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Essays on the Gender Wage Gap in China and the Returns to Higher Education in the United States

Rui Xu
Syracuse University

Abstract

This dissertation presents three separate essays. The first two essays explore the gender wage gap and its dynamics in urban China from 1995 to 2018. The first chapter decomposes the gender wage gap based on the observed wage for workers with a precise measure of the hourly wages. The first chapter examines the observed average gender wage gap in China in hourly wages from 1995 to 2018. Using data from the China Household Income Survey (CHIP) 1995 – 2013 and the China Family Panel Studies (CFPS) 2014 and 2018. This chapter computes wage earners' working hours and hourly wages based on the available information to account for the labor supply's intensive margin. This chapter shows a pattern of increase in the gender wage gap in terms of hourly wages in the survey years of 1995-2007 and a pattern of decrease in 2007 - 2013. By extending the study period to 2018, this paper provides additional evidence that the observed wage-earners gender wage differentials have continued to decrease from 2013 - 2018 in urban China. This chapter finds that educational achievement and the returns to education favor female workers on average; however, the returns to potential experience are the main contributors to the "unexplained" component of the gender wage gap. This chapter also finds that the changes in the gender wage gap are heterogeneous across groups. Individuals without a college degree and working in foreign-owned firms are more likely to experience gender wage differential changes in hourly wages compared with those with at least a college degree and working in State-Owned Enterprises(SOEs).

The second chapter explores the gender wage gap dynamics by accounting for employment

composition. This chapter examines changes in the gender gap of the wage distribution in China from 1995 to 2018. To effectively account for changes in employment composition, we employ nonparametric bounds. Our methodology adopts a weak quartile dominance assumption, a monotone instrumental variable, and a stochastic dominance assumption to tighten the bounds. The results show statistically significant evidence that, over the years from 1995 to 2018, the median gender wage gap for the young workers (age 25-45) who are non-college-educated has increased by 0.17 - 0.62 log points. To estimate potential changes in the evolution of the gender wage gap suggested in the literature, we split up our analysis into two periods from 1995 - 2007 and 2007 - 2018. The results show larger changes in the gender wage gap compared to estimates in existing studies. In the eailer period, we find a significant increase by 0.19 - 0.63 log points in the median gender wage gap among the young workers who are college-educated. In the second period, the bounds estimates are less conclusive and suggest a decrease in the median gender wage gap among the college-educated young workers by 0.12 - 0.59 log points, but their 95% CI does not exclude a zero change. The estimates of the gender wage gap at the 75^{th} wage percentile show a similar pattern as the changes at the median wage, while the statistical implications at the 25^{th} percentile are inconclusive.

Chapter three examines the returns to higher education in the United States with particular attention to individuals induced by the recession to attend a Master's Program. Unlucky college undergraduates entering the labor market in a recession suffer a persistent loss in their earnings in the medium- to long-term. Due to this "scarring effect," the opportunity cost for graduate school attendance decreases when an individual is exposed to a recession. This paper examines whether staying in school can help the unlucky cohort in terms of future labor market outcomes. There are two channels: delaying the time to enter the labor force and human capital accumulation. I find that graduating during a recession increases the probability of pursuing a graduate degree by 3 percentage points, and the return for the induced graduate degree is about 23% in future annual salary. At the same time, there is no statistically significant effect on the employment probability for those graduate degree holders induced by the recession.

These findings provide evidence that the main benefit those induced graduate degree holders gain is from the additional accumulated human capital; the effect of delayed labor force entrance is negligible. I also find younger non-white females in non-STEM majors from non-research universities are more sensitive to the recession when making the graduate school decision.

ESSAYS ON THE GENDER WAGE GAP IN CHINA AND THE RETURNS TO HIGHER EDUCATION IN THE UNITED STATES

by

Rui Xu

M.A., University of Texas at Austin, 2017

B.A., Baylor University, 2016

B.A., Sichuan University, 2015

Dissertation

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Contents

List of Figures

List of Tables

Chapter 1

Gender Wage Gap in Urban China: Change and Decomposition

1.1 Introduction

Researchers have documented a substantial reduction in the average gender wage gap in the United States during the 1980s and a stable gender wage gap from 1980 to 2010 (Blau and Kahn, 2017). The story is quite different in China. In recent years, China has experienced a transition of gender pay gaps. The average observed wage earnings gap between males and females had progressively widened since 1988 (Gustafsson and Li, 2000; Gustafsson and Wan, 2020).

Broad shifts in the Chinese urban labor market set the background of the gender wage gap. Since 1988 to date, the labor market structure in China has gone through dramatic structural changes (e.g., Li et al., 2012; Meng, 2012). Before 1995, China's unemployment rate was lower than other countries average. Since the mid-1990s, the Chinese government began privatizing small and medium-sized state-owned enterprises (SOEs), which triggered large-scale layoffs. The unemployment rate jumped to a level even higher than that of the high-income countries, peaking above 10% in 2002-2003, then slowly drifted down (Feng et al., 2017). In the same period when the unemployment rate increased, the overall urban labor force participation rate dropped from over 82% to around 75%. The labor force participation rate has remained low ever since, and these changes fell most heavily on the unskilled women (Feng et al., 2017), which can be potentially due to the increase of the returns to education and the high wage elasticity of women (Hare, 2019).

The implementation of the minimum wage policy in 2004, the establishment and formalized Labor Contract Law in 2008, and the 2010 Social Security Law aimed to help protect low-skilled,low-paid, and vulnerable workers. Since women are disproportionately located in these groups, these policies can potentially reduce the gender wage gap. In late 2015, the Chinese government relaxed the one-child policy in China and replaced it with the two-child policy, which may have profound labor market impacts on women. Employers are reportedly reluctant to hire female workers with a "high risk" of becoming pregnant, taking maternity leave, and influencing productivity by raising children. All the policies mentioned above have the potential to change the gender wage gap, and analyzing the impact needs the latest data to be examined.

This chapter uses data from the China Household Income Survey (CHIP) 1995-2013 and the China Family Panel Studies (CFPS), 2014 and 2018 to analyze the average gender wage gap and based on the Oaxaca-Blinder decomposition methodology to understand the sources of the gender gap in hourly wage. Specifically, this chapter answers the question of how much of the gender gap can be "explained" by male-female differences in human capital (education and labor market experience) and occupational choices, and how much of the gender wage gap cannot be explained by those differences.

Previous studies usually rely on monthly or yearly earnings to measure the gender gap in earnings in the context of China since surveys in China usually asks for self-reported earnings. However, the hourly wage measure is crucial in analyzing the gender wage gap, especially in China. According to the National Bureau of Statistics of China, as of 2018, males, on average, spent 315 minutes or 5.25 hours per day on paid work, while females, on average, only spent 215 minutes or 3.58 hours. Due to this gender differential in working hours, it is essential to construct the hourly wage measure in studying the gender wage gap.

By constructing the hourly wages, I find a pattern of increase in the gender wage gap in the survey years of 1995-2007 for 0.10 log points for the whole period. Since the Chinese Household Income Project has a long period of releasing the survey data, the data after 2013 has yet to be available. Therefore we know little about the gender wage gap in urban China after 2013 and whether the pattern has changed. This paper construct and harmonize different datasets to have a harmonized time series of the gender wage gap over time. By extending the study period to 2018, I provide additional evidence that the observed wage-earners gender wage differentials have continued to decrease from 2013 - 2018 in urban China. The decomposition results also show that in recent years, the returns to education also favor female workers on average. On the other hand, I find that the potential experience and the base wages are the primary sources contributing to the existing gender wage gap in hourly wages. When looking into sub-populations defined by educational achievement, ownership of the firm of employment, I find that the changes in the gender wage gap are heterogeneous across groups. Individuals without a college degree and working in foreign-owned firms are more likely to experience gender wage differential variance in hourly wages than those with at least a college degree and working in state-owned enterprises (SOEs).

The main contributions of this paper are in two aspects. First, to the best of my knowledge, this is the first study trying to harmonize two different nationally representative datasets to estimate the gender wage gap from 1995 to 2018 to provide an analysis of the gender wage gap in Urban China for a more extended period. Second, different from previous literature that used earnings as the measure for the gender wage gap (e.g.,Chi and Li, 2014; Song et al., 2019), I use the measure of the hourly wage. In this way, by using hourly wages, I provide statistical evidence of changes in the gender wage gap, avoiding biases due to the labor supply's intensive margin (hours worked). This paper only focuses on those working individuals, a group whose composition may change over time. To effectively account for changes in employment, the dissertation's second chapter employs the nonparametric bounds to examine changes in the gender gap in wages.

The rest of the paper is organized as follows. Section 2 introduces the related literature, while Section 3 describes the data set and sample construction. Section 4 introduces the empirical strategy, and Section 5 presents the key results. A brief conclusion follows.

1.2 Related Literature

In the past twenty years, the literature has explored the gender wage differentials for urban workers in China. Gustafsson and Li (2000) uses the Chinese Household Income Project(CHIP) data for 1988 and 1995 and find that the average female earnings were 15.6% lower than for males in 1988, and the gender wage gap remained unchanged across the study period that females earned 17.5% less than males in 1995. However, a portion of the gender gap in earnings that could not be explained by the the gender differential over observed characteristics exists. Using the same data, Shu et al. (2007) reached similar conclusions.

However, with the reconstruction of the state-owned enterprises (SOEs) and the lifelong stable relationships between workers and work units terminated, studies reported a widened gender wage gap since the economic reform. Ng (2007) used Urban Household Survey (UHS) data with the latest observations from 1997 to report a widened gender pay gap compared to previous year in 1988 and 1995, consistent with the finding of a fall in the average female wage compared with the average male wage from 86% in 1988 to 76% in 2003 (Zhang et al., 2008). Additionally, with UHS in the years 1987, 1996, and 2004, Chi and Li (2008) reported a widening trend that is largely contributed by the fact that the labor market situation had worsened for females compared to males. Liu (2011) showed a large increase in the gender pay gap at the 10^{th} percentile of the wage distribution from 10.5% in 1997 to 17.7% in 2004 using China Health and Nutrition Survey; however, the gender wage gap fell from 15.1% to 6.9% at the 90^{th} percentile of the wage distribution during the same time period. Therefore the mean gender gap in earnings hardly changed. Using OLS estimation, Chi and Li (2014) find that males earned 34 - 38% more than women from 2005 to 2009. However, Song et al. (2019) record a temporary narrowing in the gender earnings gap from 35.4% in 2007 to 27% in 2013, indicating that the trend of increasing the gender wage gap has stopped.

Besides estimating the gender wage gap, many other studies employed the human capital model and Oaxaca-Blinder's decomposition method to look at the factors influencing the gender wage gap in China in recent decades. For example, Meng (1998a) and Meng (1998b) look at the determinants of the gender wage gap among rural-urban migrants in China and show that occupation segregation and the level of industrial marketization contribute to the gender wage gap. Liu et al. (2000) and Maurer-Fazio and Hughes (2002) show that the privatization and marketization in the 1990s enlarged the gender wage gap in China. Using rural data in China from 1988 to 1995, Rozelle et al. (2002) does not find evidence that privatization and market reforms have affected the gender wage gap in rural China. Shu et al. (2007) shows that globalization perpetuates the gender wage differential by absorbing women in exporting-orientated manufacturing jobs that offer lower wages. Song et al. (2014) focuses on the urban low-income workers in China in 2007 and shows that the gender wage gap unexplained by marital status, age, and education account for 60% of the total gender wage gap. Ma (2018) uses the China Household Income Panel (CHIP) 2002-2013 and shows that intra-sector gender wage differential contributed more to the observed wage differential and up to 80% of the gender wage differential is unexplained by education, occupation, and working experience. Additionally, both Hare (2019) and Zhao et al. (2019) find that the increase in females' gain in the observed labor market characteristics, such as education attainment, have helped in closing the gender earnings gap; however, those decreases in the earnings gap have been offset by the increase in men's labor market return to working experience.

Most of the previous literature relies on the observed earnings in terms of self-reported yearly or monthly earnings without including people who are not working. However, the observed earnings would be determined by the working hours and the hourly wage. Therefore, to account for the intensive margin of the labor supply, I construct the hourly wages for each wage-earner relying on the available information. Since the CHIP data only cover up to year 2013, relying only on CHIP, previous literature has explored the gender wage gap in Urban China from 1995 - 2013; however, we know little about the gender wage gap in urban China after 2013 and whether the pattern has changed. Building upon the previous literature, this paper harmonizes two nationally representative surveys to extend the study of the gender wage gap in China into 2018 for the first time.

1.3 Data and Variable Definitions

This study uses both household-level and individual-level data from two surveys. We use the Chinese Household Income Project (CHIP) 1995, 2002, 2007, 2013. Since there are no data available after 2013 through CHIP, I compliment the dataset with the China Family Panel Study (CFPS) 2014, 2018. Using CHIP and CFPS together enables us to analyze the gender wage gap in China from the mid-1990s to the late 2010s. This section provides an introduction to CHIP and CFPS, discusses the challenges we encounter while using data from those two surveys together, explains how we construct our key variables and introduces our analytic sample.

1.3.1 CHIP and CFPS

CHIP was part of a collaborative research project on income and inequality in China organized by Chinese and international researchers and institutions, including the Chinese Academy of Social Sciences and the School of Economics and Business Administration at Beijing Normal University. CHIP is a nationally representative household-level survey to estimate income, wealth, consumption, and related economic measures in rural and urban areas in China. CHIP uses a stratified random sampling process to collect data for three different samples – rural, urban, and migrant groups in 22 provinces, all at household and individual levels. CHIP samples are cross-sectional and are subsamples taken from the National Bureau of Statistics (NBS) samples used to obtain the official household statistics published in the annual Statistical Yearbook of China.

CFPS is a nationally representative, bi-annual longitudinal survey of the Chinese communities, families, and individuals conducted by the Institution of Social Science Survey of Peking University since 2010. Both CHIP and CFPS include individual-level demographics and detailed information on wage income and wealth, making it possible to analyze the national trend of wage inequality.

1.3.2 CHIP and CFPS Data Harmonization

Although both CHIP and CFPS are nationally representative surveys, their samples are drawn from different provinces in China.[1] Therefore, I need to make sure I use the correct sampling weights to make those two samples comparable. In the CFPS samples, I use "the individual-level national sampling weights" provided in the data set. In CHIP, I use the sample weights based on regional and provincial total population for CHIP samples following Li et al. (2017) for CHIP 2007 and 2013. Since Li et al. (2017) only provides the sampling weight information for 2007 and 2013 but not for the earlier years, I do not apply weights for the CHIP 1995 and 2002.[2]

Information about each individual's working hours is necessary to construct the hourly wage variable given yearly earnings. Since CHIP 1988 does not have information about hours worked, I have to exclude it from our analysis. Additionally, we exclude CFPS 2010, 2012, and 2016 from our analysis due to missing values in key variables. Specifically, in CFPS 2010 and 2012, I found abnormal employment rates, especially for non-college-educated females in the raw sample. As a reference, the employment to population ratio was 67.75% in

[1]Table A.1 in the Appendix lists the covered provinces for each survey by year.

[2]Not applying these sampling weights is also consistent with the previous studies that used CHIP 1995 and 2002 (for example Xing and Li, 2012; Zhu, 2016; Yang and Gao, 2018), which also makes the results more comparable to the literature.

2010 for individuals aged 15+ according to the World Bank; however, in CFPS 2010, after applying sampling weights, the employment ratio is only 63.25% for individuals aged 25 – 55. We also noticed that, compared to the CHIP sample, the CFPS sample generally has a lower employment rate. However, compared to CHIP 2007, CHIP 2013, and CFPS 2014, non-college-educated females in CFPS 2012 experienced an extremely low employment rate. The employment ratio for non-college-educated females is between 60 - 75% for CHIP 2007, CHIP 2013, and CFPS 2014; however, the employment ratio is even below 60% in CFPS 2012, which I have not found any reference to explain it. Therefore, I exclude CFPS 2010 and CFPS 2012 from the analysis. In CFPS 2016, an improper survey operation failed to collect main-job-related information for individuals who did not experience work changes between CFPS 2014 and CFPS 2016 (see CFPS Database Clean Report), which makes its data unusable as I would not measure earnings and hours worked accurately. Therefore, I use data from CHIP 1995, 2001,2007,2013 together with CFPS 2012 and 2018 to construct our sample.

This paper analyzes the gender wage gap based on the observed wages; therefore, the sample only contains wage earners. The sample includes Chinese urban wage-earners aged 25 to 55 with urban hukou who do not work in agriculture from certain provinces [3]. Wage-earners are from four levels of educational attainment and are employed in five categories for ownership of the work unit and twelve industries.

1.3.3 Sample

Our sample includes Chinese urban workers age 25 to 55 with an urban hukou and not working in the agriculture sector. I focus on urban households to mitigate the differences in social benefits between households with urban and rural hukou (Xing and Li, 2012). I exclude individuals with no household registrations or foreign residents for similar reasons.

[3]To make the hourly wages across years and surveys more comparable, I limit the individuals to certain provinces, including Beijing, Shanxi, Liaoning, Jiangsu, Guangdong, Anhui, Henan, Hubei, Yunnan, and Gansu.

An individual is classified as employed if he/she is reported to have been employed during the past year. Since I use the hourly wage in our analysis, I exclude self-employed individuals (about 7% of the total sample). There are four major educational achievement groups: Below high school degree, High School Degree, Dazhuan(equivalent to an associate degree in the U.S.), and at least a college degree.

Table 1 reports the composition of the wage earners for each year of 1995, 2002, 2007, 2013, 2014, and 2018. There are several things we need to pay special attention to. First of all, compared with the CHIP 2007 and CHIP 2013, samples in the CFPS 2014 consist of more individuals with lower educational achievement. The fraction of wage-earners with at least a college degree is above 20% in CHIP 2007 and CHIP 2013, but this fraction is only 16% in CFPS 2014, and finally, in CFPS 2018, becomes 26%, which is the same level as of CHIP 2007. Correspondingly, the average schooling years in the CFPS 2014 is 12.21 years, lower than 12.32 years in CHIP 2013 and 12.48 in CHIP 2007. Since previous studies have shown that the education level and the increased rewards of education and the gender differentials in those returns have a profound impact on the observed gender wage gap when interpreting the results, the CHIP 2013 and CFPS 2014 become less comparable in this case; therefore, I would not discuss the difference between this time pair, instead focusing on comparing 2007 - 2013 and 2014 - 2018.

Another aspect we need to pay attention to is that in CHIP 2007, we have a relatively larger proportion of younger wage-earners (aged 25 - 34) and a smaller proportion of older wage-earners(aged 46 - 55). Since there is a portion of the data that we cannot access through publicly available data, we are also missing wage earners in the Health, Social Security, and Social Work industries, individuals from the Education, culture, sports, and entertainment industries, and those from public management, social organization, and government. In addition to what has been mentioned above, for the same reason, we also miss individuals from the western part of China. Therefore, it is also not surprising that the average school years are higher in CHIP 2007 compared to CHIP 2013.

1.3.4 Construction of the Hourly Wage

There are some differences between CHIP and CFPS in the income and employment variables. Following Kanbur et al. (2021) and Li and Wan (2015) that use both CFPS and CHIP to analyze the evolution of household income inequality, we break down different income sources in CHIP (for both individual's income and household income) and reconstruct them into the same income definition as in CFPS. Earnings in our analysis measure an accounting period of one year, including regular wages, overtime compensation, allowances, and bonuses, which is the same definition as in Gustafsson and Wan (2020) and Zhu (2016). My analysis uses an individual's earnings from the major/primary job as the earnings measure. For cases where the survey does not specify an individual's major/primary job, we used the earnings from the job where an individual spent the most time and with the highest earning. Earnings are adjusted to the 2018 price level using the national urban consumer price index provided by the National Bureau of Statistics of China.

To construct the hourly wage, information about hours worked is needed. Among all the surveys, only CHIP 2002 has yearly earnings with working hours per day, working days per month, and months worked to construct hourly wages accurately. In other surveys, where the annual working hours are not directly provided, we compute annual working hours by either worked hours per week or worked hours per month, whichever is available, assuming workers work four weeks per month and 52 weeks per year. We then construct the hourly wage for our primary analysis by dividing the annual primary income by the annual total working hours, following Hering and Poncet (2010), Kamal et al. (2012), and Lovely et al. (2019). Constructing hourly wages helps us account for the intensive margin of labor supply.

Therefore, the gender wage gap in this chapter is defined as the difference between the average log hourly wage of males and the average log hourly wage of females. Figure 1.1 shows the kernel densities for the natural log of hourly wages constructed for each of the six years under study. The figure clearly illustrates that the hourly wage has grown rapidly between each pair of years before 2007, and after 2007 the growth in the hourly wages becomes much smaller.

Additionally, between most years under study, the distribution became more unequal. Figure 1.2 presents the observed log hourly wage estimates and the observed average log wage gender gap (labeled by triangles). Even though the overall trend for the observed gender gap of the average hourly wage seems flat, there is a slight increase in the gap before the year 2007, and after 2007 the gap appears to reach a plateau and shows a decreasing trend.

1.4 Empirical Strategy

1.4.1 Regression Based Gender Wage Gap

To control for the influences in characteristics between males and females, this paper adopts the two specifications of Mincer wage earnings equations using the ordinary least square (OLS). To be specific, I pooled the males and females together using the following regression equation:

$$lnwage_i = \alpha + \beta Male_i + \Sigma_j \gamma_j X_{ji} + \mu_i \tag{1.1}$$

where for each individual i the log hourly wage ($lnwage_i$) is a function of whether this individual is a female or not, plus j other characteristics. The parameter of interest, in this case, is β, which indicates the presence of the gender wage gap after controlling for other characteristics (X_j).

For the first specification, I only include the individual characteristics. Individual characteristics include the number of years in school, the quadratic term of the potential experience, dummy variable for being married, for belonging to an ethnic minority, and for being a CPC member. The potential experience is calculated for each worker from information on age and years of schooling. Furthermore, I also include province dummies. In addition to the individual characteristics, specification two also includes the employment characteristics, including the ownership of the work unit and the industry of employment.

1.4.2 Decomposition of The Gender Wage Gap

To further diagnose the component of the gender wage gap in urban China, I employ the Oaxaca-Blinder decomposition methodology. The decomposition methods have been used to look for explanations for the changes in the gender wage gap, and we can perform a standard Oaxaca decomposition for the mean wage inequality. The basis of the decomposition method is that we can use the estimates to construct a counterfactual wage for females if they had the same characteristics as males.

For each female and male sample separately, regression (1.1) is run without the dummy variables *Male*. Then with the Oaxaca-Blinder decomposition (Oaxaca (1973) and Blinder (1973)), the difference between the average log hourly wage for males and the average log hourly wage for females can be written as:

$$\begin{aligned} & lnW_m - lnW_f \\ & \qquad = (\hat{\alpha_m} + \Sigma_j \hat{\gamma_{j,m}} X_{j,m}) - (\hat{\alpha_f} + \Sigma_j \hat{\gamma_{j,f}} X_{j,f}) \\ & \qquad = [(\hat{\alpha_m} - \hat{\alpha_j}) + \Sigma_j (\hat{\gamma_{j,m}} - \hat{\gamma_{j,f}}) X_{j,m}] + \Sigma_j \hat{\gamma_{j,m}} (X_{j,m} - X_{j,f}) \end{aligned} \tag{1.2}$$

We can run the OLS and compute the mean values of X for each of the male and female group. The first term on the right-hand side of equation (1.2) represents the portion of the wage difference that can be attributed to the difference between male and female coefficients, including the constant terms. Notice that, the "intercept" component of the difference, $\hat{\alpha_m} - \hat{\alpha_j}$, is the wage structure effect for the base group, which in this analysis is the males. This part of the wage differences is also referred to as the "unexplained" portion, or the portion of difference due to the difference in returns. The "unexplained" component of the gender wage differentials is attributed to a difference in the estimated coefficients and constant terms for women and men. This “unexplained” part of the decomposition will be called the wage structure effect as it reflects differences in the coefficient β's, which is the differences in the way the characteristics of males and females are valued in the labor market. It can reflect discrimination as well as unobserved factors that are not captured by the regressions. In order to interpret the wage structure effect as a treatment effect, we need to impose some assumptions on the functional form of the wage structure for each group. Therefore, in this chapter, to interpret the estimated wage structure effect as a treatment effect of being a female, we need to impose the ignorability assumption to compute the aggregate decomposition. The ignorability assumption requires the differences associated with the returns to observable and unobservable characteristics in the structural wage functions. Therefore, the estimated decomposition term only reflects differences in the structural wage function. In other words, we assume the unobserved characteristics (such as ability) correlate with the observed characteristics in the same way for both males and females. The second term is the “explained” portion which can be attributed to differences between male and female characteristics such as age, education and so on.

1.5 Baseline Results

1.5.1 Regression Based Gender Wage Gap

The regression based gender wage gap is based on the estimation of equation 1.2, and Table 2 summarizes the main result of the pooled regression based on the first specification with only individual characteristics. Estimated parameters of interest, β's, the male wage premium, are uniformly positive and significant, indicating an urban gender wage gap that persists over time. Changes in the magnitude of the male wage premium over time confirm that the gender wage gap widened from 1995 to 2007. In 1995, males earns 7.7% more than females in hourly wages, however this number increased to 13.1% in 2002 and to 20.8% in 2007. I found that the gender wage gap in the hourly wage has continuously increased from 20.8% in 2007 to 22.1% in 2013 or 31.8% in 2014, and then decreased to 15.5% in 2018. From the table, the association between hourly wages and the level of education increased throughout the study period, with a slight decrease in its magnitude from 2002 to 2007. At the same time, the correlation between the potential experience and hourly wages decreased, whether married or not, and whether being an ethnic minority had less influence on the hourly wages during the 2010s. Being a CPC member still positively affected the hourly wages; however, the unobserved characteristics had increasing influences on the hourly wage.

Table 1.3 reports the main results of the pooled regression using the second specification, where I add the employment characteristics. The omitted category for the ownership is state-owned enterprises, and the omitted category for the employed industry is manufacturing. Similarly, the estimated β, the male wage premium, is uniformly positive and significant. Still, compared to the first specification, the coefficients in the second specification are somewhat lower, except for the one in 2007. Consistent with the continuous increase in the association between the level of education and the hourly wage in the first specification, using the second specification, I also find that for the level of education variable, the coefficients in the second specification are unsurprisingly lower, this could be as a result that the employment characteristics as the ownership and industry of the employment can absorb a large part of the gender wage differentials by the gender differentials in educational achievement.

