page 111]

	(1)	(2)	(3)	(4)
	Dependent Variables			
	Employment	Employment	Employment	Employment
Samples	(>0%)	(>25%)	(>50%)	(Log Hours)
Total sample	-0.007**	-0.006**	-0.005*	-0.005
	(0.002)	(0.002)	(0.003)	(0.006)
Male respondents	-0.007**	-0.009**	-0.010**	-0.016*
	(0.003)	(0.003)	(0.003)	(0.008)
Female respondents	-0.005*	-0.003	-0.000	0.004
	(0.003)	(0.003)	(0.004)	(0.009)
Unmarried male	-0.001	-0.004	-0.007	-0.009
respondents	(0.004)	(0.005)	(0.005)	(0.012)
Married male	-0.008*	-0.013**	-0.012*	-0.048***
respondents	(0.004)	(0.005)	(0.005)	(0.013)
Unmarried female	-0.007	-0.009*	-0.011*	-0.011
respondents	(0.004)	(0.005)	(0.005)	(0.012)
Married female	-0.012*	-0.005	0.002	0.016
respondents	(0.005)	(0.006)	(0.006)	(0.015)

Notes: The binary dependent variables are three variables of employment (1 if the respondent was employed more than 0% of weeks, more than 25% of weeks, and more than 50% of weeks in the calendar year, respectively) and the log count of annual worked hours. Regressions include such covariates as individual-level variables (age, gender, race, marital status, education, geographic division, and number of children) and demographic characteristics in 1990 of the respondent's commuting zone (log of population, fraction of population aged 65 and above, fraction of population without a college degree, fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics, shares of employment in broad industries, the share of routine jobs, and the average offshorability index). Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the individual level.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 3.11: ROBOT ADOPTION EFFECTS ON EMPLOYMENT IN INDUSTRY GROUPS (FE-2SLS) [cited on page 112]

	(1)	(2)	(3)	(4)
	Dependent Variables			
Samples	Employment (>0%)	Employment (>25%)	Employment (>50%)	Employment (Log Hours)
	Male respondents			
All industries	-0.007**	-0.009**	-0.010**	-0.016*
	(0.003)	(0.003)	(0.003)	(0.008)
Manufacturing industries	-0.000	0.007*	0.006*	-0.032
	(0.004)	(0.003)	(0.003)	(0.022)
High-skilled non-manufacturing industries	-0.006*	-0.007*	-0.006*	-0.012
	(0.003)	(0.003)	(0.003)	(0.019)
Low-skilled non-manufacturing industries	-0.004	-0.001	0.002	-0.008
	(0.004)	(0.004)	(0.004)	(0.013)
	Female respondents			
All industries	-0.005*	-0.003	-0.000	0.004
	(0.003)	(0.003)	(0.004)	(0.009)
Manufacturing industries	-0.007**	-0.003	0.001	0.033
	(0.002)	(0.002)	(0.002)	(0.059)
High-skilled non-manufacturing industries	0.006	0.009*	0.008*	0.039*
	(0.004)	(0.004)	(0.004)	(0.016)
Low-skilled non-manufacturing industries	-0.010*	-0.009*	-0.005	-0.007
	(0.004)	(0.004)	(0.005)	(0.014)

Notes: The binary dependent variables are three variables of employment (1 if the respondent was employed more than 0% of weeks, more than 25% of weeks, and more than 50% of weeks in the calendar year, respectively) and the log count of annual worked hours. Regressions include such covariates as individual-level variables (age, gender, race, marital status, education, geographic division, and number of children) and demographic characteristics in 1990 of the respondent's commuting zone (log of population, fraction of population aged 65 and above, fraction of population without a college degree, fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics, shares of employment in broad industries, the share of routine jobs, and the average offshorability index). Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the individual level.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 3.12: Robot Adoption (Alternative Definition) Effects on Employment (FE-2SLS)
[cited on page 115]

	(1)	(2)	(3)	(4)
	Dependent Variables			
	Employment	Employment	Employment	Employment
Subsamples	(>0%)	(>25%)	(>50%)	(Log Hours)
Total sample	-0.080***	-0.135***	-0.179***	-0.87***
	(0.013)	(0.020)	(0.026)	(0.06)
Male respondents	-0.037	-0.137**	-0.169**	-0.96***
	(0.027)	(0.043)	(0.057)	(0.13)
Female respondents	-0.087***	-0.117***	-0.169***	-0.78***
	(0.014)	(0.020)	(0.027)	(0.07)
Unmarried male	-0.078*	-0.209***	-0.243**	-1.20***
respondents	(0.037)	(0.059)	(0.075)	(0.17)
Married male	0.004	-0.025	0.011	-0.59**
respondents	(0.044)	(0.065)	(0.090)	(0.22)
Unmarried female	-0.093***	-0.133***	-0.186***	-0.91***
respondents	(0.017)	(0.027)	(0.037)	(0.09)
Married female	-0.062*	-0.077*	-0.124**	-0.47***
respondents	(0.024)	(0.033)	(0.047)	(0.12)

Notes: The binary dependent variables are three variables of employment (1 if the respondent was employed more than 0% of weeks, more than 25% of weeks, and more than 50% of weeks in the calendar year, respectively) and the log count of annual worked hours. Regressions include such covariates as individual-level variables (age, gender, race, marital status, education, geographic division, and number of children) and demographic characteristics in 1990 of the respondent's commuting zone (log of population, fraction of population aged 65 and above, fraction of population without a college degree, fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics, shares of employment in broad industries, the share of routine jobs, and the average offshorability index). Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the individual level.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

Table 3.13: ROBOT ADOPTION (ALTERNATIVE DEFINITION) EFFECTS ON EMPLOYMENT IN INDUSTRY GROUPS (FE-2SLS) [cited on page 116]

	(1)	(2)	(3)	(4)
	Dependent Variables			
Subsamples	Employment (>0%)	Employment (>25%)	Employment (>50%)	Employment (Log Hours)
	Male respondents			
All industries	-0.037	-0.137**	-0.169**	-0.96***
	(0.027)	(0.043)	(0.057)	(0.13)
Manufacturing industries	-0.274***	-0.439***	-0.708***	-0.96**
	(0.045)	(0.052)	(0.062)	(0.41)
High-skilled non-manufacturing industries	0.313***	0.298***	0.262***	-0.70***
	(0.062)	(0.060)	(0.060)	(0.11)
Low-skilled non-manufacturing industries	0.336***	0.128*	0.192**	-0.66***
	(0.073)	(0.071)	(0.073)	(0.06)
	Female respondents			
All industries	-0.087***	-0.117***	-0.169***	-0.78***
	(0.014)	(0.020)	(0.027)	(0.07)
Manufacturing industries	0.015	-0.053**	-0.109***	0.74
	(0.014)	(0.015)	(0.017)	(2.72)
High-skilled non-manufacturing industries	0.110***	0.090**	-0.008	-0.65***
	(0.031)	(0.031)	(0.032)	(0.10)
Low-skilled non-manufacturing industries	0.023	-0.067*	-0.114***	-0.66***
	(0.034)	(0.033)	(0.032)	(0.06)

Notes: The binary dependent variables are three variables of employment (1 if the respondent was employed more than 0% of weeks, more than 25% of weeks, and more than 50% of weeks in the calendar year, respectively) and the log count of annual worked hours. Regressions include such covariates as individual-level variables (age, gender, race, marital status, education, geographic division, and number of children) and demographic characteristics in 1990 of the respondent's commuting zone (log of population, fraction of population aged 65 and above, fraction of population without a college degree, fraction of population with at least some college, population shares of Whites, Blacks, Asians, and Hispanics, shares of employment in broad industries, the share of routine jobs, and the average offshorability index). Standard errors in parentheses are robust against heteroskedasticity and allow for arbitrary clustering at the individual level. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$.

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Appendices

Appendix A

Chapter 1 Appendix

Figure A.1: Survey Participation Rates [cited on page 13]

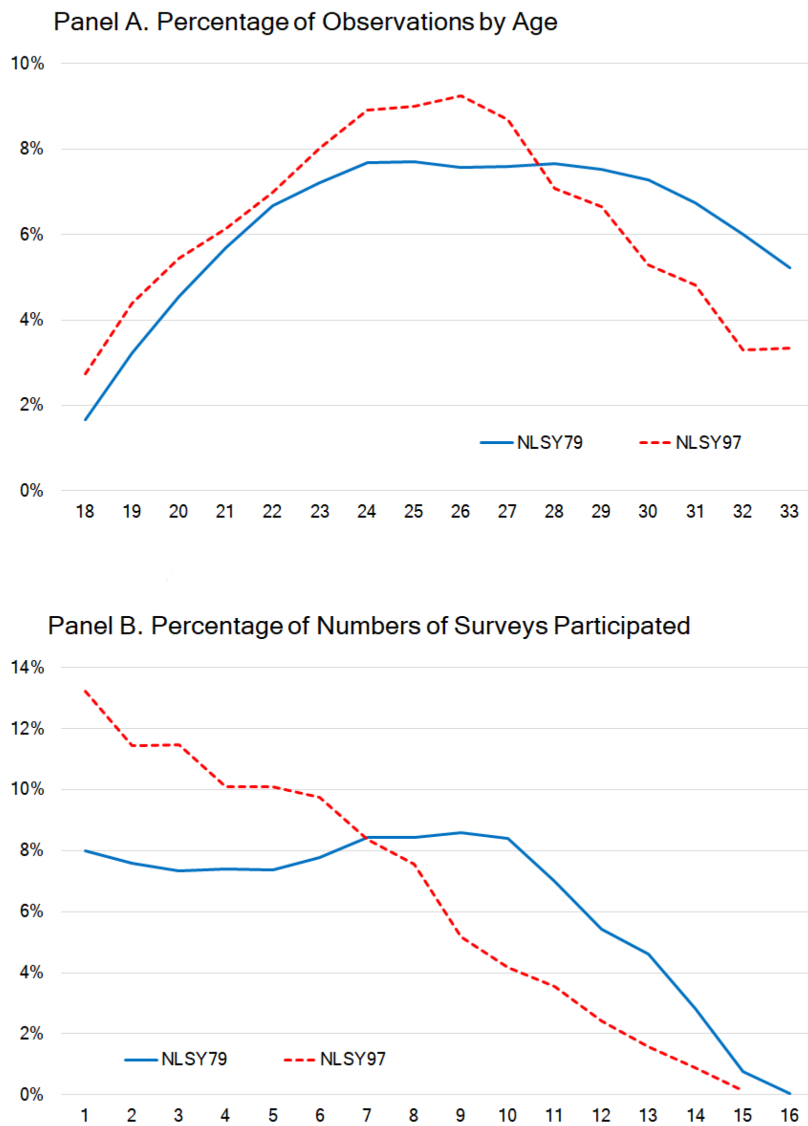

Table A.1: Descriptive Statistics of Skills Demand (SD) Levels Dummy Variables
[cited on page 16]

	NLSY79		NLSY97		Total Sample	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Physical Strength Demand (ref: Low)						
Middle	0.278	0.448			0.278	0.448
High	0.415	0.493			0.415	0.493
Reasoning SD (ref: Low)						
Middle	0.599	0.490			0.599	0.490
High	0.068	0.253			0.068	0.253
Mathematics SD (ref: Low)						
Middle	0.298	0.457			0.298	0.457
High	0.156	0.363			0.156	0.363
Language SD (ref: Low)						
Middle	0.440	0.496			0.440	0.496
High	0.068	0.253			0.068	0.253
SVP Demand (ref: Low)						
Middle	0.308	0.461			0.308	0.461
High	0.160	0.367			0.160	0.367
Basic SD (ref: Low)						
Middle			0.541	0.498	0.541	0.498
High			0.084	0.278	0.084	0.278
Complex Problem Solving SD (ref: Low)						
Middle			0.395	0.489	0.395	0.489
High			0.055	0.227	0.055	0.227
Resource Management SD (ref: Low)						
Middle			0.563	0.496	0.563	0.496
High			0.074	0.262	0.074	0.262
Social SD (ref: Low)						
Middle			0.415	0.493	0.415	0.493
High			0.275	0.446	0.275	0.446
Systems SD (ref: Low)						
Middle			0.383	0.486	0.383	0.486
High			0.067	0.249	0.067	0.249
Technical SD (ref: Low)						
Middle			0.297	0.457	0.297	0.457
High			0.286	0.452	0.286	0.452
N of respondents	7,685		4,782		12,467	
N of observations	17,247		10,693		27,940	