The coefficients estimated for the ownership of the work unit are consistent with findings in the literature, the coefficients of working in the foreign-owned enterprises are positive while the coefficients of working in the collective-owned enterprises are negative compared to the omitted group which is the SOEs. This estimation implies that compared to females employed in the state-owned enterprises, females work in the collective-owned enterprises experience less wage variations, while females employed in foreign-owned enterprises face more variations. Since proportionately fewer women than men are employed in the state or foreign-owned sectors, these wage differentials are relevant to the gender wage gap. For the industry of employment, as of 2007, only Finance in the tertiary sector industries[4] had a positive significant coefficient compared to the omitted manufacturing industry, and Wholesale, retail, and trade even has significant negative coefficients. As the employment pattern across industries is not the same for women and men, these wage differences contribute to the underlying raw gender wage gap.

1.5.2 Decomposition of Gender Wage Gap

The decomposition results of the gender differential in hourly wage are shown in Table 1.4. The "explained" component of the decomposition is the share of the difference in ln hourly wages between males and females that can be attributed to differences in the average endowments of women and men, that is, differences in the means of characteristics such as education and experience. The "unexplained" component of the difference can be attributed to differences in the estimated coefficients and constant terms for women and men. It may reflect discrimination as well as unobserved missing factors that are not captured by the regression. Also, this paper assumes that the male wage distribution is one without discrimination. The total differential in Table 1.4 reveals that the average gender wage differentials in terms of hourly wage increased from 1995 to 2007, where males earned 12.31% more than females in 1995 but 22.81% more in 2007. This gender wage differential has stayed stable from 2007 to 2013 since males earned 22.38% more than females. I also find that this gender wage differential decreased after 2013/2014; males earned 17.54% more than females in 2018.

The decomposition results reveal that the increase in the differential from 1995 to 2007 is associated with an increase in both the difference due to endowments and the differences due to the coefficients, i.e., the difference in the returns for the same characteristics for males and

[4]Tertiary sector industries include Wholesale, retail, and trade; Finance; Health industries, Social Security and Social Work; Education, culture, sports, and entertainment; Scientific Research; Public management, social organization, and government.

females, and the constant term, which indicates the difference from the initial wage setup between genders. Similarly, the decline from 2007 to 2018 (excluding 2014) is associated with declines in both these components. As shown in Table 1.4, the average observed differential of characteristics between males and females can only explain a limited proportion of the average gender wage gap in terms of hourly wage especially after 2002, and this "explained" proportion has decreased from 48.66% in 1995 to 12.01% in 2007, and further to -1.25% in 2018. The reason behind a negative proportion is that I am using the males' wage structure as the baseline wage structure; therefore, we assume the observed characteristics are, on average, higher for males than females. However, for example, as the average educational achievement for females exceeded the average educational achievement for males in 2018, the contribution of the gender differential in terms of the observed characteristics, where assuming that males with a higher average value, becomes negative.[5] In other words, changes over time in the gender gap of hourly wages, including both the increases and declines, reflect changes in both the explained and unexplained components, especially changes in the unexplained components.

Table 1.5 provides the decomposition results that allow us to look more closely at the contribution of different variables. It is clear from the table that from 1995 to 2007, the difference in the gender gap in the education level contributed significantly to an increase in the gender gap in hourly wages. However, after 2013, the coefficient of the endowment of education level turns to negative[6], which indicates that females' education gains on average has exceeded their male counterpart and helped women make headway in their wages. The returns of education also favored females in all sample years. On the other hand, it seems like the endowment of the potential experience and the returns to the potential experience has worked against women in terms of helping to enlarge the gender gap in hourly wages.

In addition to those two factors, another notable contribution is from the constant term

[5]Since the proportion of contribution to the total difference from the "explained" and "unexplained" should sum to 100%, the contribution in terms of the "unexplained" will exceed 100% when the contribution of the observed characteristics is negative.

[6]Recall that the education level is relatively low in CFPS 2014 compared with the sample in other years.

or the intercept component, which is the wage structure effect for the base group. The base group in this chapter is referring to the males. Therefore, the constant term reflects the gender differences in unobserved variables (which will be referred as "base wage" from now on), which accounts for a significant portion of the gender hourly wage gap. In the study period, the contribution of the constant term has been increased, especially after 2007. This suggests that women's base wages slipped considerably relative to men's, which could result from decreased labor demand for women compared to men in urban China. This finding would be consistent with the literature that found firms become more reluctant to hire "high-risk" females after implementing several policies such as the relaxation of the one-child policy.

Table 1.6 reports the decomposition results for individuals with the lowest educational achievement (less than high school) and those with the highest educational achievement (college graduate or above). It is clear from the table that individuals without a high school degree experienced a higher gender wage difference in hourly wage than those with at least a college degree. In addition to the total differentials, the fraction of the contribution of the gender wage differentials from the unexplained part is also higher until 2018, potentially indicating that women with the least educational achievements are more likely to be exposed to discrimination in the urban China labor market.

During the study period, China's urban labor market experienced economic reforms and the restructuring of the state-own enterprise. As noted in section 1.5.1, working in foreign-owned firms will have a significant positive effect on the earned hourly wages compared to those who worked in the SOEs. Since females and males disproportionately work in different types of firms, this will affect the gender wage gap. Table 1.7 presents the decomposition results only for individuals in SOE or foreign-owned firms. Due to the limited numbers of observations in the CFPS 2014 and CFPS 2018 for samples in the foreign-owned firms; therefore, I do not report the estimated results in the table. Compared with the results in Table 1.4, we can observe that individuals in the Foreign-owned sector experienced higher gender wage differentials than those in the SOE. They also experienced a higher gender wage difference than the average level based on the whole sample. On the other hand, females in the SOEs experience a gender differential in hourly wages similar to the average level of the gender wage differentials at the average level over the whole sample.

1.5.3 Discussion

Many studies that used earnings to measure the gender wage gap in China focus on observed wages in recent decades. The literature finds the observed wage gap between males and females progressively widened since 1995; for example Gustafsson and Wan, 2020 found the gender earnings gap increased by 0.13 log points from 1995 to 2007 using the Urban Household Income Survey(UHIS), and Song et al., 2019 found the gender gap for earnings has increased by 0.15 log point during the same period using the CHIP. The estimated change in the gap is relatively smaller in this chapter than in the literature. Using CHIP and constructing an accurate hourly wage measure, this chapter found that the gender wage gap increased by 0.10 log points from 1995 to 2007. One potential explanation for the smaller estimated results in this chapter lies in using the hourly wage instead of the monthly or yearly earnings. Since males tend to work longer hours than females, using the hourly wages can control for the gender differential in the labor supply at the intensive margin. At the same time, this relatively smaller result further emphasizes the importance of using the hourly wage in studying the gender wage gap, especially in China.

On the other hand, some literature record a temporary narrowing in the gap from 2007 to 2013; for example, Song et al., 2019 using the CHIP sample found the gender wage earnings gap narrowed by 0.04 log points between 2007 to 2013. Consistent with this finding, this chapter finds the gender wage gap narrowed by 0.043 log points from 2007 to 2013 and continued to decrease by 0.0005 log points after 2013.

By using the standard decomposition method, this chapter finds that compared to those employed in the SOEs, females employed in foreign-owned enterprises face higher wage differences compared to males, and females with at least a college degree have a more equalized hourly wages as males compared to those without a high school degree. Those results support the conclusion in the literature with a large increase in the gender wage gap at 10^{th} percentile of the wage distribution and a fall in the gender wage gap at the 90^{th} percentile from 1997 to 2004 (Liu (2011)).

1.6 Conclusion

This chapter estimated the gender wage gap in hourly wages for wage-earners in urban China. The results show a pattern of increase in the gender wage gap in the survey years of 1995-2007 of 0.10 log points. This result is lower than previous findings using yearly income by Gustafsson and Wan (2020), which show an increase in the gender earnings gap from 1988 - 2007 by 0.14 log points, and findings by Song et al. (2019), who estimates a 0.15 log points increase in the gender earnings gap from 1995 – 2007. By extending the study period to 2018, this paper provides additional evidence that the observed wage-earners gender wage differentials have continued to decrease from 2013 - 2018 in urban China. The recent narrowing in the gender wage gap is, to some extent, due to the convergence of characteristics between men and women, especially in educational achievement. The reduction in the gender wage gap is also attributed to the decrease in the "unexplained" component of the gap. The decomposition results also show that in recent years, the returns to education also favor female workers on average.

On the other hand, I find that the potential experience and the base wages are the primary sources contributing to the existing gender wage gap in hourly wages. Those findings could be consistent with the literature that firms become more reluctant to hire "high-risk" females or hire them long-term after implementing policies such as the relaxation of the one-child policy due to the potential increases in parental leave and child-care payment. The base wage here refers to the constant term that reflects the gender differences in unobserved variables, for example, the unobserved worker quality, the match quality of the worker and the job, and the firm's willingness to pay for the worker's attributes. Unfortunately, with the limited information in the survey dataset, the chapter could not further explore the detailed contribution of those aspects to the gender wage gap in China.

Further, by looking into the gender wage gap for workers from different education groups and different types of ownership, I find that the gender wage differentials in hourly wages are heterogeneous across groups. Individuals without a high school degree experience a higher gender wage difference in hourly wage than those with at least a college degree. Also, individuals in the Foreign-owned sector experienced higher gender wage differentials than those in the SOE and higher than the average. On the other hand, females in the SOEs experience the gender differential in hourly wages at a similar level of the average gender wage gap for the whole sample.

Based on the decomposition result, females without a high school degree experienced a jump in the gender wage gap in hourly wages from 2007 - 2013; however, the gender wage gap in hourly wages was stable for individuals with at least a college degree. From 2013 - 2018 the gender wage gap in hourly wage dramatically decreased for individuals without a high school degree, but the gap has been stable and slightly decreased from 2014 - 2018 for individuals with at least a college degree. Similarly, individuals employed in the SOEs seem to experience less turbulence in the gender wage gap than those employed in foreign-owned firms.

To sustain economic growth and reduce gender inequality, the labor market in urban China needs legislation and policies that would in a way to protect female workers but at the same time encourage the firms to hire females in the longer term. With recent policies to postpone the retirement age and encourage multiple births, future research can look into how those policies would heterogeneously affect the pattern of the gender wage gap and the mechanisms. Previous literature has also argued for the changes in the selection into the labor market in the past few decades, especially for females. Before 1995, China's unemployment rate was lower than other countries average. Since the mid-1990s, the Chinese government began privatizing small and medium-sized state-owned enterprises (SOEs), which triggered large-scale layoffs. The unemployment rate jumped to a level even higher than that of the high-income countries, peaking above 10% in 2002-2003, then slowly drifted down (Feng et al., 2017). In the same period when the unemployment rate increased, the overall urban labor participation rate dropped from over 82% to around 75%. The labor force participation rate has remained low ever since, and these changes fell most heavily on the unskilled women (Feng et al., 2017), which can be potentially due to the increase of the returns to education and the high wage elasticity of women (Hare, 2019). Therefore, beyond the observed gender wage gap, future research can apply nonparametric or semiparametric methods to account for the changes in employment and labor force participation in the analysis of the changes in the gender wage gap in urban China. With more recent data available, future research can also look into the different factors that lead to the heterogeneous changes in the gender wage gap, which will help to develop related policies to help reduce gender inequalities. In the second chapter of this dissertation, we examined changes in the gender wage gap of the wage distribution in China using the nonparametric bounds to account for the changes in the employment composition during the study period.

Figure 1.1: Wage Distribution in 1995 - 2018

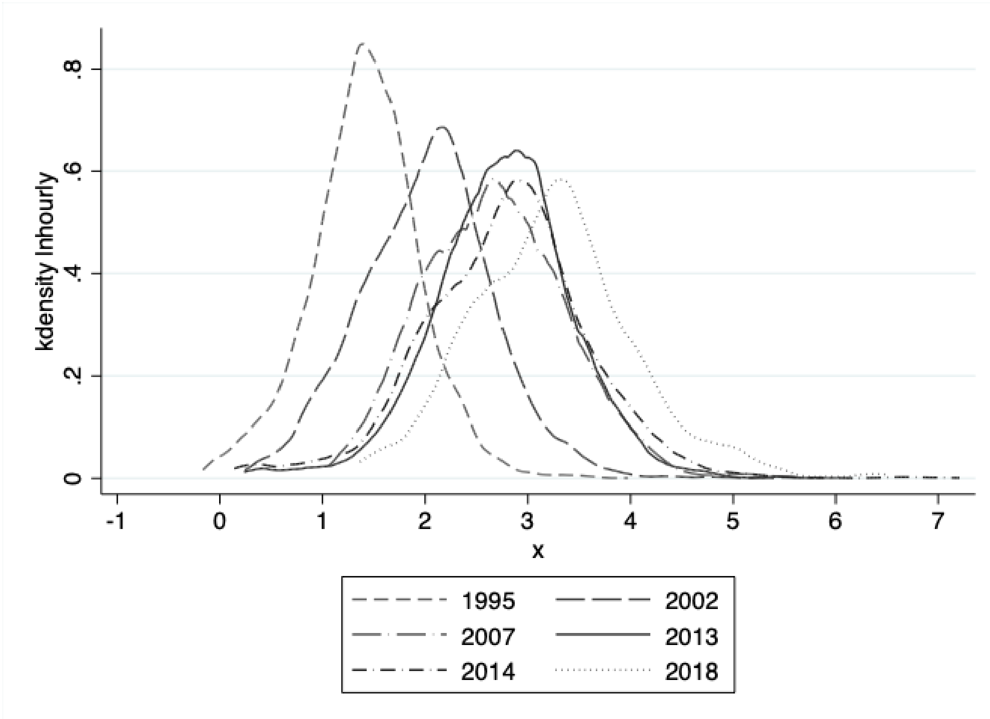

Figure 1.2: Unconditional Observed Average Wages in Urban China (log hourly wage)

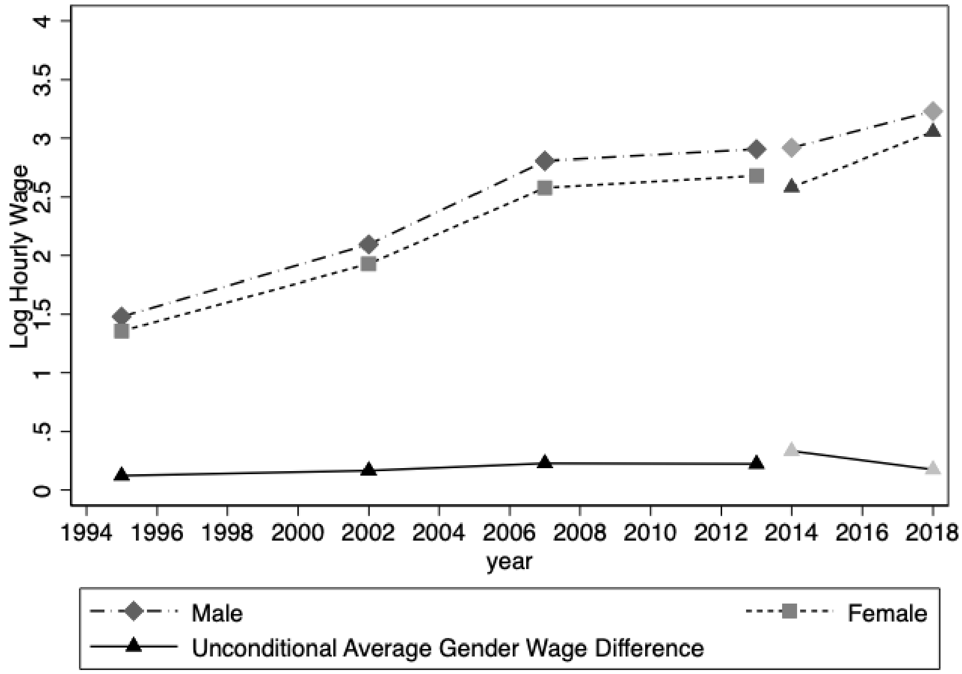

Table 1.1: Composition of Wage Earners: 1995, 2002, 2007, 2013, 2014 and 2018(%)

		1995	2002	2007	2013	2014	2018
Age Group	25 - 34	0.29	0.24	0.32	0.29	0.28	0.27
	35 - 45	0.45	0.40	0.41	0.37	0.39	0.32
	46 - 55	0.27	0.36	0.27	0.34	0.33	0.42
Gender	Male	0.52	0.55	0.56	0.55	0.54	0.55
	Female	0.48	0.45	0.44	0.45	0.46	0.45
Education	Below High School	0.34	0.23	0.16	0.24	0.32	0.23
	High School or Equivalent	0.41	0.41	0.37	0.23	0.29	0.28
	Dazhuan	0.17	0.25	0.25	0.28	0.23	0.22
	At least College	0.08	0.11	0.22	0.26	0.16	0.26
Ethnic Status	Majority	0.95	0.96	0.99	0.95	0.95	0.96
	Minority	0.05	0.04	0.01	0.05	0.05	0.04
Ownership of	SOE	0.84	0.38	0.21	0.21	0.21	0.23
Work Unit	Collective	0.15	0.08	0.05	0.05	0.00	0.00
	Foreign	0.01	0.02	0.02	0.04	0.04	0.02
	Private	0.00	0.06	0.18	0.35	0.44	0.44
	Other	0.00	0.46	0.53	0.35	0.31	0.30
Industry	Mining	0.01	0.02	0.01	0.04	0.01	0.01
	Manufacturing	0.41	0.26	0.21	0.16	0.26	0.25
	Construction	0.03	0.03	0.03	0.05	0.04	0.04
	Transportation, storage, post and commun.	0.06	0.08	0.11	0.07	0.06	0.08
	Wholesale,retail and trades	0.14	0.09	0.10	0.13	0.18	0.14
	Finance	0.02	0.03	0.08	0.04	0.03	0.04
	Consulting and Services	0.04	0.11	0.35	0.17	0.11	0.11
	Health, Social Security and Social Work	0.05	0.06		0.04	0.04	0.04
	Education,culture,sports and entertainment	0.08	0.10		0.11	0.09	0.12
	Scientific Research	0.03	0.02	0.04	0.01	0.00	0.01
	Public management, social org and gov	0.14	0.14		0.13	0.12	0.11
	Other	0.01	0.02		0.00	0.01	0.00
Region	Coastal	0.43	0.44	0.46	0.47	0.46	0.48
	Central	0.39	0.40	0.54	0.39	0.38	0.34
	Western	0.18	0.16		0.13	0.16	0.18
	Age (mean)	39.35	40.83	39.09	40.05	40.28	41.24
	School Years(mean)	10.83	11.66	12.48	12.32	12.21	12.89

Table 1.2: Estimates of Mincer-type equation using OLS(Specification 1)

	1995	2002	2007	2013	2014	2018
Male	0.0770***	0.131***	0.208***	0.221***	0.318***	0.155***
	(0.0112)	(0.0136)	(0.0245)	(0.0171)	(0.0484)	(0.0447)
School Years	0.0496***	0.0831***	0.0780***	0.0957***	0.0950***	0.0966***
	(0.00227)	(0.00297)	(0.00488)	(0.00369)	(0.00929)	(0.00969)
Experience	0.0286***	0.0152***	0.0110*	0.0236***	-0.00312	0.00149
	(0.00334)	(0.00389)	(0.00574)	(0.00403)	(0.0115)	(0.0103)
Exp Sq/100	-0.0349***	-0.00568	-0.0161	-0.0342***	0.0177	-0.000301
	(0.00714)	(0.00815)	(0.0130)	(0.00898)	(0.0258)	(0.0232)
Married	0.118***	0.113***	0.110**	0.0280	-0.0520	-0.0104
	(0.0280)	(0.0283)	(0.0437)	(0.0299)	(0.0804)	(0.0643)
Ethnic Minority	-0.0839***	0.00163	-0.232**	-0.0123	-0.0138	0.0486
	(0.0269)	(0.0340)	(0.104)	(0.0405)	(0.118)	(0.116)
CPC Member	0.0803***	0.125***		0.107***	-0.0202	0.247***
	(0.0132)	(0.0154)		(0.0214)	(0.0824)	(0.0574)
Constant	0.477***	0.907***	1.375***	1.460***	1.701***	2.238***
	(0.0526)	(0.0636)	(0.100)	(0.0742)	(0.217)	(0.223)
N	6777	6923	2557	4920	904	883

Notes: 1) The dependent variable is the hourly wages in log form, deflated to the year 2018; 2) Apart from the variables above, the province dummies are included; 3) Standard errors in parentheses; 4)* $p < 0.10, **p < 0.05$, *** $p < 0.01$ 5) The CPC membership variable in 2007 were not included in the survey; 6) Source: Computations are based on Chinese Household Income Project (CHIP) 1995, 2002, 2007, 2013 and Chinese Family Panel Study (CFPS) 2014 and 2018.

Table 1.3: Estimates of Mincer-type equation using OLS (Specification 2)

	1995	2002	2007	2013	2014	2018
Male	0.066***	0.129***	0.214***	0.190***	0.302***	0.132***
	(0.011)	(0.013)	(0.024)	(0.017)	(0.051)	(0.047)
School Year	0.040***	0.060***	0.072***	0.086***	0.087***	0.082***
	(0.002)	(0.003)	(0.005)	(0.004)	(0.010)	(0.010)
Experience	0.030***	0.018***	0.011*	0.026***	-0.002	0.003
	(0.003)	(0.004)	(0.006)	(0.004)	(0.012)	(0.010)
Exp Sq/100	-0.038***	-0.016**	-0.017	-0.040***	0.014	-0.007
	(0.007)	(0.008)	(0.013)	(0.009)	(0.026)	(0.023)
Married	0.128***	0.108***	0.099**	0.018	-0.084	-0.043
	(0.028)	(0.027)	(0.043)	(0.029)	(0.080)	(0.064)
Ethnic Minority	-0.080***	0.002	-0.201**	-0.011	-0.031	0.032
	(0.026)	(0.033)	(0.103)	(0.040)	(0.118)	(0.115)
CPC Member	0.069***	0.093***		0.106***	0.003	0.219***
	(0.013)	(0.015)		(0.022)	(0.083)	(0.060)
Collective Owned	-0.211***	-0.253***	-0.160***	-0.171***		
	(0.016)	(0.026)	(0.058)	(0.041)		
Foreign Owned	0.129**	0.164***	0.197**	0.242***	0.207	0.0451
	(0.108)	(0.044)	(0.078)	(0.050)	(0.144)	(0.160)
Private Owned	0.210	-0.234***	-0.201***	-0.0237	-0.0914	-0.103
	(0.055)	(0.043)	(0.081)	(0.048)	(0.139)	(0.149)
Other		-0.011	0.062**	-0.097***	0.007	-0.019
		(0.017)	(0.032)	(0.029)	(0.085)	(0.082)

Table 1.3 (cont.) Estimates of Mincer-type equation using OLS (Specification 2)

	1995	2002	2007	2013	2014	2018
Mining	0.147**	0.032	0.069	0.277***	0.511*	-0.269
	(0.057)	(0.049)	(0.122)	(0.046)	(0.298)	(0.249)
Construction	0.005	0.029	0.013	0.173***	0.302**	0.232**
	(0.032)	(0.035)	(0.068)	(0.040)	(0.129)	(0.111)
Transportation,storage, post and commun.	0.094***	0.143***	0.016	0.106***	0.130	0.0025
	(0.024)	(0.024)	(0.039)	(0.033)	(0.103)	(0.086)
Wholesale, retail and trade	-0.0395**	-0.0981***	-0.0741*	-0.110***	-0.0469	-0.156**
	(0.016)	(0.024)	(0.041)	(0.027)	(0.073)	(0.071)
Finance	0.231***	0.274***	0.198***	0.353***	0.100	0.449***
	(0.040)	(0.038)	(0.045)	(0.046)	(0.143)	(0.122)
Health industries, Social Security and Social Work	0.061**	0.246***		0.047	0.080	-0.014
	(0.025)	(0.030)		(0.044)	(0.132)	(0.123)
Education, culture,sports and entertainment	0.068***	0.360***		0.169***	0.044	0.094
	(0.022)	(0.026)		(0.033)	(0.103)	(0.087)
Scientific Research	0.183***	0.333***	0.0740	0.148*	0.659	0.404
	(0.035)	(0.046)	(0.059)	(0.081)	(0.419)	(0.297)
Public management, social org and gov	0.029	0.193***		0.062*	-0.094	-0.048
	(0.018)	(0.024)		(0.033)	(0.101)	(0.099)
Other	0.059	0.032			0.239	0.543
	(0.066)	(0.044)			(0.249)	(0.380)
Constant	0.570***	1.122***	1.484***	1.609***	1.880***	2.579***
	(0.053)	(0.063)	(0.106)	(0.078)	(0.241)	(0.235)
N	6777	6923	2557	4920	904	883

Notes: 1) The dependent variable is the hourly wages in log form, deflated to the year 2018; 2) Apart from the variables above, the province dummies are included; 3) Standard errors in parentheses; 4)* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ 5) The CPC membership variable in 2007 were not included in the survey. Additionally, there is no individual in the health industries, education, or public management industry in 2007. There are no observations for workers in the collective-owned firms in the CFPS survey (the years 2014 and 2018); 6) Source: Computations are based on the Chinese Household Income Project (CHIP) 1995, 2002, 2007, 2013 and the Chinese Family Panel Study (CFPS) 2014 and 2018.

Table 1.4: Decomposition of the ln Hourly Wage Difference between Genders(without ownership, occupation, and sector controls)

	1995	**2002**	**2007**	**2013**	**2014**	**2018**
Total Differential	0.1231	0.1662	0.2281	0.2238	0.3342	0.1754
Amount attributable to:						
endowments	0.0599	0.0646	0.0274	0.0019	0.0209	-0.0022
returns	0.0632	0.1016	0.2007	0.2219	0.3133	0.1776
% of total explained by the endowments	48.66%	38.87%	12.01%	2.32%	6.25%	-1.25%
% of total unexplained	51.34%	61.13%	87.99%	97.63%	93.75%	101.25%

Table 1.5: Decomposition of the Gender Differences in Urban China (without ownership, occupation, and sector controls)

	1995			**2002**			**2007**		
	Endowments	**Returns**	**Total**	**Endowments**	**Returns**	**Total**	**Endowments**	**Returns**	**Total**
Education Level	0.0326	-0.0714	-0.0388	0.0216	-0.1686	-0.1470	0.0236	-0.0850	- 0.0614
	(51.10%)	(-120.61%)	(-315.19%)	(33.08%)	(-167.10%)	(88.45%)	(89.06%)	(-42.14%)	(-26.92%)
Experience	0.0139	0.0896	0.1035	0.0280	0.0649	0.0929	0.0054	- 0.0461	- 0.0407
	(21.79%)	(151.35%)	(84.08%)	(42.88%)	(64.32%)	(55.90%)	(20.38%)	(-22.86%)	(-17.84%)
Marriage Status	-0.0007	0.0137	0.013	0.0001	0.0220	0.0221	-0.0002	0.1573	0.1571
	(-1.10%)	(23.14%)	(10.56%)	(1.53%)	(21.80%)	(13.30%)	(-0.75%)	(77.99%)	(68.87%)
Ethnic Minority	0.0003	0.0019	0.0022	-0.0000	- 0.0047	- 0.0047	-0.0004	-0.0027	- 0.0031
	(-1.10%)	(3.21%)	(1.79%)	(-0.00%)	(-4.66%)	(-2.83%)	(-1.51%)	(-1.34%)	(-1.36%)
CPC Memmber	0.0175	-0.0204	-0.0029	0.0141	-0.0078	0.0063			
	(-1.10%)	(-34.46%)	(-2.36%)	(21.59%)	(-7.73%)	(3.79%)			
Province	0.0002	-0.0573	-0.0571	0.0016	- 0.1000	-0.0984	- 0.0019	0.2903	0.2884
	(0.31%)	(-96.79%)	(-46.39%)	(2.45%)	(-99.11%)	(-59.21%)	(-33.96%)	(143.94%)	(126.44%)
Constant		0.1031	0.1031		0.4249	0.4249		-0.1121	-0.1121
		(174.16%)	(83.75%)		(421.11%)	(255.66%)		(-55.58%)	(-49.15%)
Total	0.0638	0.0592	0.1231	0.0653	0.1009	0.1662	0.0265	0.2017	0.2281
	(51.83%)	(48.09%)		(39.29%)	(60.71%)		(11.62%)	(88.43%)	

	2013			**2014**			**2018**		
	Endowments	**Returns**	**Total**	**Endowments**	**Returns**	**Total**	**Endowments**	**Returns**	**Total**
Education Level	-0.0168	-0.0615	-0.0783	0.0166	-0.2824	-0.2658	-0.0190	-0.1272	- 0.1462
	(-323.07%)	(28.15%)	(34.99%)	(79.43%)	(-90.11%)	(-79.53%)	(8.64%)	(-71.66%)	(-83.35%)
Experience	0.0089	0.0965	0.1054	0.0028	-0.2577	-0.2549	0.0051	-0.0749	- 0.0698
	(171.15%)	(44.16%)	(47.10%)	(13.40%)	(-82.23%)	(-76.27%)	(-231.82%)	(-42.20%)	(-39.79%)
Marriage Status	0.0012	0.0532	0.0544	-0.0020	-0.0205	-0.0225	-0.0003	0.1263	0.1260
	(23.08%)	(24.35%)	(24.31%)	(-9.57%)	(-6.54%)	(-6.73%)	(13.64%)	(71.15%)	(71.84%)
Ethnic Minority	0.0001	-0.0077	-0.0076	-0.0010	0.0178	0.0168	-0.0001	0.0009	0.0008
	(1.92%)	(-3.52%)	(-3.44%)	(-4.78%)	(5.68%)	(5.03%)	(4.55%)	(0.51%)	(0.46%)
CPC Memmber	0.0093	-0.0016	-0.0077	0.0016	0.2055	0.2071	0.0190	-0.0048	- 0.0491
	(178.85%)	(-0.73 %)	(-3.44%)	(7.66%)	(65.57%)	(61.87%)	(-8.64%)	(-2.70%)	(-27.99%)
Province	0.0026	-0.0473	-0.0447	0.0029	0.0458	0.0487	-0.0022	-0.0681	-0.0703
	(50%)	(-21.65%)	(-19.97%)	(13.88%)	(14.61%)	(14.57%)	(100%)	(-38.37%)	(-40.08%)
Constant		0.1869	0.1869		0.6047	0.6047		0.3253	0.3253
		(85.83%)	(83.51%)		(192.94%)	(180.94%)		(183.27%)	(185.46%)
Total	0.0052	0.2185	0.2238	0.0209	0.3134	0.3342	-0.0022	0.1775	0.1754
	(2.32%)	(97.63%)		(6.35%)	(93.78%)		(-1.25%)	(101.20%)	

Table 1.6: Decomposition of the ln Hourly Wage Difference between Genders by educational achievement(without ownership, occupation, and sector controls)

	1995	**2002**	**2007**	**2013**	**2014**	**2018**
	A. Without a High School Degree					
Total Differential	0.1601	0.2613	0.2301	0.3106	0.4583	0.2743
Amount attributable to:						
endowments	0.0262	0.0567	0.0046	0.0006	0.0081	0.0169
returns	0.1339	0.2046	0.2255	0.3099	0.4502	0.2574
% of total explained by the endowments	16.36%	21.70%	2.00%	1.93%	1.77%	6.16%
% of total unexplained	83.64%	78.30%	98.00%	99.77%	98.23%	93.84%
	B. With at least College Degree					
Total Differential	0.0722	0.0424	0.1600	0.1635	0.1995	0.1754
The amount attributable to:						
endowments	0.0491	0.0497	0.0163	0.0057	0.0145	0.0124
returns	0.0231	-0.0073	0.1437	0.1578	0.1850	0.1630
% of total explained by the endowments	68.01%	117.45%	10.19%	3.49%	7.27%	7.07%
% of total unexplained	31.99%	-17.45%	89.81%	96.51%	92.73%	92.93%

Table 1.7: Decomposition of the ln Hourly Wage Difference between Genders by Ownership of the Work Unit (without ownership, occupation, and sector controls)

	1995	**2002**	**2007**	**2013**	**2014**	**2018**
			A. SOE			
Total Differential	0.1231	0.1662	0.2282	0.2238	0.3342	0.1753
The amount attributable to:						
endowments	0.0371	0.0414	-0.0349	0.0120	-0.0126	-0.0061
returns	0.0859	0.1248	0.2631	0.2112	0.3468	0.1815
% of total explained by the endowments	30.14%	24.91%	-15.29%	5.36%	-3.77%	-3.48%
% of total unexplained	69.78%	75.09%	115.29%	94.37%	103.77%	103.54%
			B. Foreign-Owned			
Total Differential	0.1448	0.2390	0.0672	0.3218		
The amount attributable to:						
endowments	-0.0271	0.0997	-0.0597	0.0173		
returns	0.1719	0.1393	0.1269	0.3045		
% of total explained by the endowments	68.01%	117.45%	10.19%	3.49%		
% of total unexplained	31.99%	-17.45%	89.81%	96.51%		

Table A.1: Provinces Covered by Each Survey

Survey	**Covered Provinces**
CHIP 1995	Beijing, Shanxi, Liaoning, Jiangsu,Anhui, Henan, Hubei, Guangdong, Sichuan, Yunan, Gansu
CHIP 2002	Beijing, Shanxi, Liaoning, Jiangsu,Anhui, Henan, Hubei, Guangdong, Chongqing, Yunan, Gansu
CHIP 2007	Shanghai,Jiangsu, Zhejiang, Anhui, Henan, Hubei, Guangdong, Chongqing, Sichuan
CHIP 2013	Beijing, Shanxi, Liaoning, Jiangsu, Anhui, Henan, Hubei, Hunan, Guangdong, Chongqing, Sichuan, Yunan, Gansu
CFPS 2014 **CFPS 2018**	Beijing, Tianjin, Hebei, Shanxi, inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxin, Hainan, Chongqing, Sichuan, Guizhou, Yunan, Shaanxi, Gansu, Ningxia, Xinjiang

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Chapter 2

Gender Wage Differentials in China from 1995 to 2018: Distributional Evidence Accounting for Employment Composition using Partial Identification

2.1 Introduction

Reducing the gender wage gap brings multiple benefits to the economy such as promoting economic growth (Schober and Winter-Ebmer, 2011), potentially improving women's healthcare access (Fee, 1991) and mental health (Platt and Keyes, 2016), reducing domestic violence against women (Aizer, 2010), and increasing women's fertility autonomy (Qian and Jin, 2018). To reduce the gender wage gap, it is necessary to estimate the gender wage gap changes in recent decades and its trend. Researchers have documented a substantial reduction in the gender wage gap in the United States during the 1980s and a stable gender wage gap from 1980 to 2010 (Blau and Kahn, 2017).

The story is quite different in China. In recent years, China has experienced a transition of gender pay gaps. The observed wage earnings gap between males and females has progressively widened since 1988 (Gustafsson and Li, 2000; Gustafsson and Wan, 2020). Gustafsson and Li (2000) use the Urban Household Income Survey and find that the average gender wage gap has increased from 15.6% in 1988 to 17.5% in 1995. For a later period, Chi and Li (2014) find that the average gender earnings gap has increased from 2005 to 2009; estimates from Heckman's selection-correction model, which accounts for selection into employment, suggest an overall underestimated raw observed gender earnings gap by 12 - 14%. In more recent years, Song et al. (2019) used China Household Income Survey (CHIP) and recorded a temporary narrowing in the gender earnings gap from 29% in 2007 to 25% in 2013.

The existing literature has mostly focused on measuring the average gender earnings gaps conditional on employment. Instead, this study aims to re-examine changes in the gender wage differentials at the median, the 25^{th} and the 75^{th} wage quantiles in China from 1995-

2018, while effectively accounting for changes in employment composition and the intensive margin of labor supply (i.e., hours worked). We use data from the China Household Income Survey (CHIP) 1995-2013 and the China Family Panel Studies (CFPS), 2014 and 2018.

Controlling for selection into employment is particularly important in estimating the gender wage gap in China. Since 1988, the labor market structure in China has gone through dramatic structural changes (e.g., Li et al., 2012; Meng, 2012). Before 1995, China's unemployment rate was lower than other countries' unemployment rate. Since the mid-1990s, the Chinese government began privatizing small and medium-sized state-owned enterprises (SOEs), which triggered large-scale layoffs. The unemployment rate jumped to a level even higher than that of the high-income countries, peaking above 10% in 2002-2003, then slowly drifting down (Feng et al., 2017). In the same period when the unemployment rate increased, the overall urban labor participation rate dropped from over 82% to around 75%. The labor force participation rate has remained low ever since. These changes fell most heavily on the unskilled women (Feng et al., 2017), which can be potentially due to the increase of the returns to education and the high wage elasticity of women (Hare, 2019). Additionally, in late 2015, the Chinese government relaxed the one-child policy in China and replaced it with the two-child policy, which may have profound labor market impacts on women. For example, employers may be concerned that they need to pay for maternity leaves multiple times for each female employee and may be more reluctant to hire women after the two-child policy taking effect. Importantly, the estimated gender wage gap may be biased due to changes in labor force participation by gender over the years. For example, some highly-educated and likely high-wage women might be deterred by discrimination in the labor market as a result of child-bearing. If high-wage women are increasingly exiting the labor market, the observed gender wage gap may be inflated.

In the literature of gender wage gap estimation, methods employed to control for selection into employment include the Heckman selection-correction model (Blau and Beller, 1988; Mulligan and Rubinstein, 2008; Chi and Li, 2014), semiparametric quantile-copula (Maasoumi and Wang, 2019), the sample restriction and identification at infinity (Mulligan and Rubinstein, 2008; Machado, 2017), imputation of unobserved wage offers (Blau and Kahn, 2006; Blau et al., 2021), and bounding techniques (Blundell et al., 2007). Each method has its respective strengths and drawbacks. The Heckman selection-correction model yields precise estimates for gender wage gaps; however, the identification relies on strong assumptions about instrumental variables that affect employment but not wages (i.e., the exclusion restriction assumption). The nonparametric quantile-copula approach deals with selection into employment by computing the reservation wages of the non-working and allows for time-varying selection. However, it also relies on the exclusion restriction of the instrumental variables. The identification at infinity does not impose restrictions on the direction of the selection to employment; however, it restricts the sample among a population group that would "always work", which may not be representative of the population. The wage imputation method relies on the assumption that selection into employment is based on observed variables. Therefore, rich panel data with individuals' wage histories is usually needed for the imputation method, and this requirement may not be satisfied in all settings. The nonparametric bounds method we employ does not require exclusion restriction assumptions, although sometimes it may lead to wide bounds.

To account for differences in labor force participation (employment composition), we use bounds introduced by Manski (1994), Manski and Pepper (2000), and Blundell et al. (2007). We start with the worst-case bounds on the wage distribution in Manski (1994) and then employ additional assumptions substantiated by economic theory to tighten the bounds. The first assumption we use is the quartile dominance assumption. This assumption requires that conditional on age, education, and sex, the quartiles of the wage distribution (wages at the $25th$, $50th$, $75th$ percentile) of the non-working population not be higher than the corresponding quartiles of the wage distribution of the working population. We also employ a stronger version of this assumption – the stochastic dominance assumption, which requires the wage distribution of the working population to stochastically dominate the non-working population's. These two assumptions are based on a positive selection into labor force participation, which is implied by standard models of labor supply (e.g., Gronau, 1974; Blundell et al., 2007). To assess those assumptions, we estimate the log residual wage conditional on age, education, and survey year using CHIP 1995-2013 and CFPS 2014-2018. For males and females, respectively, the residual wage of those who are continuously employed is higher than the residual wage distribution of those who have non-working spells across all percentiles, except for three incidences – the 90th percentile for males over 45, and the 90th and the 95th percentiles for females under 45. Aside from the above exceptions, which occur at very high wage percentiles, the evidence from the residual wage analysis supports our quartile and stochastic dominance assumptions. Our third assumption employs the income of other household members as a monotone instrumental variable (MIV) for the wage of individuals. Specifically, we assume that for individuals with family members with higher income, their wage distribution would likely first-order stochastically dominates those with relatively lower-income family members. A theoretical justification of this assumption rests on the notion of assortative mating (Becker (1973); Nie and Xing (2019)) and the inter-generational income persistence (Feng et al., 2021; Gong et al., 2010).

After controlling for labor force participation and the hours worked, our bounds estimates show stronger evidence of an increase in the gender wage gap in the 1995-2007 period. The increase in the gender wage gap is most statistically significant among the young (under age 45), the college-educated, and at the median and high percentiles of the wage distribution. Specifically, the bounds estimates suggest a statistically significant increase of the gender wage gap for the young college-educated at the median wage of at least 0.19 log points, and at the 75th percentile of at least 0.21 log points. The estimated bounds at the 25th percentile for the young college graduates also suggest an increase in the gender wage gap of at least 0.11 log points, however, this 95% confidence interval (CI) does not exclude a zero change. The estimates for the 2007-2018 period do not exclude a zero change for most age and education groups. The bounds at the median wage suggest a decrease in the gender wage gap of at least 0.12 log points among the young college graduates, and at the 75th wage percentile a 0.05 log points decrease for the same group, while the 95% confidence intervals (CIs) does not exclude a zero change. This suggests a decrease in the gender wage gap at the median among young college graduates. Still, there is no statistically significant change in the gender wage gap at a higher quantile of the wage distribution for the same group of individuals.

The main contributions of this paper are in four aspects. First, to the best of our knowledge, we are the first to use bounds as the primary method to control for selection into employment in estimating the gender wage gap in China. Second, to conduct our analysis, we harmonize two nationally representative datasets to estimate the gender wage gap from 1995 to 2018. Different from previous literature that used earnings as the measure for the gender wage gap (e.g.,Chi and Li, 2014; Song et al., 2019), we construct a measure for the hourly wage. In this way we provide statistical evidence of changes in the gender wage gap avoiding biases due to labor supply's intensive (hours worked) and extensive (employed v.s. unemployed) margins, respectively. Third, we go beyond the median gender wage gap by analyzing the gender wage gap dynamics in China at the 25^{th} and 75^{th} percentiles of the wage distribution, thereby providing a fuller picture that includes the lower and upper sides of the wage distribution. Fourth, we improve statistical inference on the bounds using MIVs in Blundell et al. (2007). Bounds that use MIVs involve maximum and minimum operators, for which the standard inference breaks down (Hirano and Porter, 2012). We adopt a method proposed by Chernozhukov et al. (2013) to bias-corrected and obtain asymptotically valid confidence intervals for these bounds.

2.2 Bounds on the Wage Distribution Accounting for Employment

Let W be the log wage and X be control variables such as gender, age, education, and the survey year. Let E indicate whether a person is employed, with $E = 1$ being employed and $E = 0$ otherwise. The probability of being employed given characteristics $X = x$ is written as $P(x)$. We write the cumulative distribution function (CDF) of W given $X = x$ by $F(w|x)$, given $X = x$ and $E = 1$ by $F(w|x, E = 1)$, and given $X = x$ and $E = 0$ by $F(w|x, E = 0)$. We have

$$F(w|x) = F(w|x, E = 1)P(x) + F(w|x, E = 0)[1 - P(x)] \tag{2.1}$$

In equation (2.1), data only identifies $F(w|x, E = 1)$ and $P(x)$. $F(w|x, E = 0)$, which is the wage distribution of the population who did not take up employment, is not observed in the data. We partially identify the wage distribution of the unemployed, $F(w|x, E = 0)$ using comparably weak assumptions.

2.2.1 The Worst Case Bounds

The worst case bounds following Manski (1994) and Blundell et al. (2007) substitute the inequality that follows from the definition of a CDF

$$0 \leq F(w|x, E = 0) \leq 1$$

into equation (2.1) to bound the log wage cumulative distribution function of the total population ($F(w|x)$) as:

$$F(w|x, E = 1)P(x) \leq F(w|x) \leq F(w|x, E = 1)P(x) + [1 - P(x)] \tag{2.2}$$

The bounds can then be translated to give the worst case bounds on the conditional quantiles. Denote the q-th quantile of $F(w|x)$ by $w^q(x)$, then

$$w^{q(l)}(x) \leq w^q(x) \leq w^{q(u)}(x)$$

where the log wage $w^{q(l)}(x)$ is the lower bound and the log wage $w^{q(u)}(x)$ is the upper bound that respectively solve the following two equations with respect to w,

$$q = F(w|x, E = 1)P(x) + [1 - P(x)] \tag{2.3}$$

and

$$q = F(w|x, E = 1)P(x) \tag{2.4}$$

Since $F(w|x, E = 1)P(x)$ cannot be smaller than zero, equation (2.3) cannot be smaller than $[1 - P(x)]$; likewise, since $F(w|x, E = 1)$ cannot be greater than 1, equation (2.4) cannot be larger than $P(x)$. Due to the lower limit of equation (2.3) and the upper limit of equation (2.4), using the worst case bounds, we can only identify the lower bounds to log wage quantiles $q \geq 1 - P(x)$ and upper bounds for quantiles $q \leq P(x)$ (Blundell et al., 2007). The worst-case bounds are likely to be wide in practice. Therefore, we impose restrictions on the log wage distribution to obtain narrower bounds.

2.2.2 Stochastic Dominance and Quartile Dominance

The standard labor supply model suggests that when the substitution effect of a change in the wage dominates its income effect, individuals that command higher wages will be more likely to work, ceteris paribus (Blundell and MaCurdy, 1999). Thus, as in Blundell et al. (2007), we impose a stochastic dominance assumption between the wage distributions of the workers and non-workers. That is, we assume that conditional on $X = x$, the wages of those observed working first-order stochastically dominates those of the non-workers. This assumption is based on the notion that workers are more productive than non-workers; therefore, at each percentile of the distribution, the workers' observed wages would not be lower than non-workers' potential wages. Blundell et al. (2007) show that this positive selection into employment requires that the difference between the observed wage and the reservation wage, denoted by $w - w^R$ should be positively correlated with w. Intuitively, we can expect individuals with a higher preference to work to have a low reservation wage w^R and have invested more in human capital in the past, and the accumulated human capital yields higher wages w and greater differences from w^R (Blundell et al., 2007).

This assumption seems plausible in the case of China. In the recent decades of China's labor market, the increase in the non-working population has mostly been driven by the unskilled workers (e.g., Feng et al., 2017; Gustafsson and Ding, 2011), which implies that the working population consists of workers with relatively higher human capital. In addition, Li et al. (2016) show that the college premiums from 1990-2000 in China have increased. Li et al. (2017) predict that with investment in physical capital and skill-biased technological change, the return to human capital in China will continue to increase. If individuals with more human capital are more likely to be employed and paid more, this increase in return to human capital in China continues to make the stochastic dominance assumption more convincing.

Following Blundell et al. (2007), we formulate the stochastic dominance assumption in our application as

$$F(w|x, E = 1) \leq F(w|x, E = 0) \quad \forall w, \quad \forall x \tag{2.5}$$

for each w with $0 \leq F(w|x) \leq 1$ or, equivalently,

$$Pr(E = 1|W \leq w, x) \leq Pr(E = 1|W > w, x).$$

Under this assumption, the wage distribution of the unemployed $F(w|x, E = 0)$ in the total wage distribution in equation (2.1) is lower-bounded by the wage distribution of the employed $F(w|x, E = 1)$. We can replace $F(w|x, E = 0)$ with $F(w|x, E = 1)$ in the lower bound of equation (2.1) and the bounds on the distribution of the wage becomes

$$F(w|x, E = 1) \leq F(w|x) \leq F(w|x, E = 1)P(x) + [1 - P(x)] \tag{2.6}$$

Similar to the case of the worst case bounds, the bounds for the conditional wage quantiles under the stochastic dominance assumptions are $w_s^{q(l)}(x) \leq w^q(x) \leq w_s^{q(u)}(x)$, where $w_s^{q(l)}(x)$ and $w_s^{q(u)}(x)$ respectively solve the following two equations with respect to w,

$$q = F(w|x, E = 1)P(x) + [1 - P(x)] \tag{2.7}$$

and

$$q = F(w|x, E = 1) \tag{2.8}$$

The stochastic dominance assumption may not be satisfied in some scenarios. For example, for individuals in households who have accumulated financial assets and human capital, a negative correlation between $w - w^R$ and w might undermine the stochastic dominance assumption (Blundell et al., 2007). In light of these scenarios in which positive selection into employment may not be satisfied, we employ a weaker restriction - a quartile dominance assumption. This assumption restricts that the 25th, 50th, and the 75th wage quantiles for those not working to be not higher than the corresponding wage quantiles of the observed wage distribution. This assumption implies the following bounds for the distribution of log wages of the unemployed.

$$\begin{aligned}
0 \leq &F(w|x, E = 0) \leq 1, \quad \text{if} \quad w < w^{25(E=1)}(x), \\
0.25 \leq &F(w|x, E = 0) \leq 1, \quad \text{if} \quad w^{25(E=1)}(x) \leq w < w^{50(E=1)}(x), \\
0.5 \leq &F(w|x, E = 0) \leq 1, \quad \text{if} \quad w^{50(E=1)}(x) \leq w < w^{75(E=1)}(x), \\
0.75 \leq &F(w|x, E = 0) \leq 1, \quad \text{if} \quad w \geq w^{75(E=1)}(x),
\end{aligned} \tag{2.9}$$

Under the quartile dominant assumption, in equation (2.9), since the three wage quartiles (i.e., the $25th$, $50th$, and $75th$ wage quantiles) of the employed should not be lower than the respective counterpart wage quartiles of the unemployed, when wage w is higher than the $25th$ quantile wage of the employed ($w^{25(E=1)}$), the wage distribution of the unemployed

$F(w|x, E = 0)$ is lower-bounded by 0.25, and similarly when w is higher than the $50th$ or the $75th$ quartile wages of the employed. Therefore, the bounds for the wage distribution are:

$$
\begin{aligned}
&F(w|x, E=1)P(x) \\
&\qquad \le F(w|x) \\
&\qquad \le F(w|x, E=1)P(x) + (1 - P(x)), \quad \text{if} \quad w < w^{25(E=1)}(x), \\
&F(w|x, E=1)P(x) + 0.25(1 - P(x)) \\
&\qquad \le F(w|x) \\
&\qquad \le F(w|x, E=1)P(x) + (1 - P(x)), \quad \text{if} \quad w^{25(E=1)}(x) \le w < w^{50(E=1)}(x), \\
&F(w|x, E=1)P(x) + 0.5(1 - P(x)) \\
&\qquad \le F(w|x) \\
&\qquad \le F(w|x, E=1)P(x) + (1 - P(x)), \quad \text{if} \quad w^{50(E=1)}(x) \le w < w^{75(E=1)}(x), \\
&F(w|x, E=1)P(x) + 0.75(1 - P(x)) \\
&\qquad \le F(w|x) \\
&\qquad \le F(w|x, E=1)P(x) + (1 - P(x)), \quad \text{if} \quad w \ge w^{75(E=1)}(x)
\end{aligned}
\tag{2.10}
$$

In the set of bounds in equation (2.10), the bounds for $w^{25(E=1)}(x) \le w < w^{50(E=1)}(x)$ is obtained by replacing $F(w|x, E = 0)$ with 0.25 in the lower bound of the total wage distribution in equation (2.1). Similarly, the bounds when $w^{50(E=1)}(x) \le w < w^{75(E=1)}(x)$ and $w \ge w^{75(E=1)}(x)$ are obtained by replacing $F(w|x, E = 0)$ with 0.5 and 0.75 respectively. The corresponding bounds for the conditional wage quantiles under the quartile dominance assumptions are $w_q^{q(l)}(x) \le w_q^q(x) \le w_q^{q(u)}(x)$, where $w_q^{q(l)}(x)$ and $w_q^{q(u)}(x)$ respectively solve the following two equations (11) and (12) with respect to w,

$$
q = F(w|x, E=1)P(x) + [1 - P(x)] \tag{2.11}
$$

and

$$
\begin{aligned}
&q = F(w|x, E=1)P(x), && \text{if} \quad w < w^{25(E=1)}(x), \\
&q = F(w|x, E=1)P(x) + 0.25(1 - P(x)), && \text{if} \quad w^{25(E=1)}(x) \le w < w^{50(E=1)}(x), \\
&q = F(w|x, E=1)P(x) + 0.5(1 - P(x)), && \text{if} \quad w^{50(E=1)}(x) \le w < w^{75(E=1)}(x), \\
&q = F(w|x, E=1)P(x) + 0.75(1 - P(x)), && \text{if} \quad w \ge w^{75(E=1)}(x).
\end{aligned}
\tag{2.12}
$$

We assume the log wage at the three wage quartiles of the employed individuals should be lower than the respective counterpart wage quartiles of the unemployed; however, we do not observe the log wage distribution for those who are not employed. Instead, using the panel data, we can compare the wage distribution for individuals who continuously work during the observed periods and the wage distribution for those experience an unemployment spell. We find empirical evidence in our data that supports the stochastic and quartile dominance assumptions. In Figure 1, we compare the distribution of residual wages by gender, age, and work history of workers who have been continuously employed and of workers with spells of unemployment using the China Family Panel Studies (CFPS), 2014 and 2018 [1]. The residual wages are obtained in a regression controlling for age, age squared, college degree attainment, province of residence, and survey year dummies. If the wage percentiles of workers without unemployment spells are higher than those of workers with unemployment spells, we consider it is in line with the positive selection into employment. The darker lines indicate the residual wages across percentiles for workers who do not have spells of unemployment in their work history. The lighter lines are for the workers with spells of unemployment. The results show that the residual wages of males and females who do not have unemployment spells are consistently higher than the wages of males and females who do have unemployment spells from the 5th quantile to the 95th quantile, except for three incidences – the 90th percentile for males over 45, and the 90th and the 95th percentiles for females under 45. The above exceptions occur at very high wage percentiles, suggesting that the stochastic dominance assumption, which implies that any wage quantiles of the unemployed should not be higher than the employed, may fail at very high wage quantiles for young women and older men. In Figure 1, we use boxes to indicate the $25th$, $50th$ and the $75th$ wage quantiles. The residual wage quantile estimates offer support for the weaker quartile dominance assumption in all samples.