Appendix B

Chapter 2 Appendix

Table B.1: Total Employment (numbers of workers) in Manufacturing Industries by Occupational Groups [cited on page 68]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	2757	(8975)	688	(2628)	2941	(8560)	646	(2218)	3351	(9342)	720	(2349)	3619	(9916)	926	(2884)
Business and financial operations	480	(1563)	443	(1596)	533	(1545)	520	(1541)	510	(1467)	543	(1597)	582	(1695)	618	(1866)
Computer and mathematical science	370	(1429)	160	(665)	547	(1909)	185	(653)	479	(1680)	145	(501)	522	(1756)	155	(524)
Architecture and engineering	1574	(5503)	181	(650)	1538	(4777)	215	(688)	1443	(4459)	216	(719)	1565	(4882)	262	(893)
Life, physical, and social science	626	(1868)	173	(572)	240	(746)	121	(429)	228	(743)	134	(507)	216	(715)	137	(490)
Community and social service occupation	3	(11)	3	(11)	2	(8)	2	(10)	1	(9)	1	(8)	3	(13)	3	(15)
Legal	19	(88)	12	(61)	19	(82)	17	(71)	22	(93)	22	(94)	24	(96)	26	(114)
Education, training, and library	23	(74)	19	(66)	22	(58)	16	(47)	23	(64)	14	(44)	29	(77)	17	(44)
Arts, design, entertainment, sports, and media	354	(1347)	273	(1204)	198	(693)	130	(468)	180	(660)	121	(472)	186	(657)	126	(459)
Healthcare practitioner and technical	33	(120)	41	(119)	28	(83)	32	(103)	23	(64)	22	(65)	39	(98)	33	(99)
Healthcare support	2	(8)	6	(18)	3	(14)	5	(19)	3	(12)	3	(14)	4	(15)	5	(20)
Protective service	108	(311)	19	(65)	63	(144)	19	(46)	49	(114)	19	(55)	49	(116)	19	(54)
Food preparation and serving related	32	(100)	37	(106)	26	(82)	26	(62)	20	(76)	20	(66)	34	(110)	34	(103)
Building and grounds cleaning and maintenance	383	(923)	81	(186)	265	(567)	70	(149)	256	(587)	59	(130)	249	(522)	58	(155)
Personal care and service	10	(33)	11	(36)	6	(22)	6	(20)	3	(13)	5	(18)	5	(18)	7	(25)
Sales and related	858	(2846)	371	(1298)	697	(2125)	303	(1013)	697	(2134)	316	(1079)	665	(1951)	306	(1015)
Office and administrative support	1163	(3616)	2795	(8580)	1037	(2908)	2403	(6393)	885	(2540)	2050	(5457)	846	(2277)	1677	(4402)
Farming, fishing, and forestry	121	(231)	4	(9)	33	(54)	12	(31)	25	(51)	12	(41)	21	(41)	10	(50)
Construction and extraction	7212	(19176)	209	(541)	8426	(19720)	244	(511)	10145	(26442)	268	(594)	9276	(24952)	277	(683)
Installation, maintenance, and repair	1529	(3627)	73	(190)	1802	(3728)	89	(204)	1662	(3448)	66	(146)	1650	(3439)	58	(145)
Production	8067	(21315)	4176	(10631)	7807	(18060)	3594	(8717)	6636	(15665)	2616	(6880)	6286	(13980)	2323	(5772)
Transportation and material moving	2339	(4751)	521	(1177)	2002	(3776)	411	(835)	1979	(3919)	369	(811)	1948	(3848)	379	(885)
TOTAL	28062	(75827)	10298	(29476)	28234	(67443)	9068	(23383)	28621	(71224)	7742	(20812)	27819	(68687)	7457	(19812)

Notes: This table presents unweighted averages and standard deviations of total employment (numbers of workers) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table B.2: Total Employment (shares by gender) in Manufacturing Industries by Occupational Groups [cited on page 68]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	83.1	(6.1)	16.9	(6.1)	86.1	(5.4)	13.9	(5.4)	86.1	(5.6)	13.9	(5.6)	83.2	(5.0)	16.8	(5.0)
Business and financial operations	57.0	(16.4)	43.0	(16.4)	51.5	(16.5)	48.5	(16.5)	47.9	(16.1)	52.1	(16.1)	48.1	(13.3)	51.9	(13.3)
Computer and mathematical science	71.7	(24.9)	28.3	(24.9)	74.5	(22.1)	25.5	(22.1)	77.1	(20.4)	22.9	(20.4)	77.9	(17.9)	22.1	(17.9)
Architecture and engineering	89.7	(8.2)	10.3	(8.2)	88.1	(7.9)	11.9	(7.9)	87.0	(8.7)	13.0	(8.7)	86.2	(7.8)	13.8	(7.8)
Life, physical, and social science	77.2	(17.3)	22.8	(17.3)	69.6	(22.6)	30.4	(22.6)	67.4	(24.8)	32.6	(24.8)	66.0	(21.7)	34.0	(21.7)
Community and social service occupation	54.4	(46.3)	45.6	(46.3)	46.3	(46.8)	53.7	(46.8)	44.6	(48.2)	55.4	(48.2)	47.1	(45.8)	52.9	(45.8)
Legal	64.9	(39.3)	35.1	(39.3)	44.0	(40.9)	56.0	(40.9)	47.4	(41.1)	52.6	(41.1)	46.9	(41.1)	53.1	(41.1)
Education, training, and library	52.7	(38.6)	47.3	(38.6)	61.2	(38.3)	38.8	(38.3)	69.5	(36.4)	30.5	(36.4)	62.0	(37.3)	38.0	(37.3)
Arts, design, entertainment, sports, and media	53.1	(19.6)	46.9	(19.6)	54.1	(26.5)	45.9	(26.5)	57.2	(28.2)	42.8	(28.2)	60.0	(25.0)	40.0	(25.0)
Healthcare practitioner and technical	41.1	(35.5)	58.9	(35.5)	48.5	(37.8)	51.5	(37.8)	54.3	(38.4)	45.7	(38.4)	60.1	(33.0)	39.9	(33.0)
Healthcare support	24.5	(38.7)	75.5	(38.7)	36.6	(44.5)	63.4	(44.5)	42.6	(46.4)	57.4	(46.4)	46.7	(45.0)	53.3	(45.0)
Protective service	84.8	(20.7)	15.2	(20.7)	73.4	(29.1)	26.6	(29.1)	71.0	(31.8)	29.0	(31.8)	74.6	(29.2)	25.4	(29.2)
Food preparation and serving related	37.7	(34.3)	62.3	(34.3)	40.7	(35.2)	59.3	(35.2)	46.8	(39.9)	53.2	(39.9)	42.0	(36.2)	58.0	(36.2)
Building and grounds cleaning and maintenance	79.8	(15.7)	20.2	(15.7)	78.3	(16.9)	21.7	(16.9)	79.5	(16.3)	20.5	(16.3)	81.1	(14.8)	18.9	(14.8)
Personal care and service	53.1	(42.4)	46.9	(42.4)	48.9	(44.8)	51.1	(44.8)	32.8	(42.4)	67.2	(42.4)	52.5	(45.8)	47.5	(45.8)
Sales and related	68.1	(14.3)	31.9	(14.3)	71.4	(13.6)	28.6	(13.6)	71.1	(16.7)	28.9	(16.7)	71.2	(14.3)	28.8	(14.3)
Office and administrative support	28.0	(6.8)	72.0	(6.8)	28.2	(7.7)	71.8	(7.7)	28.6	(8.1)	71.4	(8.1)	31.5	(8.8)	68.5	(8.8)
Farming, fishing, and forestry	96.4	(9.9)	3.6	(9.9)	79.2	(24.5)	20.8	(24.5)	74.6	(31.5)	25.4	(31.5)	74.2	(33.1)	25.8	(33.1)
Construction and extraction	96.9	(1.4)	3.1	(1.4)	97.0	(1.3)	3.0	(1.3)	97.2	(1.3)	2.8	(1.3)	97.2	(1.4)	2.8	(1.4)
Installation, maintenance, and repair	96.1	(3.3)	3.9	(3.3)	95.8	(3.3)	4.2	(3.3)	96.5	(3.2)	3.5	(3.2)	97.0	(2.7)	3.0	(2.7)
Production	67.2	(10.7)	32.8	(10.7)	70.2	(8.3)	29.8	(8.3)	73.3	(7.2)	26.7	(7.2)	75.6	(6.7)	24.4	(6.7)
Transportation and material moving	83.9	(7.2)	16.1	(7.2)	84.2	(6.5)	15.8	(6.5)	85.6	(7.0)	14.4	(7.0)	85.3	(5.8)	14.7	(5.8)
TOTAL	75.4	(6.6)	24.6	(6.6)	77.9	(5.5)	22.1	(5.5)	80.5	(4.7)	19.5	(4.7)	80.9	(4.1)	19.1	(4.1)

Notes: This table presents unweighted averages and standard deviations of total employment (shares by gender) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table B.3: Total Employment (shares by occupational groups) in Manufacturing Industries by Occupational Groups [cited on page 68]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	7.3	(2.2)	4.9	(2.8)	7.7	(2.4)	4.7	(2.7)	9.2	(2.6)	6.4	(3.4)	10.6	(2.7)	9.4	(4.0)
Business and financial operations	1.2	(0.5)	2.9	(1.8)	1.3	(0.6)	4.4	(2.1)	1.1	(0.6)	5.0	(2.4)	1.4	(0.7)	6.2	(2.7)
Computer and mathematical science	0.5	(0.7)	0.7	(1.0)	0.8	(1.0)	1.0	(1.1)	0.8	(0.8)	0.9	(1.0)	1.0	(0.8)	1.2	(1.2)
Architecture and engineering	3.4	(2.0)	1.2	(1.2)	3.4	(1.9)	1.6	(1.3)	3.2	(1.8)	1.9	(1.6)	3.7	(2.0)	2.5	(1.6)
Life, physical, and social science	1.6	(1.0)	1.5	(1.3)	0.6	(0.5)	1.0	(1.3)	0.6	(0.5)	1.2	(1.3)	0.6	(0.5)	1.4	(1.4)
Community and social service occupation	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.0	(0.1)
Legal	0.0	(0.1)	0.0	(0.2)	0.0	(0.1)	0.1	(0.2)	0.0	(0.1)	0.1	(0.3)	0.0	(0.1)	0.2	(0.4)
Education, training, and library	0.1	(0.1)	0.1	(0.3)	0.1	(0.1)	0.1	(0.3)	0.1	(0.1)	0.1	(0.4)	0.1	(0.2)	0.2	(0.4)
Arts, design, entertainment, sports, and media	0.7	(0.5)	2.2	(1.8)	0.4	(0.3)	1.2	(1.1)	0.4	(0.3)	1.1	(1.1)	0.4	(0.3)	1.3	(1.2)
Healthcare practitioner and technical	0.1	(0.1)	0.3	(0.4)	0.1	(0.1)	0.3	(0.4)	0.1	(0.1)	0.3	(0.6)	0.1	(0.2)	0.4	(0.6)
Healthcare support	0.0	(0.0)	0.1	(0.3)	0.0	(0.0)	0.1	(0.2)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.1	(0.3)
Protective service	0.4	(0.3)	0.2	(0.4)	0.2	(0.2)	0.4	(0.7)	0.2	(0.3)	0.4	(0.7)	0.2	(0.3)	0.4	(0.7)
Food preparation and serving related	0.1	(0.1)	0.5	(0.8)	0.1	(0.1)	0.4	(0.5)	0.1	(0.1)	0.2	(0.5)	0.1	(0.2)	0.5	(0.7)
Building and grounds cleaning and maintenance	1.5	(0.6)	1.1	(0.9)	1.1	(0.6)	1.1	(1.1)	1.1	(0.6)	1.2	(1.2)	1.1	(0.6)	1.1	(1.2)
Personal care and service	0.0	(0.1)	0.1	(0.3)	0.0	(0.1)	0.1	(0.2)	0.0	(0.0)	0.1	(0.5)	0.0	(0.1)	0.1	(0.5)
Sales and related	2.1	(1.1)	3.2	(2.0)	1.5	(0.8)	2.3	(1.5)	1.5	(0.8)	2.5	(1.8)	1.6	(0.7)	2.9	(2.0)
Office and administrative support	3.2	(1.1)	26.3	(8.3)	2.9	(1.1)	26.4	(7.4)	2.6	(0.9)	27.4	(8.4)	2.6	(0.9)	25.0	(7.5)
Farming, fishing, and forestry	1.0	(1.5)	0.2	(0.4)	0.3	(0.3)	0.4	(0.8)	0.2	(0.3)	0.4	(0.9)	0.1	(0.2)	0.3	(0.7)
Construction and extraction	29.9	(9.2)	3.3	(2.5)	33.9	(10.3)	4.2	(3.5)	37.4	(10.5)	5.1	(3.9)	34.7	(9.3)	4.6	(3.2)
Installation, maintenance, and repair	6.2	(1.7)	0.7	(0.6)	7.2	(1.9)	1.1	(0.9)	6.6	(1.6)	1.0	(0.9)	6.8	(1.6)	0.9	(0.9)
Production	28.8	(8.5)	43.6	(15.4)	28.9	(8.8)	42.9	(13.1)	25.5	(8.9)	38.1	(13.2)	25.3	(8.2)	34.6	(12.5)
Transportation and material moving	11.8	(3.4)	6.7	(2.9)	9.5	(2.9)	6.2	(2.8)	9.5	(3.0)	6.6	(3.6)	9.4	(3.0)	6.9	(3.5)