2.2.3 Monotone Instrumental Variables

Under the exclusion restriction (ER), traditional instrumental variables can help to tighten the bounds in equation (2) (Manski, 1994; Blundell et al., 2007). The literature has used instrumental variables (IVs) to tackle the employment selection, such as an indicator of a young child aged less than six years (Chi and Li, 2014), and the number of young children in the household (Mulligan and Rubinstein, 2008). However, these instrumental variables may not satisfy the ER, which requires that the IV can only affect wages through employment (Angrist et al., 1999). For example, in cases of using the number of young children as the IV, fertility decisions may affect wage and earnings independently of employment status. For example, Bratti (2015) shows that postponing fertility raises women's wages, in which case the number of children may affect earnings independently of employment, violating the ER.

Given that it is hard to find a valid traditional IV for employment that is independent of $F(w|x)$, we instead follow Manski and Pepper (2000) and adopt the following weaker monotone IV (MIV) assumption, which does not require an exclusion restriction condition-to tighten the bounds:

$$F(w|x,z') \leq F(w|x,z), \quad \forall w,x,z,z' \quad with \quad z < z'. \tag{2.13}$$

Equation (2.13) assumes that a higher value of the MIV Z will lead to a distribution of wages that first-order stochastically dominates the distribution of wages with lower values of Z. In our application, Z is the average income of the other household members in an individual's household. The rationale of the MIV assumption is predicated on the human capital assortative mating behavior in China (Han, 2010; Nie and Xing, 2019) and the

[1] See the Data Section for details of the sample

documented inter-generational income persistence in China (Feng et al., 2021; Gong et al., 2010). First, people tend to marry spouses with similar human capital and earning potential (assortative mating). For people with higher-income spouses, their wage distribution would likely first-order stochastically dominate those whose spouses have lower income. Second, inter-generational income persistence may also contribute to the monotone relationship in equation (2.13). Specifically, if children with higher-income parents are likely to earn more, the wage distribution of workers who live with their high-income parents will stochastically dominate the workers who live with their lower-income parents.

To exploit the MIV restriction, we can find the tightest bounds over the spourt of Z and ehn integreate out Z. Therefore, under the MIV assumption, for a value of $Z = z_1$, we can find the highest lower bound ($F^1(w|x, z_1)$) for the distribution of the wage[2] over $z \geq z_1$ in the support of Z:

$$F(w|x, z_1) \geq F^1(w|x, z_1) \equiv \max_{z \geq z_1} \{F(w|x, z, E = 1)P(x, z)\}. \tag{2.14}$$

and the lowest upper bound($F^u(w|x, z_1)$) over $z \leq z_1$ in the support of Z:

$$F(w|x, z_1) \leq F^u(w|x, z_1) \equiv \min_{z \leq z_1} \{F(w|x, z, E = 1)P(x, z) + 1 - P(x, z)\}. \tag{2.15}$$

Regarding the bounds on the wage quantiles, for a value of $Z = z_1$, we have $w^{q(l)}_{miv}(x, z_1) \leq w^q(x, z_1) \leq w^{q(u)}_{miv}(x, z_1)$, where $w^{q(l)}_{miv}(x, z_1)$ and $w^{q(u)}_{miv}(x, z_1)$ respectively solve the following two equations with respect to w,

$$q = F^u(w|x, z_1) \equiv \min_{z \leq z_1} \{F(w|x, z, E = 1)P(x, z) + 1 - P(x, z)\}, \tag{2.16}$$

and

$$q = F^l(w|x, z_1) \equiv \max_{z \geq z_1} \{F(w|x, z, E = 1)P(x, z)\}. \tag{2.17}$$

The bounds on $w^q(x)$ can then be constructed by integrating over the distribution of Z given $X = x$, that is,

$$E_Z[w^{q(l)}_{miv}|x] \leq w^q(x) \leq E_Z[w^{q(u)}_{miv}|x]. \tag{2.18}$$

Our approaches to estimating the gender wage differentials are motivated by the fact that the assumptions needed for point identification are not easy to justify and satisfy in practice. The worst-case bounds do not rely on any assumptions; therefore, bounds derived under other weak assumptions are theoretically narrower than the worst-case bounds. The stochastic dominance and quartile dominance assumption express the notion that workers are likely to be more productive than nonworkers, and we show evidence of this positive selection. Since the quartile dominance assumption is a weaker version of the stochastic dominance assumption, the estimated bounds should be narrower under the stochastic dominance assumption. We also relax the exclusion restriction and use a weaker monotonicity assumption that allows for the positive relationship between wages and the instrument,

[2]Please see Appendix B for computation and inference details.

which is the average of other members' income in the worker's household. Theoretically, the tightest bounds should be under the combination of stochastic assumption and MIV.

2.2.4 Bounds on the Gender Wage Gap and its Change over Time

Our goal is to conduct inference on the gender wage gap dynamics from 1995-2018 in China. We use the bounds of males and females' wage quantiles to estimate the gender wage gap over the wage distribution and its changes over different points in time. For example, let the lower bound and the upper bound for males' wage quantile q with education and age characteristics x in year t be $w^{q(l)}(male, x, t)$ and $w^{q(u)}(male, x, t)$, and the female's equivalent bounds be $w^{q(l)}(female, x, t)$ and $w^{q(u)}(female, x, t)$. The bounds for the gender wage gap at the quantile q, $D_t^q(x) = w^q(male, x, t) - w^q(female, x, t)$ are:[3]

$$w^{q(l)}(male, x, t) - w^{q(u)}(female, x, t) \leq D_t^q(x) \leq w^{q(u)}(male, x, t) - w^{q(l)}(female, x, t). \tag{2.19}$$

Similarly, the lower bound of the change in the gender wage gap from year t to year s, $\Delta D_{st}^{q(l)}$, where $s > t$, is given by,

$$\{w^{q(l)}(male, x, s) - w^{q(u)}(female, x, s)\} - \{w^{q(u)}(male, x, t) - w^{q(l)}(female, x, t)\}, \tag{2.20}$$

and the upper bound, $\Delta D_{st}^{q(u)}$, where $s > t$, is given by,

$$\{w^{q(u)}(male, x, s) - w^{q(l)}(female, x, s)\} - \{w^{q(l)}(male, x, t) - w^{q(u)}(female, x, t)\}. \tag{2.21}$$

2.3 Estimation and Inference

Our main focus will be the bounds on the quantiles of the wage distribution. To estimate these, we first estimate the bounds on the distribution of wages. We now describe the nonparametric estimation procedure we have used. The conditioning vector X includes gender, education, age, and time. Estimating the worst case bounds and the bounds with monotonicity requires estimating the employment probability and the distribution of wages observed amongst the workers for each possible set of characteristics X. We define two education groups: those who with at most a high school degree (Non-College Group) and those who with at least a college degree or a Dazhuan degree (College Group). We also limit the number of age groups to two: those below 45 (young) and those above 45 (old). We construct confidence intervals for the changes in the differentials over time using the bootstrap and applying the results of Imbens and Manski (2004) and Chernozhukov et al. (2013).

Our bounds under the MIV assumption contains maximum or minimum operators (see equations (2.14)-(2.17)). Hirano and Porter (2012) show that for bounds that contain maximum or minimum operators, standard inference breaks down, which prevent us from using

[3]These bounds can be computed under different combinations of the assumptions presented in Section 2.2 and 2.3.

the confidence intervals in Blundell et al. (2007). To obtain valid confidence regions for the true wage percentile parameters of interest, we estimate these confidence intervals using the method proposed by Chernozhukov et al. (2013). In this section we briefly describe Chernozhukov et al. (2013) as applied to our bounds.

Let the bounds for a parameter θ_0 (e.g., the median wage) be given by $[\theta_0^l, \theta_0^u]$, where $\theta_0^l = \max_{\upsilon \in \mathcal{V}^l=\{1,\ldots,m^l\}} \theta^l(\upsilon)$ and $\theta_0^u = \min_{\upsilon \in \mathcal{V}^u=\{1,\ldots,m^l\}} \theta^u(\upsilon)$. Chernozhukov et al. (2013) calls $\theta^l(\upsilon)$ and $\theta^u(\upsilon)$ bounding functions. We follow Flores and Flores-Lagunes (2013) and let υ index the bounding functions and m^l and m^u be, respectively, the number of terms inside the max and min operators. For example, suppose the wage distribution $F(w_1|x, z_1)$ has two lower bound candidates $\max_{z \geq z_1}\{F(w_1|x, z_1, E = 1)P(x, z_1), F(w_1|x, z_2, E = 1)P(x, z_2)\}$, and we can write $\theta_0^l = \max_{\upsilon \in \mathcal{V}^l=\{1,2\}} \theta^l(\upsilon) = \max\{\theta^l(1), \theta^l(2)\}$, with $\theta^l(1) = F(w_1|x, z_1, E = 1)P(x, z_1)$ and $\theta^l(2) = F(w_1|x, z_2, E = 1)P(x, z_2)$. The sample analog estimators of the bounding functions $\theta^l(\upsilon)$ and $\theta^u(\upsilon)$ are consistent and asymptotically normally distributed, because they are simple functions of proportions.

Chernozhukov et al. (2013) employ precision-corrected estimates of the bounding functions to construct the confidence regions for the bounds $[\theta_0^l, \theta_0^u]$. Specifically, the precision adjustment is done by adding to each estimated bounding function (i.e., each bound candidates) the product of its pointwise standard error and an appropriate critical value, $\kappa(p)$. With different choices of $\kappa(p)$, we may obtain the confidence regions for either the true parameter value or the identified set, and half-median unbiased estimators for the lower and the upper bounds.[4] The bounding function estimates that have higher standard errors receive larger adjustments. For example, the precision-corrected estimator of the lower bound θ_0^l is given by

$$\hat{\theta}^l(p) = \max_{\upsilon \in \mathcal{V}^l} [\hat{\theta}^l(\upsilon) - \kappa^l_{n, \hat{V}_n^l}(p) s^l(\upsilon)], \tag{2.22}$$

where $\hat{\theta}^l(\upsilon)$ is the sample analog estimator of $\theta^l(\upsilon)$ and $s^l(\upsilon)$ is its standard error. Chernozhukov et al. (2013) compute the critical value $\kappa^l_{n, \hat{V}_n^l}(p)$ based on simulation methods and a preliminary estimator $\hat{V}_n^l = arg \max_{\upsilon \in \mathcal{V}^l} \theta^l(\upsilon)$, and p is determined by the confidence level of choice. Intuitively, $\hat{V}_n^l$ selects those bounding functions that are close enough to binding to affect the asymptotic distribution of the estimator of the lower bound. We obtain the precision-corrected estimator of the upper bound θ_0^u in a similar way. Since the critical value and the standard error in equation (2.22) are both non-negative, the bias-corrected bounds tend to be wider than the uncorrected ones. Further details on our specific implementation steps are provided in Appendix B.

2.4 Data and Variable Definitions

This study uses both household-level and individual-level data from two surveys. We use the Chinese Household Income Project (CHIP) for the year of 1995, 2002, 2007, 2013, and the China Family Panel Study (CFPS) for the year of 2014 and 2018. Using CHIP

[4]The property half-median-unbiasedness means that the lower bound estimator is less than the true value of the lower bound with probability at least one half asymptotically, while the reverse holds for the upper bound (Chernozhukov et al., 2013).

and CFPS together enables us to analyze the dynamics of the gender wage gap in China from the mid-1990s to the late 2010s. This section describes CHIP and CFPS, discusses the challenges we encounter while using data from those two surveys together, explains how we construct our key variables, and introduces our analytic sample.

2.4.1 CHIP and CFPS

CHIP was carried out as part of a collaborative research project on income and inequality in China organized by Chinese and international researchers and institutions, including the Chinese Academy of Social Sciences and the School of Economics and Business Administration at Beijing Normal University. CHIP is a nationally representative household-level survey aimed at estimating income, wealth, consumption, and related economic measures in rural and urban areas in China. CHIP uses a stratified random sampling process to collect data for three different samples – rural, urban, and migrant groups in 22 provinces, all at household and individual levels. CHIP samples are cross-sectional and are subsamples taken from the National Bureau of Statistics (NBS) samples used to obtain the official household statistics published in the annual Statistical Yearbook of China. CFPS is a nationally representative, bi-annual longitudinal survey of the Chinese communities, families, and individuals, conducted by the Institution of Social Science Survey of Peking University since 2010. Both CHIP and CFPS include individual-level demographics and detailed information on wage income and wealth, making it possible to analyze the national trend of wage inequality.

2.4.2 CHIP and CFPS Data Harmonization

Although both CHIP and CFPS are nationally representative surveys, their samples are drawn from different provinces in China.[5] Therefore, we need to make sure we use the correct sampling weights to make those two samples comparable. In the CFPS samples, we use "the individual-level national sampling weights" provided in the data set. In CHIP, we use the sample weights based on regional and provincial total population for CHIP samples, following Li et al. (2017) for CHIP 2007 and 2013. Since Li et al. (2017) only provide the sampling weight information for the years 2007 and 2013 but not for the earlier years, we do not apply weights for the CHIP 1995 and 2002.[6]

To construct the hourly wage variable given yearly earnings, information about each individual's working hours is necessary. Since CHIP 1988 does not have information about hours worked, we are forced to exclude it from our analysis. Additionally, we exclude CFPS 2010, 2012, and 2016 from our analysis due to missing values in key variables. Specifically, in CFPS 2010 and 2012, we found abnormal employment rates, especially for non-college-educated females in the raw sample. As a reference, the employment to population ratio was 67.75% in 2010 for individuals aged 15+ according to the World Bank; however, in CFPS 2010, after applying sampling weights, the employment to population ratio is only 55.41% for the same age group, and 63.25% for individuals aged 25 – 55. We also noticed

[5] Table A.10 in the Appendix lists the covered provinces for each survey by year.

[6] Not applying these sampling weights is also consistent with the previous studies that used CHIP 1995 and 2002 (for example, Xing and Li, 2012; Zhu, 2016; Yang and Gao, 2018), which also makes our results more comparable to the literature.

that, compared to the CHIP sample, the CFPS sample generally has a lower employment rate. However, compared to CHIP 2007, CHIP 2013, and CFPS 2014, non-college-educated females in CFPS 2012 experienced an extremely low employment rate. The employment ratio for non-college-educated females is between 60 - 75% for CHIP 2007, CHIP 2013, and CFPS 2014; however, the employment ratio is even below 60% in CFPS 2012, which we have not found any reference in explaining. Therefore, we exclude CFPS 2010 and CFPS 2012 from our analysis. In CFPS 2016, an improper operation failed to collect main-job-related information for individuals who did not experience work changes between CFPS 2014 and CFPS 2016 (see CFPS Database Clean Report), which makes these data not usable to us as we would not be able to measure earnings and hours worked accurately for everyone in the sample. Therefore, we use data from CHIP 1995, 2001, 2007, 2013 together with CFPS 2012 and 2016 to construct our analytic sample. This sample includes Chinese urban residents aged 25 to 55 with an urban hukou who do not work in the agriculture sector.

2.4.3 Key Variables Construction

There are some differences between CHIP and CFPS in the income and employment variables. Following Kanbur et al. (2021) and Li and Wan (2015) both of whom use CFPS and CHIP data to analyze the evolution of household income inequality, we break down different income sources in CHIP (for both individual's income and household income) and reconstruct them into the same income definition as in CFPS. Below we discuss how we construct each key variable.

Hourly Wage

In our analysis, earnings are measured in an accounting period of one year. They include regular wages, overtime compensation, allowances, and bonuses. This is the same definition employed in Gustafsson and Wan (2020) and Zhu (2016). We use an individual's earnings from the major/primary job as the earnings measure in our analysis. For cases where the survey does not specify a major/primary job for an individual, we used the earnings from the job where an individual spent the most time and which had the highest-earning. Earnings are adjusted to the 2018 prices level using the national urban consumer price index provided by the National Bureau of Statistics of China.

To construct the hourly wage, information about hours worked is needed. Among all the surveys, only CHIP 2002 has yearly earnings with working hours per day, working days per month, and months worked to accurately construct hourly wage. In other surveys, where the annual working hours are not directly provided, we compute annual working hours by either worked hours per week or worked hours per month, whichever is available, assuming workers work four weeks per month and 52 weeks per year. We then construct the hourly wage for our primary analysis by dividing the annual primary income by the annual total working hours, following Hering and Poncet (2010), Kamal et al. (2012), and Lovely et al. (2019). Constructing hourly wages helps us account for the intensive margin of labor supply.

The left panel of Figure 2 presents the observed log wage gender gap at the median, and the right panel presents the observed log hourly wage estimates by gender. From the graph, we can tell that there is a progressive increase in the gap before 2007, and after 2007 the direction changes and shows a decreasing trend.

Other Household Members' Income

For bounds using the monotone instrumental variable (MIV) assumption, the MIV for employment in our analysis is the income of other household members. Specifically, we use the family income minus the person's total income and average other the size of the household minus one as the income from other family members in the household. For individuals without a family, this other member's income would be zero.

CHIP does not report the total household income; therefore, we use the sum of every household member's individual total income as the total household income. In CHIP samples, an individual's total income includes the yearly income, the subsidy from minimum living standard, living hardship subsidies from the work unit, second job, sideline income, and the monetary value of income in kind.

In CFPS, we are able to calculate the total household income directly, i.e., the sum of the household total wage income, operating income, transfer income, property income, and other income. We also construct another measure of total household income by adding up the total income of all household members. In our analysis, we take the larger amount among these two income measures as the household total income measure.[7] Similarly, we also use the larger amount between an individual's total income provided by the survey and the individual's income added up from different sources as the individual's total income in the analysis. In CFPS, the added-up individual income is the sum of wage income from all sources, operating income, subsidies, and bonuses. We assign zero to the other family members' income for individuals who live alone.

2.4.4 Sample and Summary Statistics

Our sample includes Chinese urban residents aged 25 to 55 with an urban hukou and not working in the agriculture sector. We focus on urban households to mitigate the differences in social benefits between households with urban and rural hukou (Xing and Li, 2012). We exclude individuals with no household registrations or foreign residents for similar reasons. An individual is classified as employed ($E_i = 1$) if he/she is reported to have been employed during the past year. Since we use the hourly wage in our analysis, we treat self-employed individuals as employed ($E_i = 1$) but exclude them from calculating the observed wage distribution. The observed wage distribution is conditional on the employed individuals ($E = 1$) after controlling for the observed individual characteristics x, $F(w|x, E = 1)$. We control for age and education in the analysis. We divide our sample into two age groups and two education groups. We define individuals older than 45-years-old as in the old age group and individuals aged 45 or younger as in the young age group. For those with at most a

[7]Theoretically, the added-up total household income from the household survey should be the same as the added-up total income from all household members from the individual survey. However, when we use the CFPS sample, those two numbers are not always consistent, and there are cases where we have missing values in one of the two. Therefore, we use the larger amount among those two measures as the total household income.

high school degree, we define them as non-college degree holders, and for those with either a Dazhuan degree (equivalent to an associate degree in the U.S.) or at least a college degree as college degree holders.[8]

Figure 3 shows the changes in employment (including self-employed) against age by gender. Compared to 1995, the probability of employment for males under age 45 and females under age 40 increased in 2018. However, there is a dramatic drop in the employment probability for males around 50 and females around 45. This is correlated with the usual retirement age in China, note that the Statutory Retirement Age is 60 for males and 55 for females in China.

Figure 4 illustrates that the changes in employment have been heavily skill-and-gender-biased. The employment gap between college-educated and non-college-educated females is larger than for their male counterparts. Moreover, the non-college females' employment dropped greatly in 2013. If low-skilled women are exiting employment, we anticipate the gender wage gap would be larger after considering the employment composition in the 2010s.

2.5 Results

2.5.1 Changes in the Median Gender Wage Gap

This section presents the results of estimated bounds on the changes in the median gender wage gap in China under different assumptions.Importantly, the estimated bounds account for employment composition. Figure 5 shows the results for changes from 1995 to 2018.[9] In each figure, the space between two dots represents the bounds on the change in the gender wage gap between 1995 and 2018. The thin outer lines denote the 95% confidence interval for the change in the gender wage gap. The worst-case bounds to the change in the gender wage gap (Figure 5 Panel A) all include a zero change. The large width of the worst-case bounds is partially due to the low employment rates for females, as shown in Figure 4, particularly for those without a college education. To narrow the worst-case bounds, we separately impose the quartile and stochastic dominance restrictions and utilize the MIV assumption. With the quartile dominance restriction alone (Figure 5 Panel B), except for the non-college above 45-years-old sample, the estimated bounds for all groups indicate an increase in the gender wage differential of at least 0.03 - 0.10 log points and by at most 0.21 - 0.65 log points. However, none of the 95% confidence intervals (CIs) exclude zero. Using the stronger stochastic dominance assumption (Figure 5 Panel C), the bounds are tighter across the board. Under the stochastic dominance assumption, the bounds of the young non-college indicate an increase of the gender wage gap of at least 0.17 log points to 0.62 log points, with the 95% CI excluding zero. For the young college graduates, the bounds indicate an increase in the gap of 0.05 - 0.20 log points, however, the 95% CI includes zero. For the older workers, the bounds for those without a college degree include a zero change, suggesting a potential 0.07 log points decrease and a 1.06 log points increase. The bounds for older workers with a

[8]We do not use finer age and education groups because constructing bounds on the wage distribution requires a large number of observations.

[9]Table A.1 in the appendix reports the values for the upper and lower bounds and the corresponding 95% confidence intervals (CIs) of the bounds in Figure 5.

college degree suggest an increase in the gender wage gap of 0.12 - 0.47 log points, while the 95% CIs include zero. In Panel D, the MIV bounds are considerably wider, where the lower bounds indicate 0.10 - 1.42 log points of decrease in the gender wage gap and the upper bounds indicate 0.23 - 1.38 log points of increase in the gender wage gap.[10]

To analyze changes in the trend of the gender wage gap, we split our study period into 1995 – 2007 and 2007 – 2018. The break in 2007 is motivated by the finding in Song et al. (2019) of a temporary narrowing in the gender wage gap from 2007 to 2013. Figure 6 presents the estimated bounds from 1995 to 2007.[11] It is striking to see that the worst-case bounds for the young college graduates indicate a 0.07 - 0.32 log points increase in the gender wage gap, and the 95% CIs exclude zero (Figure 6 Panel A). Since worst-case bounds do not utilize any restrictions on the wage distribution, we consider this a strong indication of an increase in the gender wage gap for this group. The bounds for older college graduates indicate an increase of 0.10 - 0.25 log points in the gender wage gap, although the CI does not exclude a zero change. The worst-case bounds for the young and older non-college graduates do not exclude zero. This implies that from 1995 to 2207, there was a statistically significant increase in the gender wage gap among young college graduates, but not other groups.

In Panel B, the bounds under the quartile restriction follow the same pattern of the worst-case bounds, with tighter bounds for the young college graduates showing an increase of the gender wage gap of 0.13 - 0.28 log points, with the 95% CI excluding zero. They indicate an increase of 0.11 - 0.20 log points for the old college graduates, with the 95% CI not excluding zero. The bounds under stochastic dominance in Panel C are the narrowest, showing an increase in the gender wage gap for the young non-college graduates of 0.04 - 0.48 log points, for the young college graduates of 0.15 - 0.27 log points, and the old college graduates of 0.12 - 0.20 log points, with only the CI for the young college graduates excludes zero. The bounds for the old non-college graduates do not exclude a zero change in the gender wage gap, showing a potential decrease of at most 0.22 log points and a potential increase of at most 0.41 log points. In Panel D, all MIV bounds include a zero change except for the young college graduates, where the estimated bounds show an increase in the gender wage gap of 0.19 - 0.63 log points and the 95% CI exclude zero change. Figure 7 presents the bounds of the change in the median gender wage differential from 2007 to 2018. The worst-case bounds in Panel A, the estimated bounds under the quartile dominance restriction in Panel B, and the bounds under the stochastic dominance restriction in Panel C include zero for every group under consideration. Under the MIV restriction, the estimated bounds for the young college graduates indicate a decrease in the gender wage gap of between 0.12 - 0.59 log points (Figure 7 Panel D), but the 95% CI does not exclude zero. The estimated bounds for the other age and education groups using the MIV include zero changes of the

[10]In the current set of the results, bounds under the MIV assumption tend to be wider than those under the median assumption and sometimes the worst-case bounds. It may be attributed to the computation procedure explained in Appendix B.1. In brief, due to a computational constraint, we needed to first compute bounds under the MIV assumption in each sub-sample conditional on the ten quantiles of the MIV (the 5^{th}, the 15^{th}, ..., and the 95^{th} quantiles), and then obtain the average of the ten bounds to obtain the bounds for each education and age group. We are in the process of improving the efficiency in the computation of these bounds.