Notes: This table presents unweighted averages and standard deviations of total employment (shares by occupational groups) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table B.4: Private Employment (numbers of workers) in Manufacturing Industries by Occupational Groups [cited on page 68]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	2142	(7122)	585	(2276)	2267	(6792)	569	(2004)	2396	(6914)	612	(2052)	2669	(7449)	799	(2547)
Business and financial operations	449	(1476)	417	(1517)	500	(1455)	497	(1480)	478	(1380)	516	(1518)	551	(1615)	589	(1786)
Computer and mathematical science	355	(1373)	153	(640)	532	(1860)	179	(636)	466	(1637)	140	(486)	509	(1714)	149	(509)
Architecture and engineering	1440	(5120)	167	(608)	1448	(4574)	205	(664)	1360	(4229)	204	(683)	1486	(4684)	249	(855)
Life, physical, and social science	592	(1783)	164	(547)	231	(727)	119	(424)	219	(722)	130	(496)	208	(698)	133	(480)
Community and social service occupation	2	(7)	1	(6)	1	(7)	1	(6)	1	(8)	1	(5)	2	(10)	3	(14)
Legal	17	(83)	11	(57)	18	(80)	16	(69)	20	(90)	21	(90)	23	(92)	25	(112)
Education, training, and library	20	(64)	16	(57)	20	(53)	14	(43)	21	(61)	13	(40)	27	(71)	16	(41)
Arts, design, entertainment, sports, and media	300	(1135)	219	(965)	173	(622)	103	(388)	158	(589)	101	(406)	167	(591)	108	(407)
Healthcare practitioner and technical	30	(106)	38	(110)	25	(77)	31	(101)	22	(60)	21	(61)	37	(93)	32	(97)
Healthcare support	2	(7)	4	(15)	3	(11)	5	(17)	3	(12)	3	(14)	4	(13)	5	(19)
Protective service	95	(276)	17	(57)	57	(133)	17	(42)	44	(103)	17	(52)	45	(104)	17	(49)
Food preparation and serving related	30	(93)	34	(95)	24	(73)	24	(58)	18	(68)	19	(64)	33	(106)	32	(96)
Building and grounds cleaning and maintenance	347	(826)	73	(165)	242	(517)	63	(135)	236	(543)	53	(116)	225	(466)	53	(142)
Personal care and service	9	(29)	9	(27)	5	(20)	5	(18)	2	(12)	5	(16)	5	(16)	6	(24)
Sales and related	765	(2536)	337	(1189)	620	(1882)	283	(949)	629	(1907)	292	(992)	612	(1787)	286	(943)
Office and administrative support	1099	(3411)	2560	(7974)	997	(2787)	2207	(5947)	843	(2412)	1847	(4981)	809	(2182)	1523	(4033)
Farming, fishing, and forestry	74	(172)	3	(8)	30	(51)	11	(30)	23	(48)	11	(41)	18	(39)	9	(48)
Construction and extraction	5432	(14940)	149	(398)	6164	(14886)	160	(353)	7417	(20000)	167	(380)	6936	(18975)	194	(509)
Installation, maintenance, and repair	1388	(3305)	69	(177)	1656	(3426)	84	(195)	1503	(3103)	62	(136)	1485	(3060)	54	(136)
Production	7650	(20079)	4003	(10082)	7467	(17210)	3464	(8378)	6299	(14812)	2480	(6540)	5995	(13300)	2200	(5493)
Transportation and material moving	2157	(4430)	499	(1121)	1879	(3581)	398	(807)	1853	(3712)	353	(779)	1837	(3649)	363	(849)
TOTAL	24395	(66377)	9528	(27208)	24359	(58653)	8456	(21924)	24011	(60089)	7067	(19140)	23680	(58282)	6846	(18327)

Notes: This table presents unweighted averages and standard deviations of private employment (numbers of workers) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table B.5: **Private Employment (shares by gender) in Manufacturing Industries by Occupational Groups** [cited on page 68]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	81.4	(8.2)	18.6	(8.2)	84.3	(6.8)	15.7	(6.8)	83.4	(7.7)	16.6	(7.7)	80.8	(6.6)	19.2	(6.6)
Business and financial operations	57.3	(18.1)	42.7	(18.1)	51.8	(17.2)	48.2	(17.2)	47.5	(17.0)	52.5	(17.0)	47.9	(14.1)	52.1	(14.1)
Computer and mathematical science	71.8	(25.3)	28.2	(25.3)	75.9	(21.8)	24.1	(21.8)	77.8	(20.3)	22.2	(20.3)	78.1	(18.0)	21.9	(18.0)
Architecture and engineering	89.0	(9.2)	11.0	(9.2)	87.6	(8.5)	12.4	(8.5)	87.0	(9.4)	13.0	(9.4)	86.0	(8.3)	14.0	(8.3)
Life, physical, and social science	76.5	(19.4)	23.5	(19.4)	68.9	(23.2)	31.1	(23.2)	67.3	(25.0)	32.7	(25.0)	65.6	(22.0)	34.4	(22.0)
Community and social service occupation	61.2	(46.5)	38.8	(46.5)	49.3	(47.9)	50.7	(47.9)	50.7	(48.9)	49.3	(48.9)	45.6	(46.7)	54.4	(46.7)
Legal	62.0	(40.1)	38.0	(40.1)	43.9	(40.8)	56.1	(40.8)	46.0	(40.7)	54.0	(40.7)	48.3	(42.0)	51.7	(42.0)
Education, training, and library	56.2	(39.0)	43.8	(39.0)	61.8	(39.3)	38.2	(39.3)	69.9	(36.4)	30.1	(36.4)	62.3	(38.0)	37.7	(38.0)
Arts, design, entertainment, sports, and media	53.3	(22.2)	46.7	(22.2)	60.4	(29.7)	39.6	(29.7)	58.9	(29.4)	41.1	(29.4)	62.5	(27.1)	37.5	(27.1)
Healthcare practitioner and technical	40.9	(36.4)	59.1	(36.4)	46.5	(38.0)	53.5	(38.0)	53.1	(39.0)	46.9	(39.0)	60.1	(33.4)	39.9	(33.4)
Healthcare support	22.7	(38.3)	77.3	(38.3)	34.8	(44.6)	65.2	(44.6)	43.5	(46.7)	56.5	(46.7)	50.9	(45.8)	49.1	(45.8)
Protective service	82.4	(25.7)	17.6	(25.7)	73.9	(30.1)	26.1	(30.1)	72.3	(31.9)	27.7	(31.9)	74.8	(29.7)	25.2	(29.7)
Food preparation and serving related	38.0	(35.3)	62.0	(35.3)	39.6	(35.8)	60.4	(35.8)	47.3	(40.5)	52.7	(40.5)	42.2	(36.5)	57.8	(36.5)
Building and grounds cleaning and maintenance	81.8	(13.4)	18.2	(13.4)	78.7	(16.6)	21.3	(16.6)	79.6	(17.5)	20.4	(17.5)	81.7	(15.1)	18.3	(15.1)
Personal care and service	53.5	(43.6)	46.5	(43.6)	51.7	(44.7)	48.3	(44.7)	30.4	(42.0)	69.6	(42.0)	53.9	(45.6)	46.1	(45.6)
Sales and related	68.2	(15.4)	31.8	(15.4)	70.5	(15.5)	29.5	(15.5)	71.1	(17.2)	28.9	(17.2)	70.9	(15.7)	29.1	(15.7)
Office and administrative support	29.1	(7.7)	70.9	(7.7)	29.7	(7.9)	70.3	(7.9)	30.7	(8.5)	69.3	(8.5)	33.0	(9.0)	67.0	(9.0)
Farming, fishing, and forestry	96.5	(8.1)	3.5	(8.1)	78.1	(26.4)	21.9	(26.4)	73.5	(32.6)	26.5	(32.6)	73.1	(34.0)	26.9	(34.0)
Construction and extraction	97.0	(1.8)	3.0	(1.8)	97.3	(1.4)	2.7	(1.4)	97.6	(1.5)	2.4	(1.5)	97.5	(1.5)	2.5	(1.5)
Installation, maintenance, and repair	96.0	(3.6)	4.0	(3.6)	95.8	(3.4)	4.2	(3.4)	96.4	(3.6)	3.6	(3.6)	97.0	(2.8)	3.0	(2.8)
Production	66.9	(11.0)	33.1	(11.0)	70.3	(8.6)	29.7	(8.6)	73.6	(7.5)	26.4	(7.5)	76.0	(7.0)	24.0	(7.0)
Transportation and material moving	83.1	(7.4)	16.9	(7.4)	83.8	(6.7)	16.2	(6.7)	85.1	(7.3)	14.9	(7.3)	84.9	(6.2)	15.1	(6.2)
TOTAL	73.9	(7.2)	26.1	(7.2)	76.5	(6.1)	23.5	(6.1)	79.2	(5.4)	20.8	(5.4)	79.8	(4.6)	20.2	(4.6)

Notes: This table presents unweighted averages and standard deviations of private employment (shares by gender) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table B.6: Private Employment (shares by occupational groups) in Manufacturing Industries by Occupational Groups [cited on page 68]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	6.2	(2.1)	4.3	(2.7)	6.3	(2.3)	4.1	(2.6)	7.0	(2.5)	5.6	(3.6)	8.6	(2.5)	8.3	(4.0)
Business and financial operations	1.3	(0.6)	2.9	(2.0)	1.4	(0.7)	4.5	(2.3)	1.3	(0.7)	5.3	(2.6)	1.5	(0.8)	6.5	(2.9)
Computer and mathematical science	0.6	(0.8)	0.7	(1.0)	1.0	(1.1)	1.0	(1.2)	0.9	(0.9)	0.9	(1.1)	1.1	(0.9)	1.2	(1.2)
Architecture and engineering	3.4	(2.1)	1.2	(1.2)	3.5	(2.2)	1.6	(1.3)	3.6	(2.1)	2.0	(1.7)	4.1	(2.2)	2.6	(1.7)
Life, physical, and social science	1.8	(1.1)	1.5	(1.4)	0.7	(0.6)	1.1	(1.5)	0.7	(0.6)	1.3	(1.4)	0.7	(0.5)	1.6	(1.7)
Community and social service occupation	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.0	(0.1)	0.0	(0.1)	0.0	(0.1)
Legal	0.0	(0.1)	0.0	(0.2)	0.0	(0.1)	0.1	(0.2)	0.0	(0.1)	0.1	(0.4)	0.0	(0.1)	0.2	(0.5)
Education, training, and library	0.1	(0.1)	0.1	(0.2)	0.1	(0.1)	0.1	(0.3)	0.1	(0.1)	0.1	(0.4)	0.1	(0.2)	0.2	(0.5)
Arts, design, entertainment, sports, and media	0.7	(0.5)	2.0	(1.8)	0.4	(0.3)	0.8	(0.8)	0.4	(0.3)	1.0	(1.2)	0.5	(0.4)	1.1	(1.3)
Healthcare practitioner and technical	0.1	(0.2)	0.3	(0.5)	0.1	(0.1)	0.3	(0.5)	0.1	(0.2)	0.3	(0.7)	0.2	(0.2)	0.4	(0.6)
Healthcare support	0.0	(0.0)	0.1	(0.3)	0.0	(0.0)	0.1	(0.3)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.1	(0.3)
Protective service	0.4	(0.3)	0.2	(0.5)	0.2	(0.2)	0.4	(1.0)	0.2	(0.3)	0.4	(0.7)	0.2	(0.3)	0.4	(0.8)
Food preparation and serving related	0.1	(0.2)	0.5	(0.9)	0.1	(0.2)	0.4	(0.6)	0.1	(0.1)	0.2	(0.5)	0.1	(0.2)	0.6	(0.8)
Building and grounds cleaning and maintenance	1.6	(0.7)	1.1	(0.9)	1.2	(0.6)	1.1	(1.1)	1.2	(0.7)	1.2	(1.4)	1.2	(0.7)	1.1	(1.2)
Personal care and service	0.0	(0.1)	0.1	(0.3)	0.0	(0.1)	0.1	(0.2)	0.0	(0.0)	0.1	(0.6)	0.0	(0.1)	0.1	(0.6)
Sales and related	2.2	(1.2)	3.0	(2.1)	1.6	(0.9)	2.3	(1.6)	1.6	(0.9)	2.6	(1.9)	1.8	(0.9)	3.0	(2.2)
Office and administrative support	3.5	(1.2)	25.7	(8.7)	3.3	(1.2)	26.0	(7.8)	3.0	(1.1)	26.9	(9.1)	3.0	(0.9)	24.9	(8.1)
Farming, fishing, and forestry	0.8	(1.4)	0.1	(0.5)	0.3	(0.4)	0.4	(0.9)	0.2	(0.3)	0.4	(1.0)	0.2	(0.2)	0.3	(0.7)
Construction and extraction	25.7	(9.3)	2.6	(2.2)	28.6	(10.6)	3.0	(3.1)	32.4	(11.6)	3.5	(3.3)	30.3	(9.7)	3.3	(2.7)
Installation, maintenance, and repair	6.6	(1.8)	0.7	(0.7)	7.8	(2.1)	1.1	(0.9)	7.3	(1.8)	1.0	(1.0)	7.3	(1.7)	0.9	(1.0)
Production	32.2	(9.1)	45.6	(15.4)	32.7	(9.5)	44.9	(13.2)	29.3	(10.0)	39.8	(13.6)	28.7	(9.0)	35.9	(13.0)
Transportation and material moving	12.8	(3.7)	7.2	(3.1)	10.5	(3.1)	6.6	(3.1)	10.7	(3.3)	7.1	(3.8)	10.4	(3.2)	7.4	(3.8)