[11]Table A.2 and Table A.3 in the appendix report the corresponding estimated values for the upper and lower bounds and the corresponding 95% CIs.

gender wage gap from 2007 - 2018.

In summary, at the median of the wage distribution, the estimated bounds indicate a statistically significant increase in the gender wage gap for the young workers who are non-college-educated, and this gap has increased by 0.17 - 0.62 log points. After splitting the analysis into two time periods from 1995 - 2007 and 2007 - 2018, the estimated bounds indicate a significant increase in the median gender gap among young college graduates. We do not find any statistically significant change in the median gender wage gap in the later period for either group under consideration.

2.5.2 Changes in the 25^{th} Gender Wage Gap

Figure 8 to Figure 10 present the estimated bound on the gender wage gap changes over time at the 25^{th} quantile of the wage distribution.[12] Except for some bounds of the college-graduates in 1995-2018 and 1995-2007, the estimations indicate inconclusive changes in the gender wage gap for all the age and education groups and two different time periods.

Figure 8 shows the change from 1995 to 2018. From the figure, none of the estimated bounds excludes a zero change based on the 95% CIs. The narrowest bounds are those under the stochastic dominance assumption (Panel C). From left to right, the estimated bounds for the young non-college graduates indicate an increase in the gender wage gap of 0.04 - 1.23 log points. The bounds for the older non-college graduates rule out a decrease in the gap of at least 0.47 log points, and an increase of at least 0.89 log points. The estimated bounds for the young college-graduates suggest an increase in the gender wage gap of 0.04 - 0.36 log points. The estimated bounds for the older college-graduates suggest an increase in the gender wage gap of 0.06 - 0.90 log points.

Figure 9 presents the estimated bounds on the gender wage gap change between 1995 - 2007. For the young college-graduates group, the estimated bounds suggest similar implications as with the gender wage gap at the median wage. From the worst-case bounds to bounds under different restrictions, the estimated bounds for all groups suggest an increase in the gender wage gap of 0.03 - 0.60 log points. The estimated bounds under the stochastic dominance indicate an increase in the gender wage gap of 0.01 - 0.20 log points for the old college graduates and an increase of 0.07 - 0.32 log points for the young college graduate. The estimated bounds for the non-college groups include zero.

Figure 10 presents the estimated bounds for the change on the gender wage gap between 2007 - 2018. The estimated bounds for all groups are inconclusive for the sign of the gender wage gap changes. The tightest bounds are under stochastic dominance. The estimated lower bounds indicate a decrease on the gender wage gap of 0.08 - 0.67 log points, and the estimated upper bounds indicate an increase in the gender wage gap by 0.24 - 1.19 log points.

In a nutshell, compared to the estimation of the changes in the median gender wage gap, the results are less conclusive for the gender wage gap over time at the 25^{th} quantile of the wage distribution. Some evidence suggests an increase in the gender wage gap at the 25^{th} quantile of the wage distribution for the college-educated group, especially for young college graduates.

[12] Appendix Tables A4 - A6 present the corresponding values in these figures.

2.5.3 Changes in the 75^{th} Percentile Gender Wage Gap

Figure 11 to Figure 13 present the estimated bounds on the gender wage gap change over time at the 75^{th} quantile of the wage distribution.[13] Figure 11 shows the change from 1995 to 2018. The estimated bounds under the quartile restriction (Panel B) and the bounds under the stochastic dominance (Panel C) show an increase in the gender wage gap for young college graduates of 0.04 - 0.18 log points and 0.07 - 0.17 log points, respectively. However, none of the 95% CIs exclude a zero change. After we split up the study period, the estimated bounds show a consistent increase in the gender wage gap for college graduates (Figure 12 for 1995 - 2007). The estimated worst-case bounds suggest a 0.03 to 0.38 log points increase in the gender wage gap for young college graduates. For the old college graduates, the estimated bounds indicate an increase in the gender wage gap of 0.12 to 0.35 log points. However, none of the 95% CIs excludes a zero change (Figure 12 Panel A). The estimated bounds under quartile dominance restriction are tighter and suggest an increase in the gender wage gap for young college graduates of 0.17 - 0.30 log points, and an increase in the gender wage gap of 0.16 - 0.24 log points for old college graduates (Figure 12 Panel B). In both cases, the 95% CIs exclude zero(Figure 12 Panel B). Under the stochastic dominance restriction, the estimated bounds suggest an increase of the gender wage gap by 0.20 - 0.28 log points for the young college graduates and an increase of the gap by 0.17 - 0.22 log points for the old college graduates, with the 95% CI excluding zero (Figure 12 Panel C). The estimated MIV bounds in Figure 12 Panel D also suggest an increase in the gender wage gap for young college graduates by 0.21 - 0.62 log points, with the 95% CI excluding zero.

Figure 13 presents the estimated results during 2007 - 2018. The estimated bounds under the quartile and the stochastic dominance restrictions suggest a decrease in the gender wage gap of 0.02 to 0.22 log points (Figure 13 Panel B and C) for young college graduates. However, the 95% CI does not exclude a zero change. The estimated bounds for the other education and age groups all include zero change.

In summary, at the 75^{th} quantile of the wage distribution, the estimated bounds indicate a statistically significant increase in the gender wage gap for workers who are college-educated before 2007. After 2007, the estimated bounds indicate a decrease in the gender gap among young college graduates at the 75^{th} quantile of the wage distribution. We do not find statistically significant changes in the gender wage gap for all the other groups.

2.6 Discussion

Our estimated bounds show a pattern of an increasing gender wage gap among the young workers (age 25-45) in survey years of 1995-2007 at the median, the 25^{th} and the 75^{th} quantile of the wage distribution for employment composition of 0.15 - 0.32 log points. This result is in line with previous findings by Gustafsson and Wan (2020), which show an increase in the gender earnings gap from 1988 - 2007 by 0.14 log points, and findings by Song et al. (2019), whom estimates a 0.15 log points increase in the gender earnings gap from 1995 – 2007. By separating the estimates by different age and education groups, our results suggest that the gender wage gap increase may be larger among the young college-educated workers than the

[13] Appendix Tables A7 - A9 present the values in these figures

other groups. Specifically, our estimated lower bound estimates show an increase of 0.07 - 0.19 log points at the median, of 0.01 - 0.04 log points at the 25^{th} quantile and of 0.03 - 0.21 log points and at the 75^{th} quantile of the wage distribution. These magnitudes are greater than the estimated gender wage gap increase in Gustafsson and Wan (2020) and Song et al. (2019) which were based on the population of age 16 - 70 and 16 - 60, respectively, and which do not account for employment composition.

Our bounds for young college graduates during the period 2007 - 2018 suggest a decrease of the gender wage gap at the median of 0.12 - 0.59 log points, while the 95% CI does not exclude zero. This result suggests that the narrowing of the gender wage gap might be potentially larger in 2007-2018 than what Song et al. (2019) has previously documented, where they find the gender wage earnings gap narrowed between 2007 - 2013 by 0.04 log points without accounting for the employment composition. One potential explanation could be the self-selection of employment for females. Suppose more young high-skilled women choose to be self-employed or work for less hours in recent years, without controlling for selection to employment and labor supply, estimates may overstate the gender wage gap and understate the decrease in the gender wage gap in more recent years. This could potentially explain a larger decrease in the gender wage gap after 2007 suggested by our bounds estimates compared to Song et al. (2019).

Our results suggestively show different trends in the evolution of the gender wage gap in two time periods. Economic factors that contribute to the gender wage gap may explain the potentially different trends. In the time period of 1995 - 2007, we find results consistent with an increase in the gender wage gap among the young workers both at the median wage and at the 75^{th} wage quantile. The widened gender wage gap can be explained by the privatization and marketization in the 1990s' China (Liu et al., 2000; Maurer-Fazio and Hughes, 2002). Shu et al. (2007) also show that globalization perpetuates the gender wage differential by absorbing women in exporting-orientated manufacturing jobs that offer lower wages.

Different from 1995 - 2007, in the later period 2007 - 2018, we do not find evidence of any increase in the gender wage gap, and some weak evidence of a decrease in the gender wage gap among the young workers who are college-educated both at the median wage and at the 75^{th} wage quantile. One potential explanation for this slow-down of the gender wage gap growth can be higher returns to the schooling of women relative to men and an increase in the return to schooling in China (Ma and Iwasaki, 2021). Using panel data of the China population from 2011 - 2015, McGarry and Sun (2018) show that the gender schooling gap in China has been diminishing from birth cohorts born in the 1950s to those born in the late 1980s. Suppose women are gaining more years of schooling over birth cohorts while the return to schooling is increasing and higher for women than for men. In that case, the schooling factor may significantly contribute to the closing of the gender wage gap among college-educated young workers. However, other offsetting factors, such as gender discrimination, may also exist to slow down the closing of the gender wage gap, such as the unobserved characteristics that we have discussed in the first chapter of this dissertation, the intra-sector gender wage differential Ma (2018), as well as the increase in men's labor market return to work experience relative to females'(Hare, 2019 and Zhao et al., 2019). With more data available, future research can look into the mechanisms that contribute to those changes in the gender wage gap at different quantiles of the wage distribution with accounting for the employment composition.

2.7 Conclusion

This paper estimates China's distributional gender wage gap dynamics from 1995 to 2018. To control for selection into employment, we employ nonparametric bounds in the spirit of Manski (1994), Manski and Pepper (2000), and Blundell et al. (2007) under different assumptions. To tighten the bounds, we use a weak quartile dominance assumption, a stochastic dominance assumption, and a monotone instrumental variable (MIV).

We have found statistically significant evidence that over the years from 1995-2018, the median gender wage gap for the young workers (age 25-45) who are non-college-educated has increased by 0.17 - 0.62 log points. By splitting the study period, in the survey period between 1995-2007, we show a significant increase in the median gender wage differentials from 1995 to 2007 among young workers who are college-educated (an increase of at least 0.19 log points).

Additionally, this paper also estimates the gender wage gap change at the 25^{th} and the 75^{th} percentiles of the wage distribution. At the 25^{th} percentile, all bounds estimates do not statistically significantly exclude zero change in the gender wage gaps between 1995 - 2007 or 2007 - 2018. At the higher 75^{th} percentile of the wage distribution, in the earlier years of 1995-2007, we find significant increases in the gender wage gap in 1995-2007 for both the young and older college-educated workers. However, we do not find evidence that the increase in the gender wage gap has persisted into the 2010s.

Although we do not find that the gender wage gap in China has continued to increase after 2007, we also do not find strong evidence that the gender wage gap is closing in more recent years in any education and age groups we considered. In addition, studies such as Song et al. (2014) and Ma (2018) show majority portion of the gender wage gap is not explained by social and labor market characteristics. To sustain economic growth and reduce gender inequality, the Chinese labor market needs more protective legislation for women, such as reinforcing equal pay for work guidelines, non-discriminatory policies in hiring, and pay data collection. Future research can look into the mediating factors of the apparent slowdown of the gender wage gap in recent years and evaluate the impacts of recent policy changes, such as the two-child policy, on the gender wage gap and women's labor market outcomes.

Figure 2.1: Distribution of Residual Wage by Gender, Age and Work History

Figure 2.2: Unconditional Gender Wage Gap at the Median and the Median Log Hourly Wage by Gender

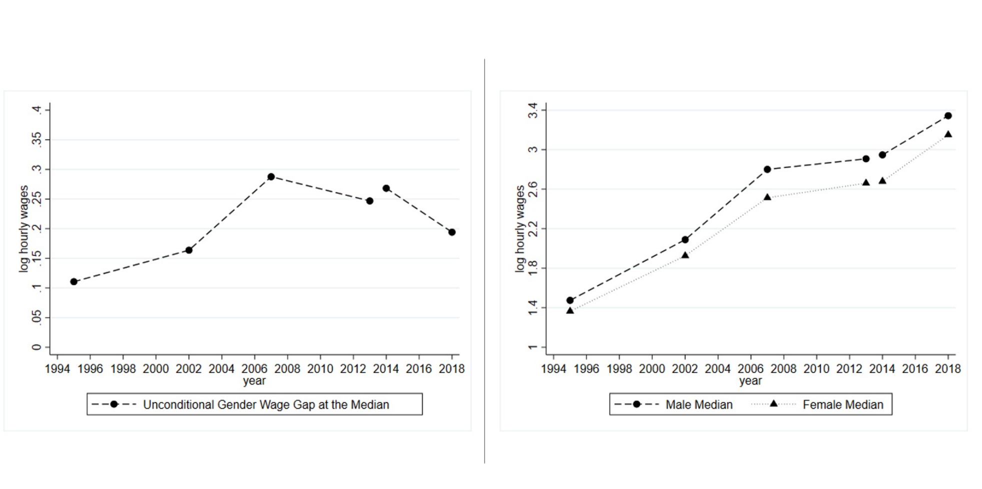


Figure 2.3: Age Profile for Employment for 1995 and 2018

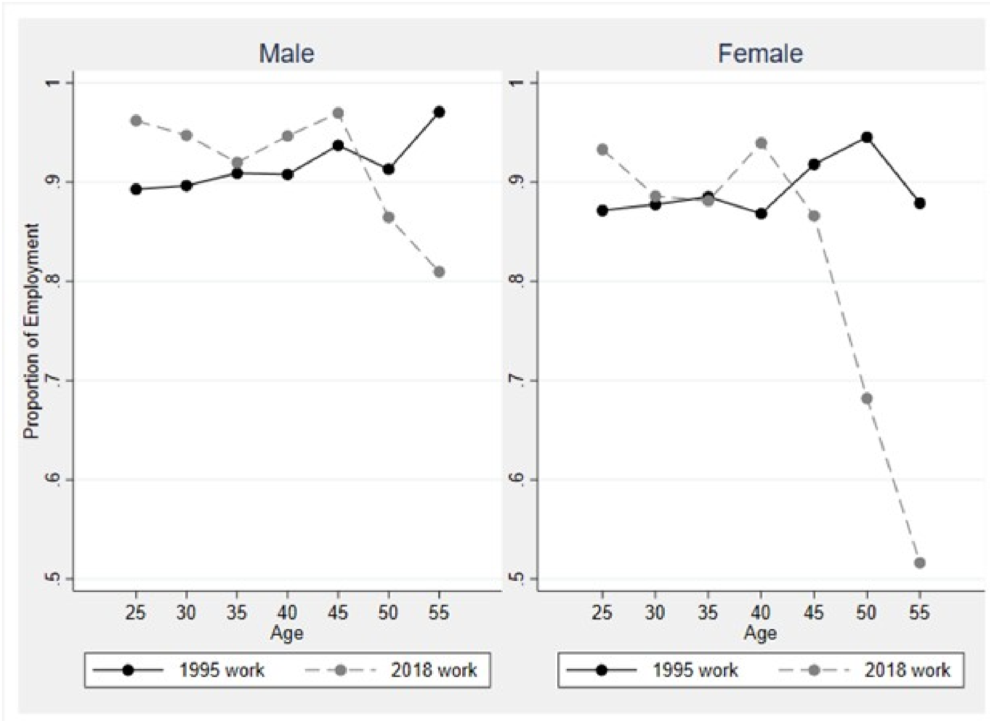


Figure 2.4: Employment by Education for Males and Females from 1995 to 2018

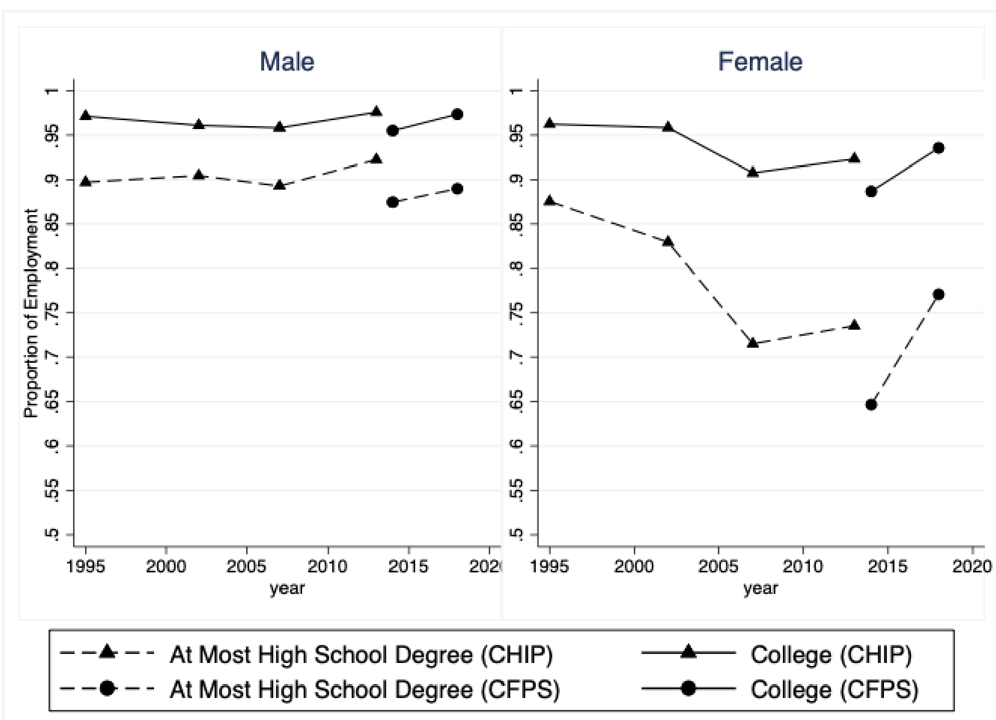


Figure 2.5: Changes in Median Gender Wage Gap under various assumptions (1995 - 2018)

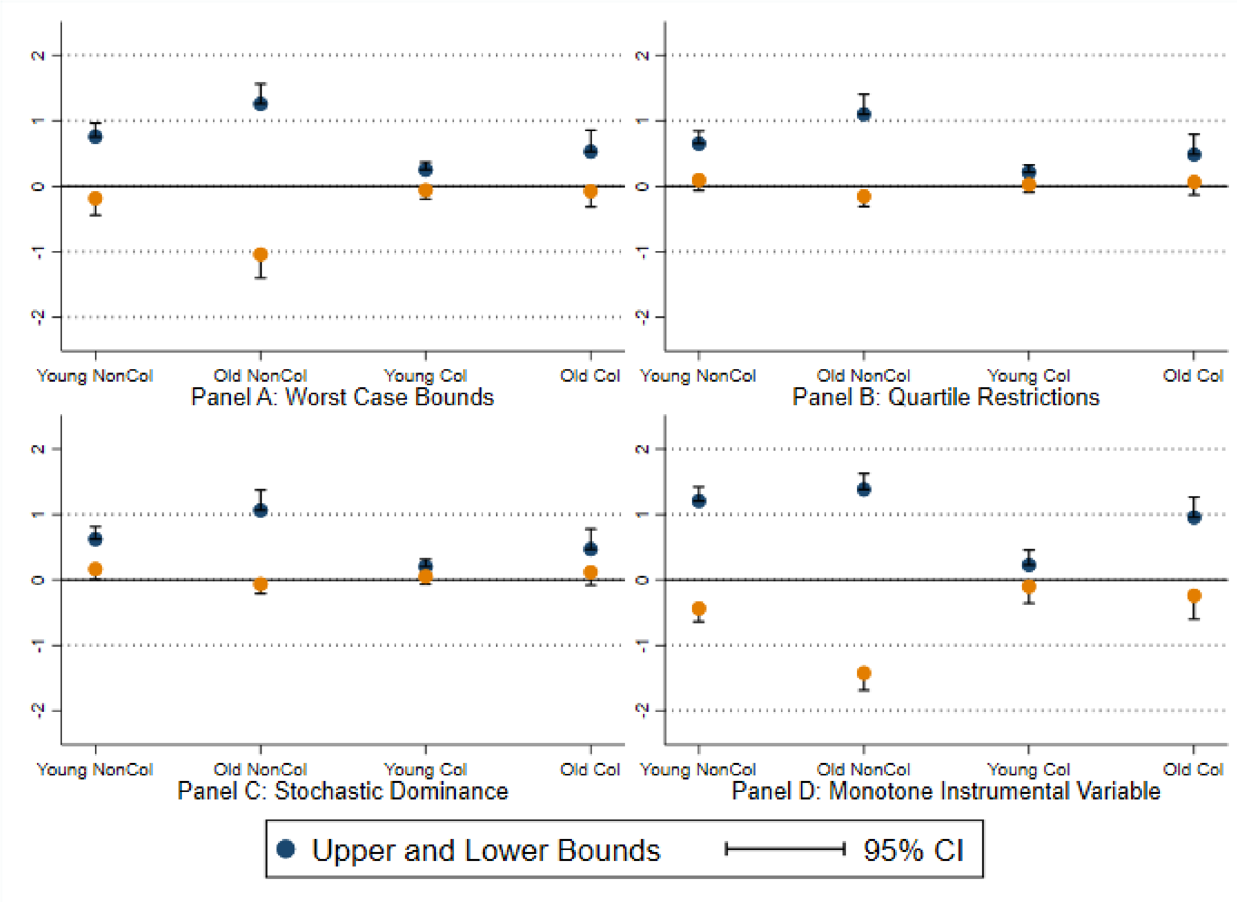


Figure 2.6: Changes in Median Gender Wage Gap under various assumptions (1995 - 2007)

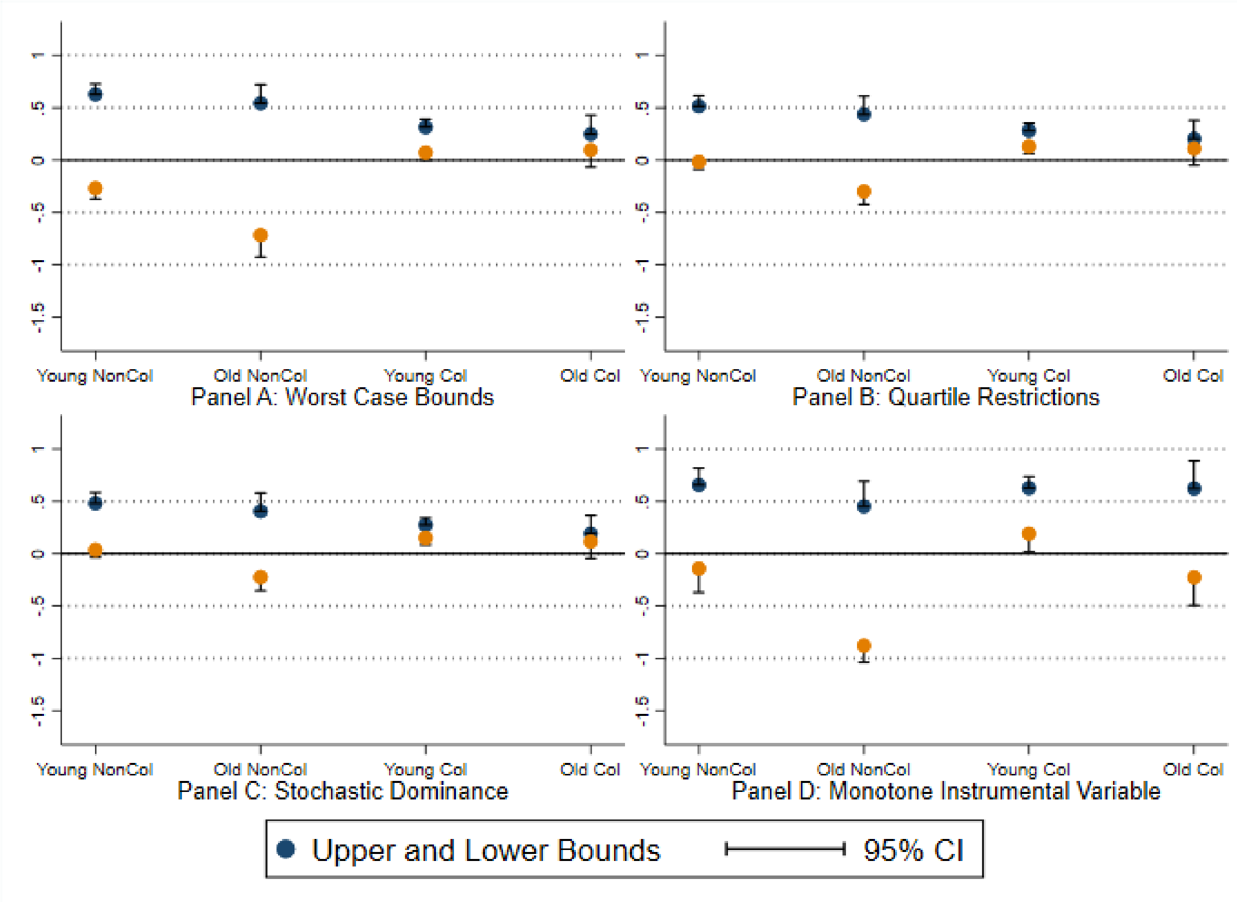


Figure 2.7: Changes in Median Gender Wage Gap under various assumptions (2007 - 2018)

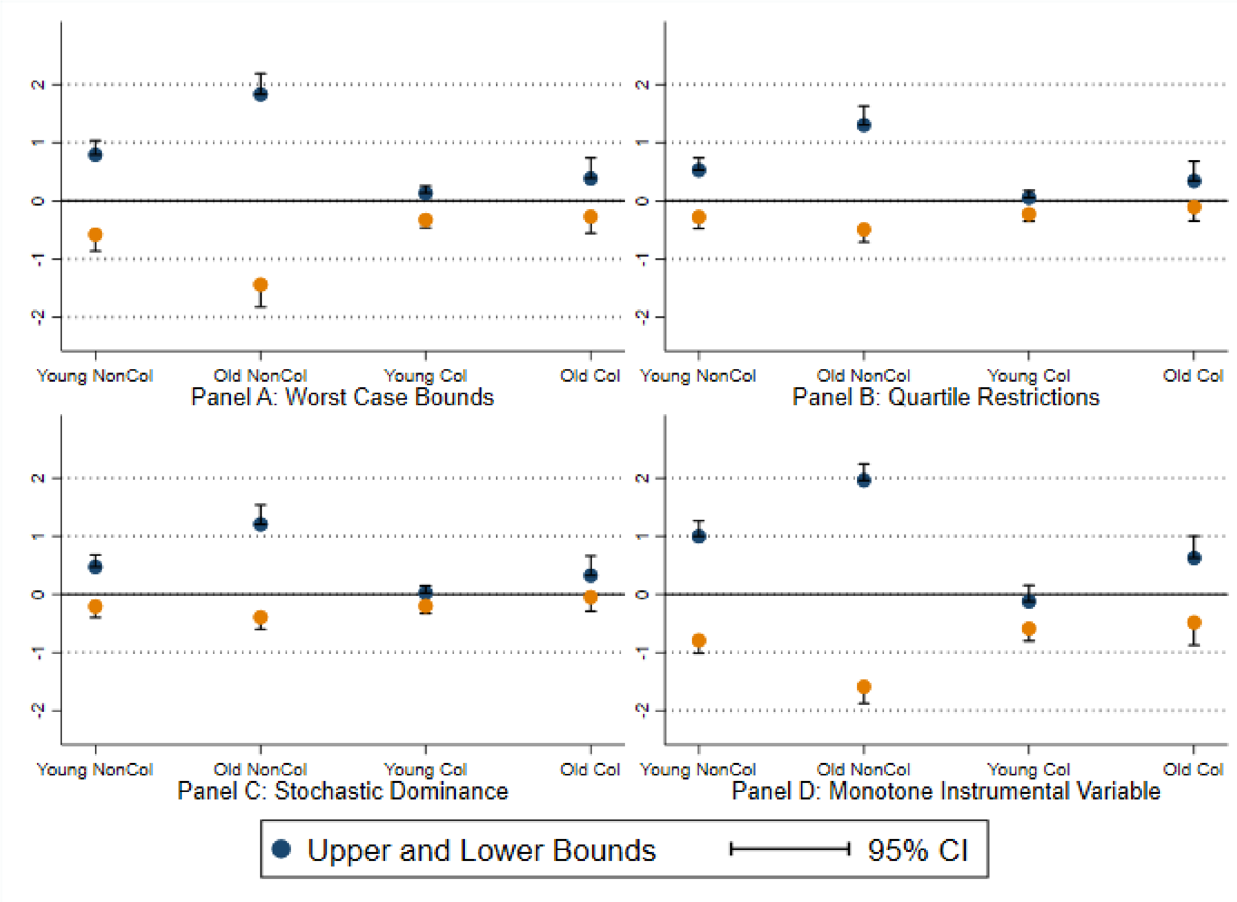


Figure 2.8: Changes in Gender Wage Gap under various assumptions at 25^{th} percentile (1995 - 2018)

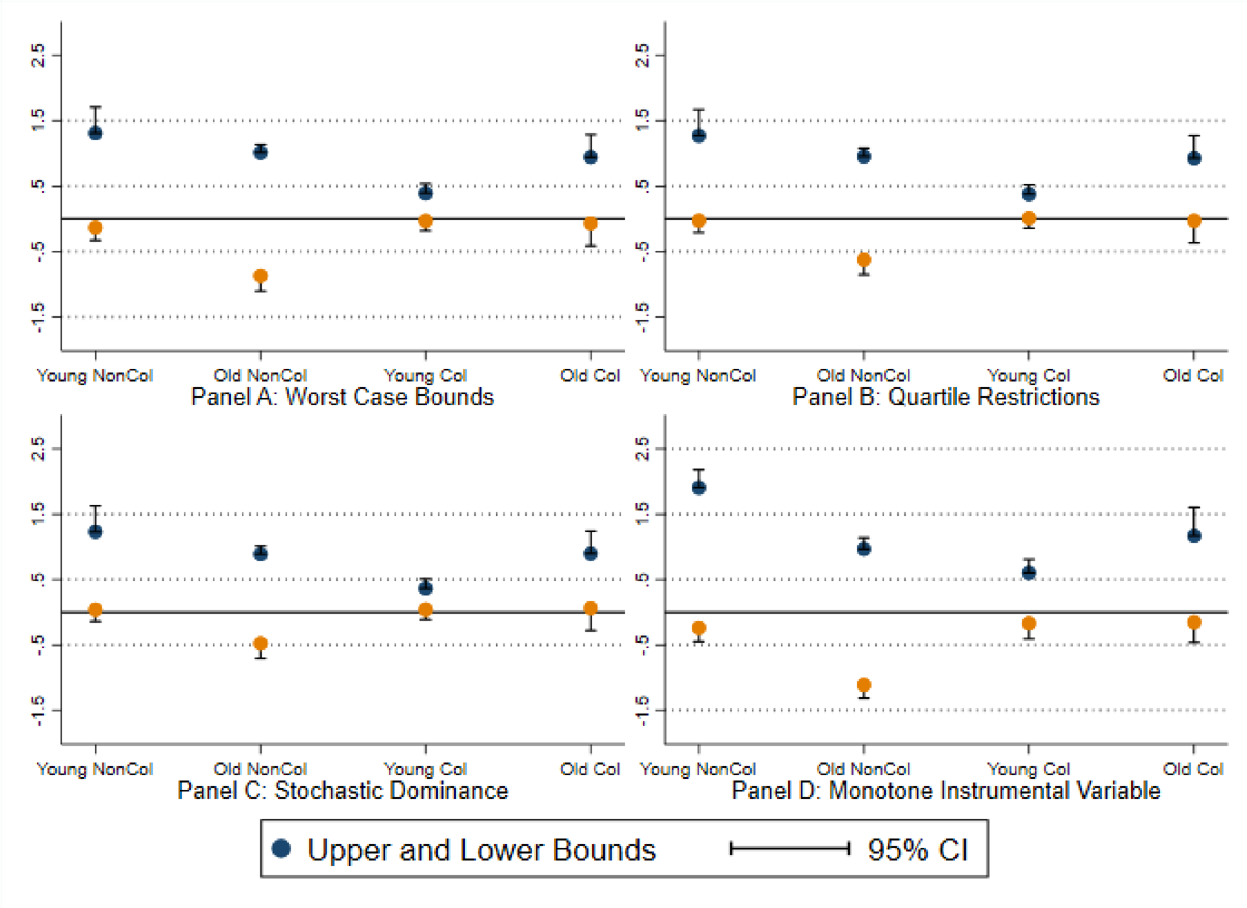


Figure 2.9: Changes in Gender Wage Gap under various assumptions at 25^{th} percentile (1995 - 2007)

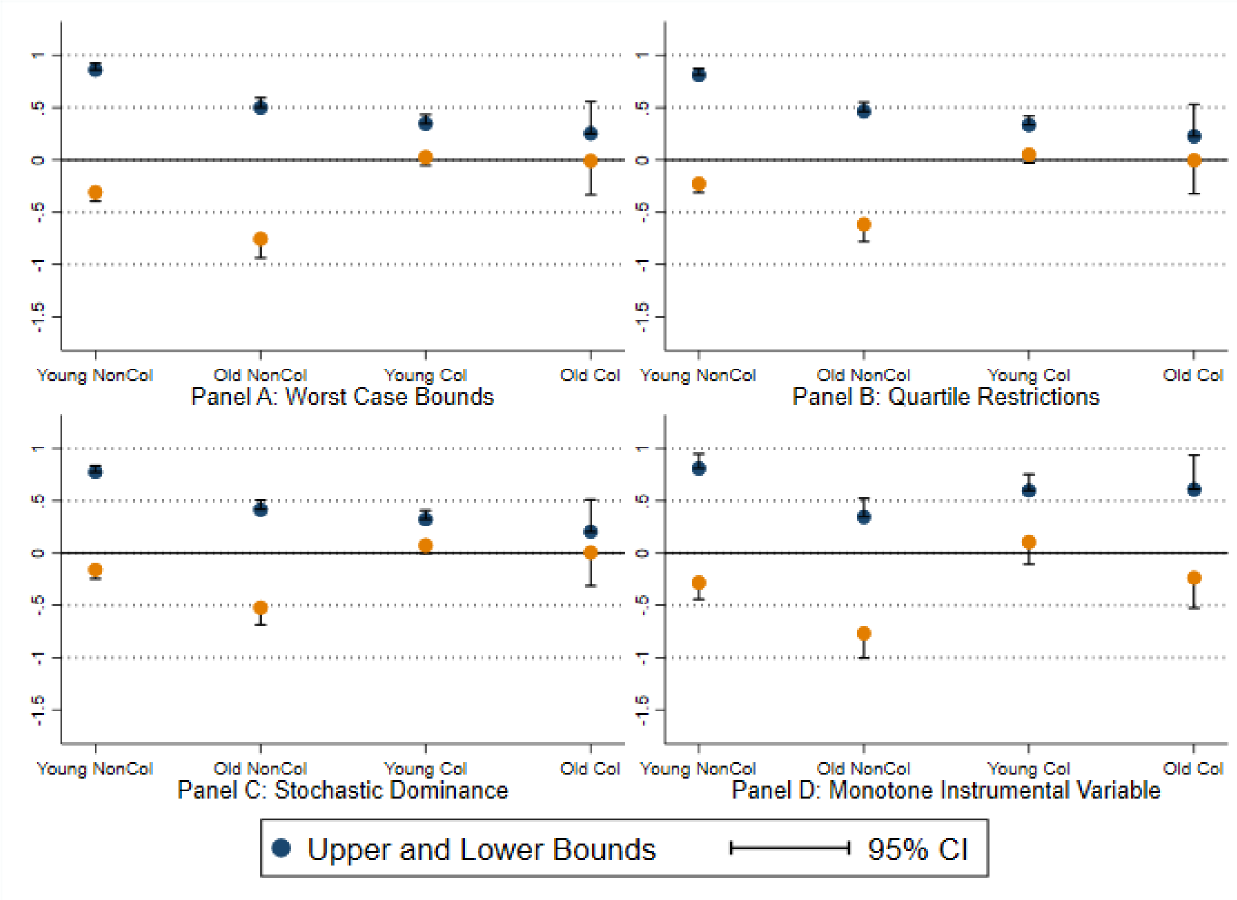


Figure 2.10: Changes in Gender Wage Gap under various assumptions at 25^{th} percentile (2007 - 2018)

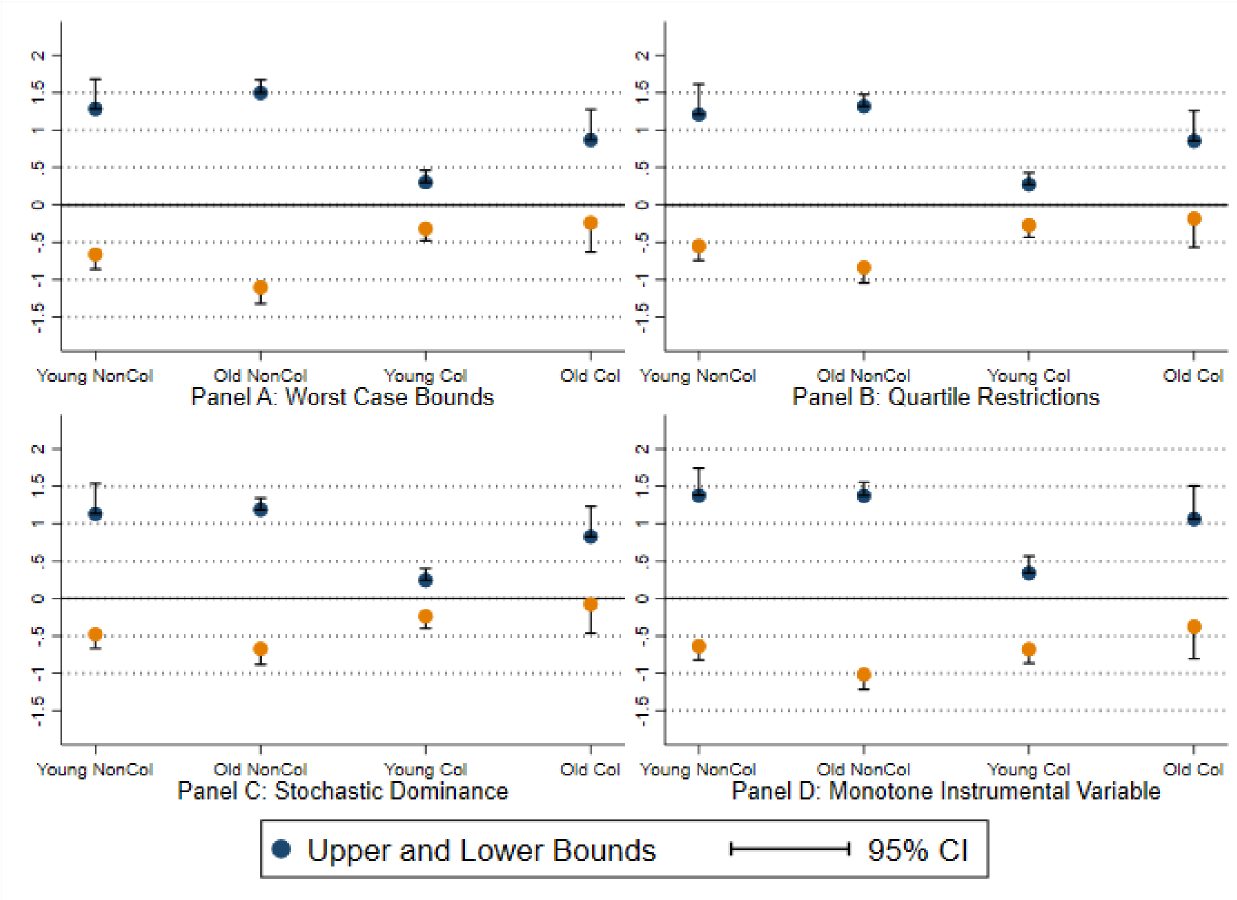


Figure 2.11: Changes in Gender Wage Gap under various assumptions at 75^{th} percentile (1995 - 2018)

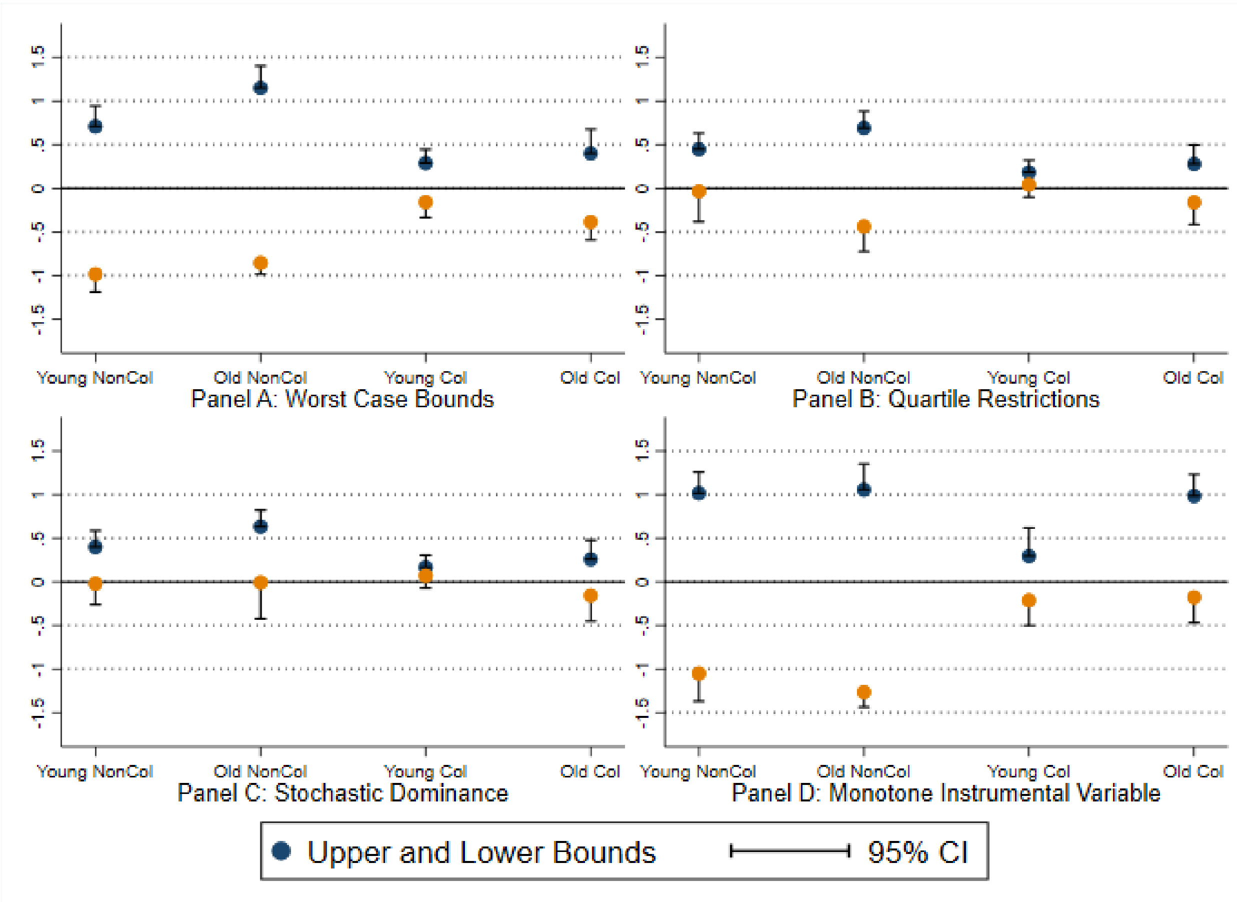


Figure 2.12: Changes in Gender Wage Gap under various assumptions at 75^{th} percentile (1995 - 2007)

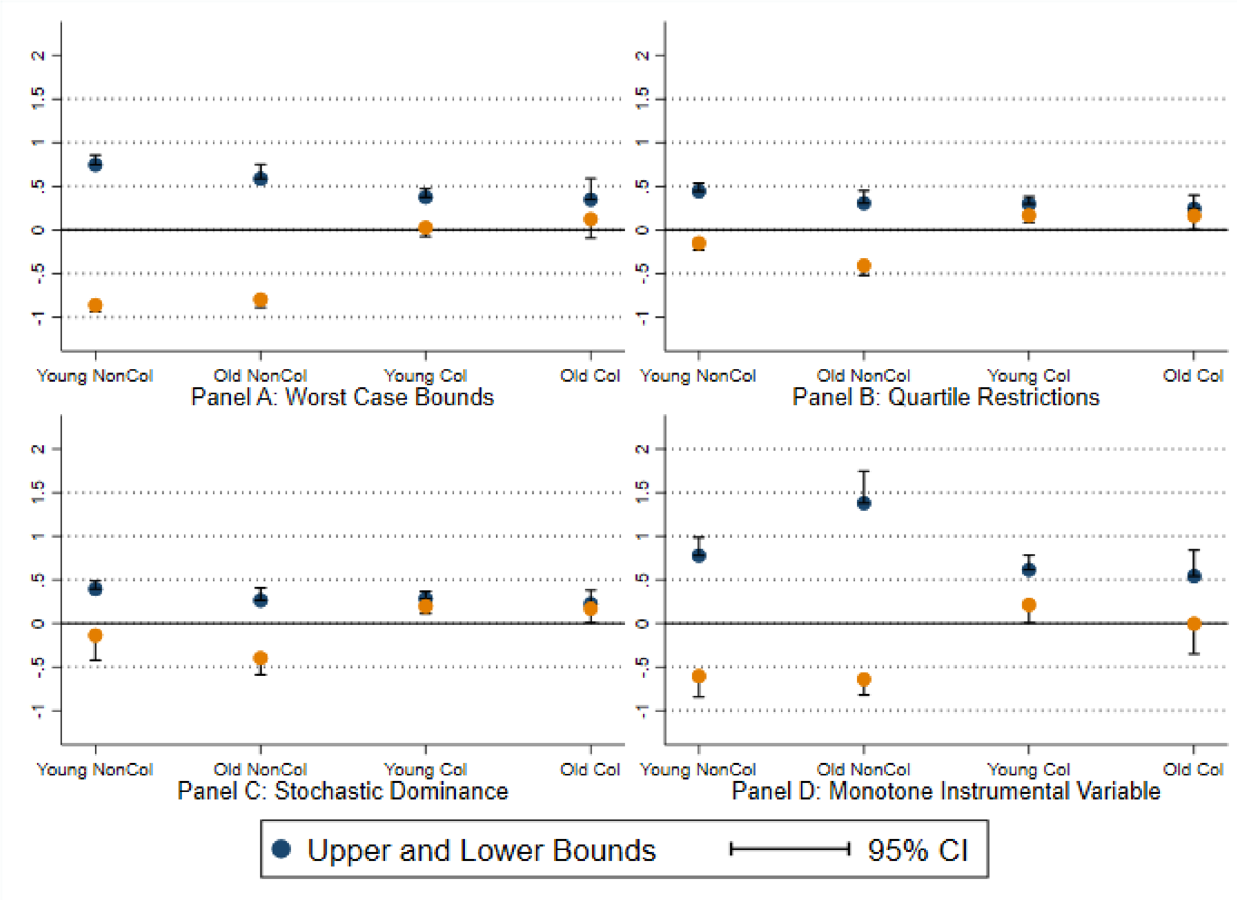
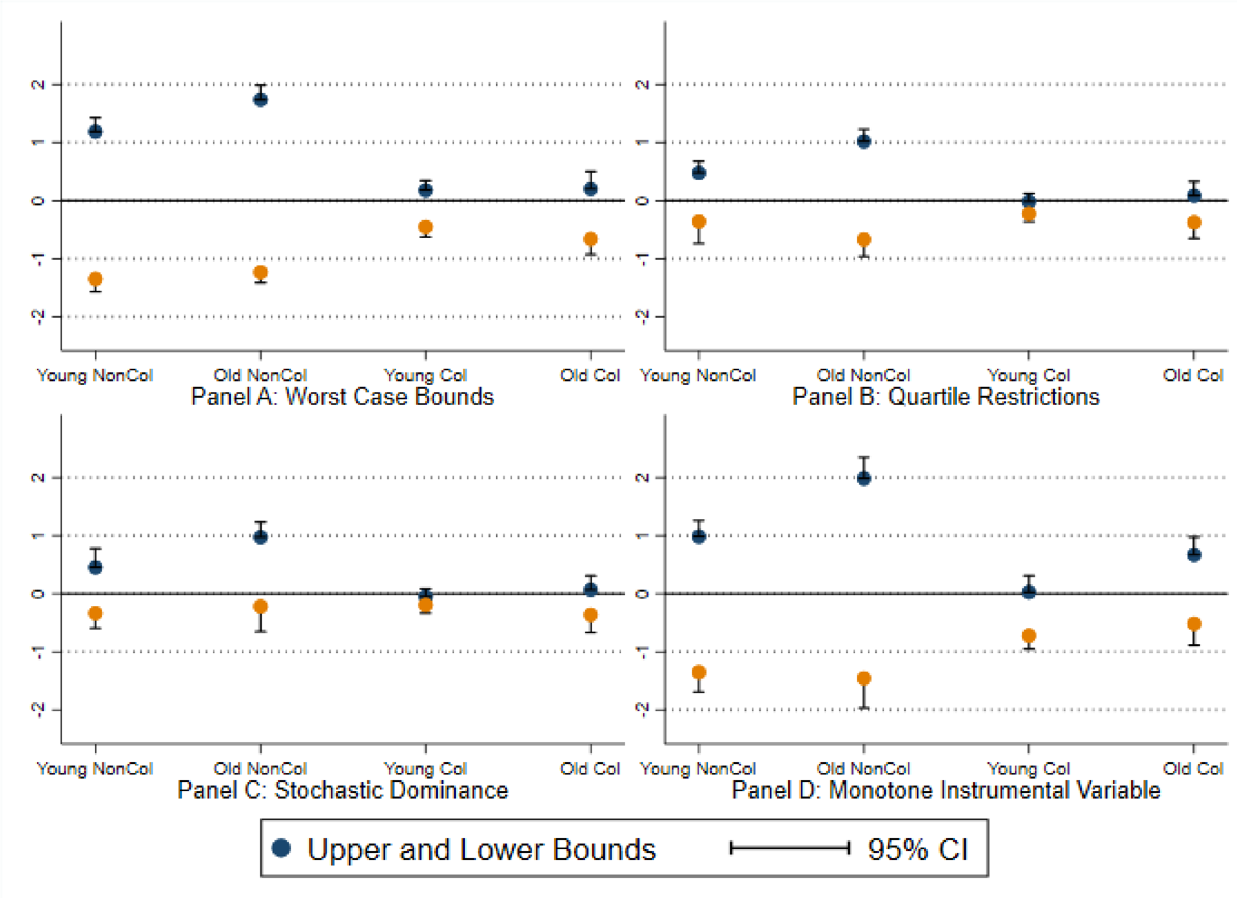


Figure 2.13: Changes in Gender Wage Gap under various assumptions at 75^{th} percentile (2007 - 2018)



Appendix A

Table A.1 : Bounds on Changes in Gender Wage Differential (1995 - 2018)