Notes: This table presents unweighted averages and standard deviations of private employment (shares by occupational groups) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table B.7: **Public Employment (numbers of workers) in Manufacturing Industries by Occupational Groups** [cited on page 68]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	64	(178)	23	(87)	41	(106)	10	(35)	61	(174)	17	(55)	73	(193)	24	(76)
Business and financial operations	16	(45)	17	(59)	8	(28)	9	(32)	10	(30)	13	(47)	12	(39)	16	(51)
Computer and mathematical science	8	(35)	6	(30)	6	(32)	4	(20)	7	(37)	4	(17)	9	(35)	4	(18)
Architecture and engineering	99	(304)	12	(43)	65	(184)	9	(32)	63	(206)	11	(39)	60	(190)	11	(41)
Life, physical, and social science	21	(56)	7	(26)	5	(16)	2	(8)	5	(17)	3	(12)	5	(17)	3	(15)
Community and social service occupation	1	(5)	1	(6)	0	(2)	1	(6)	0	(2)	0	(3)	1	(5)	0	(3)
Legal	1	(9)	1	(6)	1	(5)	0	(4)	1	(4)	1	(5)	1	(5)	1	(5)
Education, training, and library	2	(13)	2	(7)	1	(7)	1	(5)	1	(8)	1	(6)	2	(10)	1	(5)
Arts, design, entertainment, sports, and media	15	(55)	16	(78)	4	(14)	2	(8)	4	(14)	2	(11)	4	(17)	2	(11)
Healthcare practitioner and technical	2	(10)	2	(10)	1	(6)	1	(5)	1	(4)	1	(5)	1	(7)	1	(5)
Healthcare support	0	(2)	1	(6)	0	(3)	0	(3)	0	(1)	0	(1)	0	(1)	0	(4)
Protective service	12	(40)	2	(10)	5	(19)	1	(7)	5	(18)	2	(7)	4	(16)	2	(8)
Food preparation and serving related	1	(6)	2	(9)	1	(5)	1	(5)	1	(17)	0	(3)	1	(6)	1	(6)
Building and grounds cleaning and maintenance	27	(83)	5	(17)	16	(43)	3	(9)	15	(41)	3	(11)	15	(40)	3	(11)
Personal care and service	1	(4)	1	(5)	0	(3)	0	(3)	0	(2)	0	(2)	0	(2)	0	(3)
Sales and related	8	(33)	6	(22)	3	(12)	2	(10)	6	(24)	4	(19)	6	(24)	4	(17)
Office and administrative support	41	(144)	103	(330)	21	(69)	53	(146)	24	(83)	57	(164)	21	(64)	48	(137)
Farming, fishing, and forestry	2	(6)	0	(2)	2	(6)	0	(2)	1	(6)	0	(3)	1	(4)	0	(4)
Construction and extraction	418	(909)	16	(51)	368	(738)	15	(32)	447	(943)	19	(50)	421	(882)	18	(49)
Installation, maintenance, and repair	66	(183)	2	(12)	47	(115)	2	(8)	50	(120)	2	(10)	56	(138)	2	(11)
Production	191	(655)	93	(332)	103	(292)	56	(154)	135	(357)	71	(186)	124	(304)	59	(144)
Transportation and material moving	104	(202)	15	(47)	68	(124)	9	(24)	75	(138)	12	(32)	69	(135)	11	(31)
TOTAL	1101	(2812)	332	(1082)	766	(1674)	180	(468)	915	(2074)	223	(596)	886	(1971)	213	(547)

Notes: This table presents unweighted averages and standard deviations of public employment (numbers of workers) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table B.8: Public Employment (shares by gender) in Manufacturing Industries by Occupational Groups [cited on page 68]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	79.0	(26.0)	21.0	(26.0)	87.8	(22.2)	12.2	(22.2)	85.3	(23.2)	14.7	(23.2)	81.4	(23.8)	18.6	(23.8)
Business and financial operations	59.6	(40.1)	40.4	(40.1)	43.6	(42.6)	56.4	(42.6)	39.8	(41.9)	60.2	(41.9)	44.3	(41.3)	55.7	(41.3)
Computer and mathematical science	63.7	(40.2)	36.3	(40.2)	63.2	(42.8)	36.8	(42.8)	67.0	(42.1)	33.0	(42.1)	75.1	(37.7)	24.9	(37.7)
Architecture and engineering	92.2	(16.7)	7.8	(16.7)	90.2	(19.5)	9.8	(19.5)	87.6	(23.2)	12.4	(23.2)	86.9	(21.3)	13.1	(21.3)
Life, physical, and social science	77.4	(35.0)	22.6	(35.0)	78.2	(38.3)	21.8	(38.3)	60.5	(43.8)	39.5	(43.8)	70.7	(40.7)	29.3	(40.7)
Community and social service occupation	47.8	(48.7)	52.2	(48.7)	26.3	(42.1)	73.7	(42.1)	21.4	(40.7)	78.6	(40.7)	54.6	(50.0)	45.4	(50.0)
Legal	59.5	(45.0)	40.5	(45.0)	47.0	(47.9)	53.0	(47.9)	45.7	(48.7)	54.3	(48.7)	33.1	(44.7)	66.9	(44.7)
Education, training, and library	43.5	(46.8)	56.5	(46.8)	63.0	(46.5)	37.0	(46.5)	67.2	(44.4)	32.8	(44.4)	67.0	(43.4)	33.0	(43.4)
Arts, design, entertainment, sports, and media	48.8	(39.8)	51.2	(39.8)	65.5	(43.7)	34.5	(43.7)	61.4	(43.0)	38.6	(43.0)	67.8	(42.3)	32.2	(42.3)
Healthcare practitioner and technical	30.8	(43.7)	69.2	(43.7)	41.0	(48.1)	59.0	(48.1)	36.8	(47.4)	63.2	(47.4)	64.2	(46.7)	35.8	(46.7)
Healthcare support	29.2	(44.8)	70.8	(44.8)	48.4	(50.4)	51.6	(50.4)	25.0	(46.3)	75.0	(46.3)	4.4	(19.4)	95.6	(19.4)
Protective service	88.1	(28.2)	11.9	(28.2)	75.1	(40.7)	24.9	(40.7)	71.2	(41.9)	28.8	(41.9)	74.0	(40.3)	26.0	(40.3)
Food preparation and serving related	32.7	(44.0)	67.3	(44.0)	34.4	(44.8)	65.6	(44.8)	38.2	(48.6)	61.8	(48.6)	48.0	(47.5)	52.0	(47.5)
Building and grounds cleaning and maintenance	80.3	(31.1)	19.7	(31.1)	84.5	(31.1)	15.5	(31.1)	85.1	(29.7)	14.9	(29.7)	84.4	(29.6)	15.6	(29.6)
Personal care and service	46.6	(47.6)	53.4	(47.6)	52.2	(50.3)	47.8	(50.3)	37.7	(48.4)	62.3	(48.4)	46.6	(50.3)	53.4	(50.3)
Sales and related	58.7	(44.4)	41.3	(44.4)	71.6	(42.6)	28.4	(42.6)	65.1	(42.3)	34.9	(42.3)	51.4	(44.9)	48.6	(44.9)
Office and administrative support	24.7	(23.7)	75.3	(23.7)	23.9	(28.5)	76.1	(28.5)	23.1	(28.0)	76.9	(28.0)	27.3	(29.8)	72.7	(29.8)
Farming, fishing, and forestry	94.6	(18.9)	5.4	(18.9)	73.0	(42.3)	27.0	(42.3)	63.8	(48.0)	36.2	(48.0)	56.2	(49.4)	43.8	(49.4)
Construction and extraction	97.3	(3.7)	2.7	(3.7)	96.7	(4.4)	3.3	(4.4)	96.4	(5.9)	3.6	(5.9)	96.4	(5.2)	3.6	(5.2)
Installation, maintenance, and repair	98.1	(7.3)	1.9	(7.3)	96.2	(14.2)	3.8	(14.2)	97.6	(9.9)	2.4	(9.9)	96.3	(11.7)	3.7	(11.7)
Production	69.7	(20.7)	30.3	(20.7)	67.0	(24.0)	33.0	(24.0)	67.4	(24.8)	32.6	(24.8)	67.9	(22.1)	32.1	(22.1)
Transportation and material moving	90.9	(13.9)	9.1	(13.9)	90.6	(15.6)	9.4	(15.6)	91.2	(15.0)	8.8	(15.0)	90.5	(15.0)	9.5	(15.0)
TOTAL	82.0	(7.6)	18.0	(7.6)	84.7	(7.7)	15.3	(7.7)	84.1	(8.0)	15.9	(8.0)	84.4	(7.7)	15.6	(7.7)