	Worst Case	Quartile Restrictions	Stochastic Dominance	MIV
Young Non-College	(-0.1839, 0.7582)	(0.0966, 0.6525)	(0.1661, 0.6218)	(-0.4363, 1.2050)
	[-0.4410, 0.9636]	[-0.0665, 0.8449]	[0.0072, 0.8138]	[-0.6382, 1.4219]
Old Non-College	(-1.0392, 1.2585)	(-0.1525, 1.1007)	(-0.0652, 1.0626)	(-1.4235, 1.3831)
	[-1.4006 ,1.5633]	[-0.3081, 1.4067]	[-0.2080, 1.3711]	[-1.6875, 1.6209]
Young-College	(-0.0583, 0.2532)	(0.0291,0.2138)	(0.0535, 0.2029)	(-0.0988, 0.2270)
	[-0.1934, 0.3697]	[-0.0943,0.3263]	[-0.0683, 0.3154]	[-0.3595, 0.4579]
Old-College	(-0.0731,0.5305)	(0.0655, 0.4845)	(0.1200, 0.4692)	(-0.2389, 0.9548)
	[-0.3145, 0.8582]	[-0.1322, 0.7956]	[-0.0791, 0.7792]	[-0.6021, 1.2656]

Table A.2 : Bounds on Changes in Gender Wage Differential (1995 - 2007)

	Worst Case	Quartile Restrictions	Stochastic Dominance	MIV
Young Non-College	(-0.2684, 0.6283)	(-0.0159, 0.5145)	(0.0374, 0.4822)	(-0.1410, 0.6568)
	[-0.3720, 0.7277]	[-0.0887, 0.6150]	[-0.0345, 0.5840]	[-0.3695, 0.8190]
Old Non-College	(-0.7159, 0.5440)	(-0.2982,0.4364)	(-0.2237, 0.4062)	(-0.8779, 0.4525)
	[-0.9265 ,0.7223]	[-0.4255,0.6110]	[-0.3529, 0.5805]	[-1.0366, 0.6917]
Young-College	(0.0727, 0.3150)	(0.1309,0.2821)	(0.1525, 0.2740)	(0.1914, 0.6283)
	[0.0004, 0.3891]	[0.0617,0.3536]	[0.0837, 0.3445]	[0.0188, 0.7363]
Old-College	(0.0961, 0.2484)	(0.1104,0.2037)	(0.1164, 0.1919)	(-0.2255, 0.6236)
	[-0.0680, 0.4299]	[-0.0478,0.3783]	[-0.0440, 0.3681]	[-0.4937, 0.8873]

Table A.3 : Bounds on Changes in Gender Wage Differential (2007 - 2018)

	Worst Case	Quartile Restrictions	Stochastic Dominance	MIV
Young Non-College	(-0.5779, 0.7923)	(-0.2787, 0.5293)	(-0.2050, 0.4734)	(-0.7906, 0.9989)
	[-0.8652, 1.0367]	[-0.4741, 0.7383]	[-0.3974, 0.6780]	[-1.0104, 1.2641]
Old Non-College	(-1.4397, 1.8309)	(-0.4932,1.3032)	(-0.3910, 1.2060)	(-1.5870, 1.9620)
	[-1.8237, 2.1884]	[-0.7108,1.6285]	[-0.5981, 1.5356]	[-1.8733, 2.2426]
Young-College	(-0.3249, 0.1322)	(-0.2244, 0.0543)	(-0.1978, 0.0277)	(-0.5864, -0.1206)
	[-0.4630, 0.2567]	[-0.3513, 0.1727]	[-0.3234, 0.1459]	[-0.7991, 0.1534]
Old-College	(-0.2722, 0.3851)	(-0.1062,0.3422)	(-0.0458, 0.3267)	(-0.4810, 0.6281)
	[-0.5574, 0.7369]	[-0.3468,0.6784]	[-0.2886, 0.6622]	[-0.8719, 1.0035]

Table A.4 : Bounds on Changes in Gender Wage Differential at 25^{th} percentile (1995 - 2018)

	Worst Case	Quartile Restrictions	Stochastic Dominance	MIV
Young Non-College	(-0.1327, 1.3107)	(-0.0268, 1.2722)	(0.0406, 1.2321)	(-0.2383, 1.9061)
	[-0.3272, 1.7072]	[-0.2100, 1.6693]	[-0.1400, 1.6268]	[-0.4464, 2.1788]
Old Non-College	(-0.8702, 1.0143)	(-0.6224, 0.9549)	(-0.4750, 0.8891)	(-1.1090, 0.9674)
	[-1.1050, 1.1352]	[-0.8521, 1.0807]	[-0.7052, 1.0122]	[-1.3158, 1.1387]
Young-College	(-0.0302, 0.3920)	(0.0113, 0.3788)	(0.0419, 0.3640)	(-0.1677, 0.6040)
	[-0.1838, 0.5378]	[-0.1415, 0.5228]	[-0.1113, 0.5078]	[-0.4073, 0.8086]
Old-College	(-0.0677, 0.9448)	(-0.0278, 0.9266)	(0.0635, 0.8977)	(-0.1508, 1.1682)
	[-0.4119, 1.2891]	[-0.3674, 1.2723]	[-0.2770, 1.2424]	[-0.4622, 1.6009]

Table A.5 : Bounds on Changes in Gender Wage Differential at 25^{th} percentile (1995 - 2007)

	Worst Case	Quartile Restriction	Stochastic Dominance	MIV
Young Non-College	(-0.3083, 0.8612)	(-0.2266, 0.8123)	(-0.1577, 0.7747)	(-0.2834, 0.8105)
	[-0.3941, 0.9234]	[-0.3115, 0.8738]	[-0.2459, 0.8379]	[-0.4415, 0.9504]
Old Non-College	(-0.7554, 0.5009)	(-0.6158, 0.4637)	(-0.5202, 0.4166)	(-0.7669, 0.3469)
	[-0.9360, 0.5927]	[-0.7808, 0.5530]	[-0.6872, 0.5056]	[-1.0022, 0.5211]
Young-College	(0.0275, 0.3475)	(0.0527, 0.3349)	(0.0733, 0.3226)	(0.1050, 0.5982)
	[-0.0514, 0.4338]	[-0.0255, 0.4202]	[-0.0063, 0.4074]	[-0.1058, 0.7543]
Old-College	(-0.0094, 0.2532)	(-0.0042, 0.2268)	(0.0051, 0.2036)	(-0.2364, 0.6094)
	[-0.3311, 0.5586]	[-0.3237, 0.5312]	[-0.3165, 0.5098]	[-0.5254, 0.9379]

Table A.6 : Bounds on Changes in Gender Wage Differential at 25^{th} percentile (2007 - 2018)

	Worst Case	Quartile Restrictions	Stochastic Dominance	MIV
Young Non-College	(-0.6600, 1.2851)	(-0.5504, 1.2101)	(-0.4767, 1.1324)	(-0.6384, 1.3798)
	[-0.8613, 1.6839]	[-0.7410, 1.6172]	[-0.6660, 1.5416]	[-0.8204, 1.7461]
Old Non-College	(-1.1004, 1.4991)	(-0.8352, 1.3199)	(-0.6717, 1.1894)	(-1.0152, 1.3758)
	[-1.3180, 1.6742]	[-1.0434, 1.4771]	[-0.8818, 1.3463]	[-1.2153, 1.5565]
Young-College	(-0.3169, 0.3037)	(-0.2719, 0.2745)	(-0.2367, 0.2467)	(-0.6773, 0.3430)
	[-0.4765, 0.4591]	[-0.4309, 0.4286]	[-0.3970, 0.4011]	[-0.8646, 0.5683]
Old-College	(-0.2373, 0.8705)	(-0.1810, 0.8571)	(-0.0759, 0.8284)	(-0.3765, 1.0626)
	[-0.6306, 1.2769]	[-0.5661, 1.2619]	[-0.4651, 1.2328]	[-0.8031, 1.5044]

Table A.7 : Bounds on Changes in Gender Wage Differential at 75^{th} percentile (1995 - 2018)

	Worst Case	Quartile Restrictions	Stochastic Dominance	MIV
Young Non-College	(-0.9838, 0.7089)	(-0.0345, 0.4471)	(-0.0195, 0.4006)	(-1.0494, 1.0169)
	[-1.1875, 0.9431]	[-0.3839, 0.6326]	[-0.2612, 0.5864]	[-1.3701, 1.2590]
Old Non-College	(-0.8550, 1.1503)	(-0.4380, 0.6905)	(-0.0062, 0.6338)	(-1.2634, 1.0571)
	[-0.9853, 1.4019]	[-0.7229, 0.8818]	[-0.4213, 0.8222]	[-1.4339, 1.3512]
Young-College	(-0.1580, 0.2887)	(0.0418, 0.1824)	(0.0717, 0.1671)	(-0.2114, 0.2965)
	[-0.3350, 0.4461]	[-0.1021, 0.3206]	[-0.0722, 0.3064]	[-0.4995, 0.6178]
Old-College	(-0.3852, 0.4004)	(-0.1610, 0.2774)	(-0.1562, 0.2602)	(-0.1763, 0.9858)
	[-0.5926, 0.6754]	[-0.4157, 0.4984]	[-0.4506, 0.4781]	[-0.4697, 1.2311]

Table A.8 : Bounds on Changes in Gender Wage Differential at 75^{th} percentile (1995 - 2007)

	Worst Case	Quartile Restrictions	Stochastic Dominance	MIV
Young Non-College	(-0.8616, 0.7468)	(-0.1496, 0.4436)	(-0.1346, 0.3954)	(-0.6036, 0.7791)
	[-0.9371, 0.8578]	[-0.2299, 0.5375]	[-0.4215, 0.4897]	[-0.8429, 0.9855]
Old Non-College	(-0.7978, 0.5870)	(-0.4069, 0.3063)	(-0.3966, 0.2663)	(-0.6384, 1.3798)
	[-0.8887, 0.7512]	[-0.5204, 0.4487]	[-0.5883, 0.4087]	[-0.8204, 1.7461]
Young-College	(0.0261, 0.3759)	(0.1672, 0.2975)	(0.1983, 0.2836)	(0.2143, 0.6158)
	[-0.0771, 0.4717]	[0.0836, 0.3812]	[0.1150, 0.3668]	[0.0077, 0.7828]
Old-College	(0.1239, 0.3484)	(0.1621, 0.2428)	(0.1707, 0.2245)	(-0.0020, 0.5429)
	[-0.0931, 0.5886]	[0.0052, 0.3986]	[0.0108, 0.3828]	[-0.3475, 0.8417]

Table A.9 : Bounds on Changes in Gender Wage Differential at 75^{th} percentile (2007 - 2018)

	Worst Case	Quartile Dominance	Stochasrtic Dominance	MIV
Young Non-College	(-1.3482, 1.1881)	(-0.3575, 0.4761)	(-0.3343, 0.4547)	(-1.3497, 0.9854)
	[-1.5674, 1.4269]	[-0.7370, 0.6772]	[-0.5933, 0.7788]	[-1.6889, 1.2598]
Old Non-College	(-1.2313, 1.7375)	(-0.6675, 1.0205)	(-0.2173, 0.9753)	(-1.4526, 1.9861)
	[-1.4153, 1.9888]	[-0.9620, 1.2267]	[-0.6526, 1.2343]	[-1.9638, 2.3489]
Young-College	(-0.4504, 0.1791)	(-0.2242, -0.0163)	(-0.1923, -0.0508)	(-0.7191, 0.0276)
	[-0.6259, 0.3459]	[-0.3656, 0.1215]	[-0.3322, 0.0863]	[-0.9513, 0.3127]
Old-College	(-0.6596, 0.2026)	(-0.3736, 0.0851)	(-0.3603, 0.0691)	(-0.5155, 0.6714)
	[-0.9286, 0.5011]	[-0.6505, 0.3303]	[-0.6693, 0.3116]	[-0.8867, 0.9756]

Table A.10: Provinces Covered by Each Survey

Survey	Covered Provinces
CHIP 1995	Beijing, Shanxi, Liaoning, Jiangsu,Anhui, Henan, Hubei, Guangdong, Sichuan, Yunan, Gansu
CHIP 2002	Beijing, Shanxi, Liaoning, Jiangsu,Anhui, Henan, Hubei, Guangdong, Chongqing, Yunan, Gansu
CHIP 2007	Shanghai,Jiangsu, Zhejiang, Anhui, Henan, Hubei, Guangdong, Chongqing, Sichuan
CHIP 2013	Beijing, Shanxi, Liaoning, Jiangsu, Anhui, Henan, Hubei, Hunan, Guangdong, Chongqing, Sichuan, Yunan, Gansu
CFPS 2014 **CFPS 2018**	Beijing, Tianjin, Hebei, Shanxi, inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxin, Hainan, Chongqing, Sichuan, Guizhou, Yunan, Shaanxi, Gansu, Ningxia, Xinjiang

Appendix B. Estimation and Inference Implementation

In Section 3 of the paper, we have briefly described the method in Chernozhukov et al. (2013) to compute confidence regions for bounds with maximum and minimum operators. In Section B1, we explain the computation of bounds under the MIV assumption, and in Section B2, we explain the detailed steps we use to compute the half-median unbiased bounds and the confidence intervals, following the implementation in Flores and Flores-Lagunes (2013).

B.1 Inference for Bounds under the MIV assumption

The Chernozhukov et al. (2013) method requires us to apply the maximum and the minimum operators over all the bound candidates inside the lower bound $\theta^l(\upsilon)$ and the upper bound $\theta^u(v)$ bounding functions. This requirement cause a computational challenge for bounds under the monotone instrumental variable (MIV) assumption.

Specifically, under the MIV assumption, the bounds of the wage distribution and the wage quantiles are first constructed conditional on each quantile of the MIV Z. In our application, we used 10 MIV quantiles (i.e., the 5th, the 15th, ..., the 95th quantile of income from other household members). we would need to integrate these lower bounds and the upper bounds that are conditional on the MIV quantiles over the ten quantiles of the MIV to obtain the lower bounds and the upper bounds in Equation 18. In this scenario, the total number of lower and upper bounds candidates for Equation 18 may respectively surpass 3.5 million, which cause a computational challenge for us when implementing the Chernozhukov et al. (2013)

To see this issue in an example, when we compute the half-median unbiased upper bound for $w^q(x)$ in Equation 18, the bounding function of $\theta^u(v)$ contains the upper bound candidates at each of the 10 quantiles of MIV Z. **(1)** Conditional on the first MIV quantile $z = z_{5th}$, there will be 10 bound candidates, i.e., $w^q(x, z = z_{5th})$ that is solved from $q = F(w|x, z_{5th}, E = 1)P(x, z_{5th})$; $w^q(x, z = z_{15th})$ that is solved from $q = F(w|x, z_{15th}, E = 1)P(x, z_{15th})$; $w^q(x, z = z_{25th})$ that is solved from $q = F(w|x, z_{25th}, E = 1)P(x, z_{25th})$; $w^q(x, z = z_{35th})$ that is solved from $q = F(w|x, z_{35th}, E = 1)P(x, z_{35th})$, ..., and $w^q(x, z = z_{95th})$ that is solved from $q = F(w|x, z_{95th}, E = 1)P(x, z_{95th})$. **(2)** Conditional on the second MIV quantile, $z = z_{15th}$, there will be 9 bound candidates, i.e., $w^q(x, z = z_{15th})$ that is solved from $q = F(w|x, z_{15th}, E = 1)P(x, z_{15th})$; $w^q(x, z = z_{25th})$ that is solved from $q = F(w|x, z_{25th}, E = 1)P(x, z_{25th})$; $w^q(x, z = z_{35th})$ that is solved from $q = F(w|x, z_{35th}, E = 1)P(x, z_{35th})$, ..., and $w^q(x, z = z_{95th})$ that is solved from $q = F(w|x, z_{95th}, E = 1)P(x, z_{95th})$. Similarly, conditional on $25th$ quantile of the MIV, $z = z_{25th}$, there will be 8 bound candidates, and so forth for the bounds conditional on the higher MIV quantiles.

Continuing with our example, after obtaining the upper bounds for each $w^q(x, z)$, where $z = z_{5th}, z = z_{15th}, ..., z = z_{95th}$, the bounding function of the upper bound in Equation 19, $E_Z[w^q(u)_{miv}|x]$, includes bound candidates that are made of all possible combinations of the bounds conditional on the 10 MIV quantiles, which are totally $10 \times 9 \times 8 \times 7 \times 6 \times 5 \times 4 \times 3 \times 2 \times 1 = 3,628,800$ bound candidates. The large sizes of the matrices that contain the bounds candidates and the variance-covariance matrices of the bounds candidates make the computation time-consuming and not practical for our estimation purpose.

In practice, we first estimate the half-median unbiased MIV bounds and confidence intervals conditional on each of the ten MIV quantiles, with the total number of the bounds candidates not exceeding 10. We then average out the half-median unbiased MIV bounds and confidence interval estimates over the ten MIV quantiles.

B.2 Computation Steps of the Confidence Interval

In this section, we follow Flores and Flores-Lagunes (2013) and describe the detailed steps followed to implement the methodology used by Chernozhukov et al. (2013) to obtain the confidence interval for the true parameter and the half-median unbiased estimators for our lower and upper bounds.

As discussed in the paper, the precision adjustment in Chernozhukov et al. (2013) is done by subtracting or adding to each estimated bounding function (i.e., each bound candidates) the product of its pointwise standard error and an appropriate critical value, $\kappa(p)$. $\kappa(p)$ is selected based on a standardized Gaussian process $Z_n^*(v)$. For any compact set $V \in \mathcal{V}$, Chernozhukov et al. (2013) approximate using simulation the p-th quantile of $sup_{v \in V} Z_n^*(v)$, denoted by $\kappa_{n,V}(p)$, and use it in place of $\kappa(p)$. Since setting $V = \mathcal{V}^l$ for the lower bound leads to asymptotically valid but conservative inference, Chernozhukov et al. (2013) propose a preliminary set estimator $\hat{V}_n^l$ of $V_0^l = \arg max_{v \in \mathcal{V}^l} \theta^l(v)$ that they refer to an adaptive inequality selector. This preliminary set estimator $\hat{V}_n^l$ selects those bounding functions that are close enough to binding to affect the asymptotic distribution of the estimator of the lower bound. For the same reason, a preliminary set estimator $\hat{V}_n^u$ of $V_0^u = \arg min_{v \in \mathcal{V}^u} \theta^u(v)$ is used for the upper bound. The precision-corrected estimator of the lower bound θ_0^l is

$$\hat{\theta}^l(p) = \max_{v \in \mathcal{V}^l} [\hat{\theta}^l(v) - \kappa^l_{n,\hat{V}_n^l}(p) s^l(v)], \tag{2.23}$$

where $\hat{\theta}^l(v)$ is the sample analog estimator of $\theta^l(v)$ and $s^l(v)$ is its standard error.

Let $\gamma_n = [\theta_n^l(1), ..., \theta_n^l(m^l)]'$ be the vector of bounding functions and let $\hat{\gamma}_n$ be its sample analog estimator. The steps we follow to compute the set estimator $\hat{V}_n^l$ and the critical value $\kappa^l_{n,\hat{V}_n^l}(p)$ in Equation 1 are as follows.

(1) We obtain by bootstrapping a consistent estimate $\hat{\Omega}_n$ of the asymptotic variance of $\sqrt{n}(\hat{\gamma}_n - \gamma_n)$. Let $\hat{g}_n(v)'$ denote the v^{th} row $\hat{\Omega}_n^{1/2}$ and let $s_n^l(v) = \|\hat{g}_n(v)\|/\sqrt{n}$.

(2) We estimate R draws from $\mathcal{N}(0, I_{m^l})$, denoted $Z_1, ..., Z_R$, where I_{m^l} is the $m^l \times m^l$ identity matrix, and we calculate $Z_r^*(v) = \hat{g}_n(v)' Z_r / \|\hat{g}_n(v)\|$ for $r = 1, ..., R$.

(3) Let $Q_p(X)$ denote the p-th quantile of a random variable X and, following CLR, let $c_n = 1 - (.1/\log n)$. We compute $\kappa^l_{n,\mathcal{V}^l}(c_n) = Q_{c_n}(\max_{v \in \mathcal{V}^l} Z_r^*(v), r = 1, ..., R)$; that is, for each replication r we calculate the maximum of $Z_r^*(1), ..., Z_r^*(m^l)$ and take the c-th quantile of those R values. We then use $\kappa^l_{n,\mathcal{V}^l}(c_n)$ to compute $\hat{V}_n^l = \{v \in \mathcal{V}^l : \hat{\theta}^l(v) \geq max_{\tilde{v} \in \mathcal{V}^l} \{[\hat{\theta}^l(\tilde{v}) - \kappa^l_{n,\mathcal{V}^l(c_n)} s_n^l(\tilde{v})] - 2\kappa^l_{n,\mathcal{V}^l(c_n)} s_n^l(\tilde{v})\}\}$.

(4) We compute $\kappa^l_{n,\hat{V}_n^l}(p) = Q_p(max_{v \in \hat{V}_n^l} Z_r^*(v), r = 1, ..., R)$, so the critical value is based on $\hat{V}_n^l$ instead of $\mathcal{V}^l$.

The precision-corrected estimator of the upper bound θ_0^u is given by

$$\hat{\theta}^u(p) = \min_{v \in \mathcal{V}^l}[\hat{\theta}^u(v) + \kappa^u_{n,\hat{V}^l_n}(p)s^u(v)], \tag{2.24}$$

where $\hat{\theta}^u(v)$ is the sample analog estimator of $\theta^u(v)$ and $s^u(v)$ is its standard error. To compute $\kappa^u_{n,\hat{V}^l_n}(p)$ in (2), we follow the same steps above but in step (3) we replace $\hat{V}^l_n$ by $\hat{V}^u_n = \{v \in \mathcal{V}^u : \hat{\theta}^u(v) \geq \min_{\tilde{v} \in \mathcal{V}^u}[\hat{\theta}^u(\tilde{v}) + \kappa^u_{n,\mathcal{V}^u}(c_n)s^u_n(\tilde{v})] + 2\kappa^u_{n,\mathcal{V}^u}(c_n)s^u_n(v)\}$. Since the normal distribution is symmetric, we don't have to make any changes when computing the quantiles in step 3 and 4.

Half-median-unbiased estimators of the upper and lower bounds are obtained by setting $p = 1/2$ in the steps above and using Equations (1) and (2) to compute, respectively, $\hat{\theta}^l(1/2)$ and $\hat{\theta}^u(1/2)$. To construct confidence intervals for the parameter θ_0, it is important to take into account the length of the identified set. Following Chernozhukov et al. (2013) and Flores and Flores-Lagunes (2013), let $\hat{\Gamma}_n = \hat{\theta}^u_n(1/2) - \hat{\theta}^l_n(1/2)$, $\hat{\Gamma}^+_n = \max(0, \hat{\Gamma}_n)$, $\rho_n = \max\{\hat{\theta}^u_n(3/4) - \hat{\theta}^u_n(1/4), \hat{\theta}^l_n(1/4) - \hat{\theta}^l_n(3/4)\}$, $\tau_n = 1/(\rho_n \log n)$ and $\hat{p}_n = 1 - \Phi(\tau_n \hat{\Gamma}^+_n)\alpha$, where $\Phi(.)$ is the standard normal CDF. Note that $\hat{p}_n \in [1-\alpha, 1-\alpha/2]$, with $\hat{p}_n$ approaching $1-\alpha$ when $\hat{\Gamma}_n$ grows large relative to sampling error and $\hat{p}_n = 1-\alpha/2$ when $\hat{\Gamma}_n = 0$. An asymptotically valid confidence interval at the confidence level of $1-\alpha$ is given by $[\hat{\theta}^l_n(\hat{p}_n), \hat{\theta}^u_n(\hat{p}_n)]$.

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Chapter 3

The Returns to a Master's Degree: Evidence from Recession-Induced Graduate Degree Enrollment

3.1 Introduction

The macroeconomic context in which students graduate and enter the labor market matters: college graduates face substantial and long-term adverse effects when graduating into a recession. Early-career recessions may have a permanent effect on earnings up to 10-15 years for new college graduates (Kahn, 2010; Oreopoulos et al., 2012; Schwandt and Von Wachter, 2019). This has been referred to as "scarring effect." At the same time, enrollment in a post-secondary degree has become more prevalent, especially in master's degrees. From 2001 to 2021, the number of individuals aged 25 and above holding a bachelor's degree has almost doubled, while the number of master's degree holders among the same age group has more than doubled. Indeed, there is anecdotal and empirical evidence that when facing adverse economic conditions at graduation, some college students take on post-graduate education to avoid entering a depressed labor market. Hence, enrollment in graduate programs is strongly counter-cyclical (Bedard and Herman, 2008; Johnson, 2013; Bogan and Wu, 2018).

Two groups of individuals are potentially induced to immediately enroll in a master's program when facing a recession at college graduation. The first are those who intertemporally substitute their graduate education. They change the timing of their graduate education but keep their lifetime human capital the same. The second are those who are induced to attain a master's degree that they otherwise would not have gotten. They accumulate human capital with an additional degree and postpone market entry until better economic conditions.

This paper estimates the return to a master's degree using 2010-2019 data from the National Survey of College Graduates (NSCG). I construct a pooled cross-section sample containing individuals who obtained their first bachelor's degree from 1995 to 2013 and are at least six years from college graduation when reporting their annual earnings. Thus, I focus on those who obtain a master's degree shortly after graduating from college. I analyze the labor supply and earnings responses from immediately obtaining a master's degree, defined as enrolling a master's within two years after college graduation. Based on a sample of 59,841 individuals with a bachelor's degree, the OLS estimate shows that immediately attaining a master's degree increases earnings by 12%.

However, since unobserved ability may be correlated with whether and when to obtain graduate education, the OLS estimate might be biased. The previous literature has applied two strategies to overcome selection into graduate education: propensity score matching (Titus, 2007) and a fixed-effects strategy (Altonji and Zhong, 2021). Titus (2007) found a 20% return to a master's degree, while Altonji and Zhong (2021) found returns in the range of 10 to 27%. In contrast, I develop a different identification strategy by using the timing of recessions to form an instrumental variable (IV) for graduate education. Specifically, I use a recession indicator as an IV for the immediate master's degree attainment, as economic conditions at the time of graduation, which are plausibly exogenous to the individual, may affect the graduate school decision.

Indeed, my first-stage estimation indicates graduating during a recession increases the probability of pursuing a graduate degree right after college by 4 percentage points. Given that the average probability of graduate attendance is 0.12, this represents a 33% (i.e., $0.04/0.12 = 0.33$) increase in the probability of immediately obtaining a master's degree among full-time workers. The effect of the recession is heterogeneous between genders. For males, the increase in the probability of pursuing a graduate degree right after college is 0.03, and the average probability in the whole sample is 0.08, which is an overall 37% increase. For females, the increase in the probability of pursuing a graduate degree right after college is 0.03, and the average probability in the whole sample is 0.23, which is an overall 13% increase.