Notes: This table presents unweighted averages and standard deviations of public employment (shares by gender) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.

Table B.9: Public Employment (shares by occupational groups) in Manufacturing Industries by Occupational Groups
[cited on page 68]

Occupational Groups	1990				2000				2007				2017			
	Male		Female		Male		Female		Male		Female		Male		Female	
	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
Management	5.0	(3.4)	6.0	(9.0)	4.2	(3.9)	3.5	(7.8)	5.4	(4.2)	5.2	(9.9)	6.3	(4.4)	8.1	(11.6)
Business and financial operations	1.0	(1.6)	4.4	(9.5)	0.6	(1.4)	4.3	(9.9)	0.6	(1.3)	4.8	(10.0)	0.8	(1.5)	5.7	(9.0)
Computer and mathematical science	0.3	(0.8)	0.8	(4.5)	0.4	(1.1)	1.2	(5.0)	0.4	(1.5)	0.9	(3.9)	0.7	(1.6)	1.2	(4.4)
Architecture and engineering	6.7	(5.4)	2.7	(6.5)	6.9	(5.6)	4.2	(9.8)	5.1	(4.9)	4.3	(9.2)	5.0	(4.5)	4.2	(9.3)
Life, physical, and social science	1.6	(2.0)	1.9	(5.3)	0.6	(1.6)	0.5	(2.2)	0.4	(1.0)	0.9	(2.9)	0.5	(1.4)	1.1	(5.2)
Community and social service occupation	0.1	(0.4)	0.3	(1.9)	0.0	(0.2)	0.2	(1.3)	0.0	(0.1)	0.1	(1.2)	0.0	(0.3)	0.1	(1.0)
Legal	0.1	(0.3)	0.1	(0.6)	0.0	(0.3)	0.1	(1.0)	0.0	(0.3)	0.1	(0.6)	0.0	(0.4)	0.2	(1.3)
Education, training, and library	0.1	(0.5)	0.6	(3.0)	0.1	(0.6)	0.3	(1.4)	0.1	(0.5)	0.1	(0.8)	0.2	(1.2)	0.8	(4.9)
Arts, design, entertainment, sports, and media	0.8	(1.6)	3.2	(7.5)	0.3	(1.2)	0.7	(5.7)	0.5	(2.3)	0.7	(2.8)	0.3	(0.8)	0.7	(3.2)
Healthcare practitioner and technical	0.1	(0.4)	0.7	(3.6)	0.1	(0.4)	0.6	(4.3)	0.1	(0.5)	0.4	(2.2)	0.1	(0.6)	0.3	(2.1)
Healthcare support	0.0	(0.2)	0.2	(1.2)	0.0	(0.2)	0.1	(1.1)	0.0	(0.0)	0.0	(0.1)	0.0	(0.0)	0.3	(2.1)
Protective service	0.9	(1.5)	0.3	(1.3)	0.6	(1.7)	1.3	(5.8)	0.6	(1.6)	1.5	(5.9)	0.5	(1.6)	0.9	(3.9)
Food preparation and serving related	0.1	(0.4)	1.2	(5.1)	0.1	(0.5)	0.3	(1.9)	0.0	(0.2)	0.2	(1.6)	0.0	(0.3)	0.3	(1.8)
Building and grounds cleaning and maintenance	2.2	(2.5)	3.2	(9.0)	2.1	(2.7)	2.5	(9.1)	1.6	(2.3)	1.3	(4.5)	1.8	(2.7)	2.5	(8.6)
Personal care and service	0.1	(0.5)	0.5	(5.1)	0.1	(0.5)	0.4	(2.4)	0.0	(0.1)	0.2	(1.4)	0.0	(0.3)	0.2	(1.1)
Sales and related	0.6	(1.3)	2.2	(6.6)	0.3	(1.0)	0.5	(2.9)	0.3	(0.9)	1.0	(3.8)	0.4	(1.1)	1.6	(7.4)
Office and administrative support	2.4	(2.5)	31.7	(20.1)	1.7	(2.5)	30.5	(24.6)	1.7	(2.4)	27.5	(20.8)	1.7	(2.7)	24.6	(20.5)
Farming, fishing, and forestry	0.3	(0.9)	0.1	(0.5)	0.5	(2.0)	0.8	(5.0)	0.3	(1.2)	0.4	(2.2)	0.1	(0.6)	0.4	(2.9)
Construction and extraction	47.6	(12.0)	6.4	(9.6)	55.5	(12.9)	11.3	(15.6)	56.0	(14.1)	11.9	(17.0)	53.9	(12.4)	11.6	(15.9)
Installation, maintenance, and repair	5.6	(3.7)	0.4	(1.7)	5.8	(4.5)	0.9	(3.8)	5.4	(4.2)	0.6	(2.9)	6.6	(5.1)	1.0	(3.1)
Production	12.9	(7.0)	27.9	(21.6)	10.3	(7.4)	29.4	(25.8)	12.2	(8.1)	32.7	(24.7)	11.3	(8.1)	29.5	(23.6)
Transportation and material moving	11.6	(6.3)	5.2	(9.2)	9.9	(6.6)	6.4	(11.9)	9.5	(7.0)	5.2	(10.4)	9.6	(6.5)	4.7	(8.1)

Notes: This table presents unweighted averages and standard deviations of public employment (shares by occupational groups) in manufacturing industries across 722 commuting zones for 1990, 2000, 2007, and 2017, respectively.