Controlling for a wide range of covariates, the IV parameter estimates are identified by comparing the wage outcomes across college-graduate cohorts who were differentially exposed to economic downturns. The IV estimates suggest a statistically significant return of 31% for the recession-induced master's degree holders for both genders pooled together. The 95% confidence interval does not include the OLS estimate.

An important concern is how to interpret these estimates. In particular, the attained masters during a recession might be new human capital or just intertemporal substitution, i.e., shifts in the timing of master's degree attainment. To explore this, I estimate the effects on a second sample: including only those with a master's degree, comparing MA holders who attained the degrees immediately after graduation with those who attained them later in life. This sample contains 36,636 master's degree holders, and the OLS estimate shows no statistically significant difference in earnings for individuals who received a master's degree at different times. In contrast, IV estimates show a 22% return for those who obtained the master's degree immediately after graduation. Therefore, the estimates suggest that the estimated 31% return for the recession-induced master's degree holders contains both the human capital accumulation effect and the shifts in timing effect. Overall, the pooled results suggest substantial returns to a master's degree, in line with those by Titus (2007) and Altonji and Zhong (2021).

The second half of the empirical analysis focuses on the extent to which these returns are differential across subgroups of the college educated. A particular focus has been on STEM and non-STEM majors. For example, Bedard and Herman (2008) found that enrollment in master's degrees is procyclical for males in STEM majors. I also find evidence that individuals in STEM fields are less willing to obtain a master's degree immediately when graduating into a recession. For those in non-STEM curricula, I find that recessions induce them to obtain a master's degree.

Using the non-STEM subsample, with 37,325 individuals with a bachelor's degree, the OLS estimate suggests that immediately attaining a master's degree increases earnings by 12%. In contrast, the IV estimate suggests a statistically significant return of 23% on the recession-induced master's degree. The estimated effects on the sample of 20,244 master's degree holders show no statistically significant effect in both OLS and IV estimations. These results suggest that for individuals who are induced to obtain a master's degree by a recession in non-STEM fields, the changing of the timing for the labor market entry does not significantly affect earnings after (at least) six years of college graduation. The returns are heterogeneous between genders: a recession-induced master's degree provides a 33% return for males, while only an 18% return for females. When comparing the average characteristics between those recession-induced master's degree holders (so-called compliers) and individuals who choose to immediately obtain a master degree after graduation regardless of a recession (so-called always takers), I find that the former are more likely to be younger females and new grads in non-Science and Engineering curricula. They are also more likely to obtain a bachelor's degree from less research-active institutions and have less-educated parents.

This paper provides several contributions to multiple streams of the literature. It is the first study to directly analyze the labor market outcomes for those induced to attend graduate school by a recession. This paper enriches the surprisingly understudied returns to an advanced degree, especially master's degrees (Titus, 2007; Altonji and Zhong, 2021). This paper contributes to the rich line of research on "scarring effects" (Kahn, 2010; Oreopoulos et al., 2012; Altonji et al., 2016; Liu et al., 2016; Schwandt and Von Wachter, 2019) by examining the outcomes of students who react to the labor market conditions by obtaining a master's degree right after college graduation. Finally, this paper complements the numerous studies on the relationship between post-graduate enrollment and recessions (Bedard and Herman, 2008; Johnson, 2013; Bogan and Wu, 2018).

The rest of the paper is organized as follows. Section 2 introduces the related literature, while Section 3 describes the data set and the construction of the sample. Section 4 develops the conceptual framework for the individual's graduate school decision right after college. Section 5 presents the identification strategy, and Section 6 shows the empirical strategy. Section 7 presents the key results. A brief conclusion follows.

3.2 Background and Related Literature

Previous research has shown that individuals who graduate during an economic downturn will suffer significant losses compared to their luckier counterparts who graduate before and after an economic recession (Genda et al., 2010; Kahn, 2010; Oreopoulos et al., 2012; Altonji et al., 2016; Schwandt and Von Wachter, 2019). This persistent effect has been referred to as the scarring effect. According to the recent survey by Von Wachter (2020), college graduates entering a typical recessionary (a 4-5 point rise in unemployment rates) labor market, on average, experience about a 10% reduction in initial earnings. The reduction is typically larger for nonwhite individuals and those with less advantaged family backgrounds (Del Bono and Morando, 2022); and the effect could persist for ten years following graduation for graduates with degrees related to lower returns[1](Altonji et al., 2016). Researchers have also posited various explanations for this persistent negative effect. Graduating into a recession will likely be related to a low probability of employment or full-time employment (Forsythe, 2022), reduction in working time or hourly wage (Cockx and Ghirelli, 2016), a weak match of skills or interests (Modestino et al., 2016; Liu et al., 2016; Hershbein and Kahn, 2018), low-paying occupation or small firms (Altonji et al., 2016; Arellano-Bover, 2020) and fewer promotion opportunities and future employment (Oreopoulos et al., 2012). Nevertheless, the adverse effects of graduating into a recession are not limited to the labor market outcomes but also worse outcomes on health, family formation, fertility, and crime (Schwandt and von Wachter, 2020; Kawaguchi and Kondo, 2020).

Therefore, when facing depressed economic conditions at graduation, college students can postpone graduation or take on postgraduate education to avoid entering a depressed labor market. For students in better programs, higher-earnings majors, and from more advantaged backgrounds, the direct cost of education and the opportunity cost of delaying the labor market entrance is outweighed by the potential scarring effect of unemployment and a better match or job opportunities in a later labor market (Finamor (2022)). On the other hand, taking on postgraduate education can also benefit students, especially during a

[1]Lower returns majors are, for example, philosophy, religion, library science and etc.

recession. Bičáková et al. (2021a) and Bičáková et al. (2021b) showed a positive association between entering college in bad economic conditions and a wage premium in the subsequent labor market, and the effect is more significant for women. Hence, it is natural to think that those who do not postpone their college graduation would be inclined to enroll in a graduate program when facing a recession.

Figure 3.1 and Figure 3.2 display the relationship between aggregate graduate school enrollment and the unemployment rate.[2] The shaded area indicates recession periods. We can see from Figure 3.1 that overall graduate school enrollment has been steadily increasing in recent decades, rising from 1.65 million in 1995 to 3.14 million in 2020. The rate of increase also varies over time, as we can see more easily in Figure 3.2, which shows that the percentage change in aggregate graduate school enrollment is between -0.4% (in 2012) to 15% (in 2009). The correlation in Figure 3.2 is 0.32, indicating a positive association between changes in graduate school enrollment and the unemployment rate, especially during recessions.

One concern is that the enrollment for international graduate students has also increased dramatically during the same period. Hence, Figure 3.3 and Figure 3.4 display the Fall enrollment of domestic and international students separately from 2002 to 2020.[3] Figure 3.3 shows that there seems to be no positive correlation between the Fall enrollment of foreign graduates even during the recession. In contrast, we can see easily in Figure 3.4 that the percentage change in domestic Fall enrollment for graduate school is strongly correlated with the unemployment rate, especially during the recession, and the correlation in Figure 3.4 is 0.28. From looking at aggregate data, all of these graphs indicate a positive association between business cycle fluctuations and graduate school enrollment, especially among domestic students.

Indeed, Bedard and Herman (2008) found that an increase in unemployment is associated with increased enrollment in graduate school for males with higher undergraduate GPAs; the effect is more influential among those with social science majors during undergraduates. Johnson (2013) found that this effect is significant for women rather than men: one standard deviation increase in the unemployment rate is associated with a 4.3% increase in female graduate school enrollment. Altonji et al. (2016) found that a significant recession is associated with a 0.0048 increase in the probability of holding an advanced degree among those with at least five years of potential experience.

Graduate program attendance can help an individual mitigate the "scarring effect" by accumulating additional formal education with an additional degree. There is a small but growing literature regarding the returns to a graduate degree, from focusing on a particular degree [e.g., MBA (Arcidiacono et al., 2008); medical degree (Ketel et al., 2016))] to a more general graduate degree (Titus, 2007; Altonji and Zhong, 2021). The latter found a positive and significant postgraduate wage premium, which rises over time (Lindley and Machin, 2016). Titus (2007) found a 20% private returns of a master's degree, while Altonji and Zhong (2021) found the returns for a master's or professional degree is in the range of 10-27%

Previous literature has adopted different strategies to overcome the selection on students'

[2]The aggregate graduate school enrollment data are from the Integrated Postsecondary Education Data System school enrollment surveys.

[3]Fall enrollment data are from the Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System, Fall Enrollment Survey.

ability in the master's programs enrollment. Titus (2007) applied propensity score matching in estimating the average treatment effect of a master's degree. Arcidiacono et al. (2008) used the test scores required for MBA enrollment as controls, and Ketel et al. (2016) used admission lotteries to estimate the returns to medical school. Altonji and Zhong (2021) controled for experience-adjusted pre-graduate-school earning as a proxy for the potential earning. At the same time, they use person-specific fixed effects and college-graduate major combination fixed effects in their estimation of the returns to graduate school in a particular graduate field and given undergraduate major.

However, the return on education is heterogeneous, and we know little about the labor market outcomes for the new college graduates who are recession-induced master's degree holders. Building upon the existing literature, this study focuses on the returns of a master's degree for recession-induced degree holders. I focus on those who obtain a master's degree shortly after graduating from college and apply a different identification strategy by using the timing of recessions to form an instrumental variable (IV) for graduate education. Specifically, I use a recession indicator as an IV for the immediate master's degree attainment, as economic conditions at the time of graduation, which are plausibly exogenous to the individual, may affect the graduate school decision.

3.3 Data

3.3.1 The National Survey of College Graduates

I employ data from the National Survey of College Graduates (NSCG 2010 - 2019). The NSCG is a repeated cross-sectional biennial survey. It is part of the Scientists and Statistical Data System (SESTAT) conducted by the National Center for Science and Engineering Statistics (NCSES) within the National Science Foundation. The sample frame for all waves of the NSCG consists of people under age 76, living in the U.S., and having at least a bachelor's degree as the survey reference date. We only use data since the wave of 2010 because NSCG has employed a new rotating sampling strategy since the 2010 survey[4].

I append waves from 2010, 2013, 2015, 2017, and 2019 of the NSCG to build a pooled cross-sectional data focusing on individuals in the U.S. labor market with at least a bachelor's degree. The advantages of this dataset are the detailed information on postsecondary education, current and past employment, occupation, and essential demographic variables. The latter includes gender, race/Hispanic origin, and parental education level. The earnings data are based on the annualized salary at the principal employer referring to the survey date.

[4]The NSCG 2010 is drawn from respondents to the 2009 American Community Survey (ACS). The NSCG 2013 and 2015 surveys combine a subsample of the interviewees from the 2010 and 2013 waves of NSCG and a subsample of interviewees with postsecondary education from the 2011 and 2013 waves of the ACS. The NSCG 2017 and 2019 surveys combine a subsample of the interviewees from 2010, 2013, 2015, and 2017 NSCG and a subsample of interviewees with postsecondary education from the 2015 and 2017 waves of the ACS.

3.3.2 Sample Construction

The sample contains individuals who obtained their first bachelor's degree at age 20 - 24 from a US institution between 1995 and 2017. Those individuals are not currently in school either as part-time or full-time students. The rationale for the restriction on age to receive the first bachelor's degree is that older college graduates are less likely to seriously consider the decision to obtain a master's degree immediately. For a similar reason, I restrict the sample to individuals who obtained their master's degree no later than age 35. The analysis only focuses on individuals with a master's degree; therefore, individuals with a professional or Ph.D. degree are also excluded.

According to the survey, only the most recent two and the first bachelor's degrees are reported for individuals with more than three post-secondary degrees. Therefore, I exclude individuals with more than three post-secondary degrees to ensure we capture the exact education history. Individuals with previous retirement experiences are also excluded from the sample. I also drop individuals whose educational background implies an odd time order. For example, those who finished their advanced degree before they had a bachelor's degree or those who finished their bachelor's degree before they turned 18.

To make the labor market outcome comparable, I exclude individuals with a temporary residency visa and only include individuals who responded to the survey within the contiguous U.S. states. Retired individuals or individuals with any retirement history are not included in the sample. When analyzing the labor market earnings, I only focus on individuals who are full-time employed and not self-employed in the U.S., who have no missing annual salary, and who are at least two years after their most recent graduation.

Unfortunately, NSCG does not indicate full-time employment; therefore, I classify full-time employment based on individuals working at least 40 weeks per year and at least 35 hours per week (Altonji and Zhong, 2021). I also use 40 weeks to accommodate the employment arrangement for many teachers. The sample restriction to full-time workers and excluding currently enrolled students should help eliminate most problems of using earnings measured while people are still attending graduate school.

Therefore, we can consistently capture the effect of recessions on graduate school attendance and have comparable annual earnings among the sample. All earning measures have been inflation-adjusted to 2010 dollars using the Consumer Price Index. In the analysis, the timing of recessions is used as an instrument for the graduate school decision. However, there is a concern about the violation of the exclusion restriction for the instrument. There is a potential direct effect of the recession an individual is exposed to at the time of college graduation on the observed earnings. Therefore, the analysis is restricted to individuals with at least six years of experience after college graduation. The rationale of this selection lies in findings that the negative effects of the adverse economic condition at gradation usually decrease after 4-5 years and virtually disappear after 6-7 years for college graduates (Genda et al., 2010; Altonji et al., 2016; Schwandt and Von Wachter, 2019).

As a result, we have 97,941 observations in the sample, with 54,674 individuals only holding a BA degree, 21,009 immediately going for a graduate degree, and 22,258 pursuing a graduate degree later[5].

[5] Detailed summary statistics are provided in Table A1 and Table A2 in the Appendix.

3.3.3 Key Variables

The Timing of the Degree Completion

I am interested in the returns of a master's degree for individuals induced by the recession who immediately enroll in the program. Then it is crucial to capture those who attend graduate school with no work experience or a reasonably short gap between graduation from college and the start of graduate school. In this section, I provide detailed information about the timing of the BA completion and advanced degree completion.

Theoretically, there could be two potential scenarios during the recession where a student would like to apply for graduate school. On the one hand, during the graduate school application season, an individual was experiencing the prospects of a recessionary labor market, and they chose to apply for graduate school. On the other hand, at the time of graduation, an individual who experienced a recessionary labor market might decide to apply for graduate school for the next application season. In this case, individuals' decisions are conditional on the fact that they received an offer and the economic condition is still depressed [6]. For the latter case, we should allow for a one-year gap between graduate school attendance and college graduation.

Unfortunately, I do not observe individuals' start dates for each degree. Therefore, I do not know exactly whether an individual attended graduate school shortly after graduation from the survey. Consequently, I am forced to assume the start day of graduate school for the individual by subtracting an assumed average number of years required to obtain the degree for full-time students. The assumption is that it takes two years to finish a general Master's degree or an MBA and four years to finish a medical-related major[7].

Hence, "immediate graduate school attendees" are individuals whose gap between college graduation and graduate school graduation is within the average years of college degree attainment plus one year. In other words, an individual is an "immediate graduate school attendee" if she obtained a master's degree in general majors within three years, or in medical related majors within five years after her attainment of the first bachelor's degree.

Macroeconomic Conditions

I use a recession indicator variable to denote if an individual graduates from college into a severe recession. I consider the business cycle reference dates provided by the NBER "US Business Cycle Expansions and Contractions". An individual graduates into a recession if the year she obtained her first bachelor's degree is a recession year. According to the NBER classification, I borrow from Huckfeldt (2022) to define the recession year as a year of more than one quarter in recession. Hence, in my analysis, individuals who received their first bachelor's degree in 2001, 2008, and 2009 graduated into a recession.[8]

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[6] If they get the offer from a master's program, the economy improves, and they reject it, we will not be able to identify those individuals from our sample as master's degree holders.

[7] Altonji and Zhong (2021) assumes the typical time to obtain the degree for a full-time student are four years for Medicine, three years for Law, two years for an MBA, and one year for all other Master's degrees. Schwandt and Von Wachter (2019), and Bičáková et al. (2021b) assume that individuals with a Master's or Professional degree enter the labor market six years after college enrollment.

[8] Previous literature has relied on the increase in unemployment as a measure of recession; a typical recession is a 4-5 point rise in the unemployment rate (e.g., Bedard and Herman (2008); Kahn (2010);

I control for the current economic conditions when an individual's earnings are observed. To do this, I use either the national unemployment rate or the census division unemployment rate based on an individual's region of employment. The unemployment rate data is obtained from the Bureau of Labor Statistics (BLS). The national annual unemployment rate is based on the average monthly seasonally unadjusted unemployment rate[9]. The BLS produces these monthly unemployment rates based on the Current Population Survey data. Annual unemployment rates at the census division level are obtained annually from the BLS's Local Area Unemployment Statistics program.

The First Graduate Degree

The raw data from the NSCG files organize the advanced degree by the level of the degrees: it includes the first BA, the most recent degree, and a list of degrees from the highest degree to the 3^{rd} highest degree. I rule out individuals whose most recent degree is inconsistent with the highest degree. Since in the sample we only have individuals with up to three bachelor's and above degrees, we have the following categories of individuals: (1) with only the first bachelor's degree, (2) receive bachelor's degree and master's degree separately (3) receive multiple Bachelor degrees at the same time, (4) receive Bachelor degree(s) at a different time from the first BA, (5) receive the graduate degree at the same time as the first bachelor degree, (6) receive multiple graduate degrees at the same time apart from the bachelor degree

For those with one degree, this is their first bachelor's degree. For individuals holding two degrees, the second highest degree is their first bachelor's degree. If their highest degree turns out to be an advanced degree, then this advanced degree is their first graduate degree. If their highest degree is a bachelor's degree, which means they do not have a record for an advanced degree, then their first graduate degree is missing. For individuals with three degrees, their third highest degree is their first bachelor's degree. If their second highest degree is a bachelor's degree and their highest degree is an advanced one, then their first graduate degree is their highest. However, when both their second highest and the highest degree are advanced degrees, they must be put in time order to decide which advanced degree is the first graduate degree for the individual. If an individual is reported to obtain two master's degrees simultaneously, we use the field of study information reported with their highest degree. For individuals with multiple master's degrees at different times, I consider them to have other preferences and exclude them from the analysis.

Other Related Controls

Unfortunately, direct ability measures are not available in the NSCG sample. I use parental education levels and the Carnegie Classification of Institutions to approximate the individual's ability.

Empirical evidence has shown that parents' educational levels are important predictors of children's educational outcomes and occupational outcomes (Davis-Kean, 2005). I control for both mother's and father's educational attainment as a proxy for an individual's ability

Oreopoulos et al. (2012); Altonji et al. (2016); Von Wachter (2020); Bičáková et al. (2021b)).

[9] I follow Bičáková et al. (2021b), and use the series ID LNU0400000.

when estimating the probability of attending graduate school facing a recessionary labor market and the effects on earnings from obtaining a master's degree during a recession[10]. In the sample, compared to those with only a bachelor's degree and those who got a graduate degree later in life, the proportion of immediate master's degree seekers with at least some college education parents is higher. A summary of statistics on the parental education level is presented in the appendix. Hersch (2019) found that the premium to an elite undergraduate degree remains large even with extensive controls for individual characteristics, family background, and employment characteristics. Therefore, I additionally control the Carnegie Classification of Institutions of Higher Education for the institution where the individual obtained the first bachelor's degree as another proxy for an individual's ability.

Since the returns from a master's degree are heterogeneous across different fields of study (Altonji and Zhong, 2021), I also control for each individual's aggregated field of study[11]. Since the full-time employment status varies over different employment sectors and regions of employment, I controlled for three major working sections (educational institution, government, and business) and nine census divisions as of the regions of employment. I also control the job code for an individual's principal job to circumvent the wage premium from high-paying occupations. The nine categories of job code correspond to the nine categories of the fields of study.

3.4 Conceptual Framework

Assume that after college gradation in period zero, individuals live for three periods denoted as $t = 1, 2, 3$, and that everyone works in the last period. Suppose at time $t = 1$ and $t = 2$, individuals can choose between working in the labor market or pursuing a master's degree. Each of those choices grants some utility to the individual in a particular period based on the individual's characteristics. The choice also has the potential to affect utility flows in future periods. Working grants individuals earnings and the experience gained while working can raise earnings in subsequent periods. Pursuing a master's degree is costly in three ways: (1) the direct cost associated with schooling (such as tuition, fees, books, etc.); (2) the foregone earnings due to not working, and (3) any non-pecuniary costs of schooling. However, additional education through a master's degree helps individuals accumulate human capital, increasing future earnings and other non-pecuniary benefits associated with a master's degree. An individual's optimal choice at time t is the one that grants the highest expected utility. We assume that individuals are rational and seek to maximize their lifetime utility. New college graduates have the same level of education, no working experience, and are nearly the same age. Choices between working and pursuing a master's degree are determined the expected returns of the education and the returns to work, which includes both the initial wage offer and the returns to experience.

Therefore, in this three-period model, we will have three types of individuals: (1) those

[10] A detailed summary statistics for parental education level is provided in Table A3 in the Appendix

[11] The nine groups for the field of study for the first bachelor's degree and the advanced degree are: Computer and Mathematical Sciences; Biological, Agricultural and Environmental Life Sciences; Physical and Related Sciences; Social and Related Sciences; Engineering; S&E-Related Fields and Non-S&E Fields S&E stands for Science and Engineering

with only a Bachelor's Degree, (2) those who pursue a Master's degree right after college graduation (in period 1), and (3) those who pursue for a Master's degree later (in period 2). The types of individuals and their choices for each period are shown in Table 3.1.

Types	Period 1	Period 2	Period 3
Bachelor's Degree Only	Work	Work	Work
Immediately Obtained a Master's Degree	Master's	Work	Work
Obtained a Master's Degree Later	Work	Master's	Work

Table 3.1: The Different Types of Individuals and Choices

Suppose a recession occurs at time zero of college graduation, there is a negative labor demand shock, and wage offers are reduced. Suppose also that the negative impact on wages persists and reduces the accumulation of industry or occupation-specific capital due to the wage growth occurring from a smaller initial base. In that case, individuals graduating with a bachelor's degree will be more inclined to obtain a master's degree right after graduation. By doing so, they postpone their market entry and accumulate additional human capital through a master's degree. Therefore, they experience both the timing effect and the accumulation of human capital effect, and those two effects cannot be separated within this group.

On the other hand, for individuals who obtain a graduate degree later in life and who choose to work in $t = 1$, the recession will decrease their earnings as a new college graduate. With the additional assumption that the non-pecuniary costs or benefits would not change regardless of the recession, the expected returns for these individuals from working in period $t = 1$ and then obtaining a master's degree in period $t = 2$ decrease. Therefore, some individuals in this category will switch their behavior to either a bachelor's degree or obtain a master's degree in period $t = 1$. Since they differ from those with a bachelor's degree in terms of the lifetime human-capital level, when facing a recession when graduating from college, some individuals under this scenario will benefit from switching to immediately obtaining a master's degree shortly after graduation. In this case, an individual does not change his/her lifetime human capital accumulation but intertemporally substitutes the master's degree attainment. Hence, for them, there is only the timing effect. If, in the long run, there is no earnings advantage by intertemporally substituting the attainment of the master's degree, then the returns from the recession-induced master's degree attainment are the returns for a master's degree.

3.5 Identification

Let D be the binary treatment indicating that an individual immediately enrolls in a master's program, defined as enrolled within two years after graduation. Let Y be the labor market outcome of interest. However, unobserved ability may be correlated with whether and when to obtain a master's degree. The decision to enroll immediately in a master's program is endogenous. This study adopts the instrumental variable (IV) approach to solve the selection to obtain a master's degree immediately after college. Suppose Z is a binary recession indicator plausibly exogenous, $Z = 1$ if an individual graduates into a recession; otherwise, $Z = 0$. Suppose X represents a vector of predetermined variables.

Following Rubin (1974, 1977) and Rubin (1977), I define Y_0 and Y_1 as the potential outcomes an individual would attain with and without exposure to the treatment, i.e, the potential labor market outcome for the individual with or without a immediately obtained master's degree. Let D_0 represents the potential treatment status (whether immediately enrolled in a master's program) when an individual graduates without exposure to a recession after college, and D_1 represents the potential treatment status for an individual when graduates into a recessionary economic condition. The treatment status indicator variable can then be expressed as $D = ZD_1 + (1 - Z)D_0$. We observe D and Z in the sample; therefore, we know D_z for individuals with $Z = z$, but we do not observe both potential treatment indicators simultaneously. Following the terminology of Angrist et al. (1996), the population is divided into groups defined by the potential treatment indicators D_0 and D_1. Theoretically, we can identify college graduates that are induced to attend graduate school apart from those who will attend graduate school regardless of the economic conditions at the time of graduation. Since attending graduate school is a binary decision, there are only four potential combinations of D_0 and D_1. These combinations are presented in Table 3.2.

	$D_0 = 0$	$D_0 = 1$
$D_1 = 0$	Never-takers	Defiers
$D_1 = 1$	Compliers	Always-takers

Table 3.2: Potential Combinations of Potential Treatment Indicators

In my analysis, always-takers ($D_0 = D_1 = 1$) will immediately enroll for a master's degree regardless of the economic condition at graduation. On the contrary, never-takers ($D_0 = D_1 = 0$) are individuals who will never choose to attend a master's program immediately regardless of whether exposure to a recession when they graduate. This paper pays primary interest for the third group: "compliers" ($D_0 = 0$ and $D_1 = 1$). Such individuals will attend graduate school if graduating into recession ($D_1 = 1$) but otherwise will not attend graduate school ($D_0 = 0$), i.e., those individuals are recession-induced master's degree holders. There is a fourth group called "defiers" ($D_0 = 1$ and $D_1 = 0$). "Defiers" are individuals who choose to attend graduate school when they do not face the recession at graduation ($D_0 = 1$) but would not attend graduate school when they graduate into a recession ($D_1 = 0$). However, since only one of the potential treatment indicators (D_0, D_1) is observed, we cannot identify which group any particular individual belongs to.

The parameter of interest is the local average treatment effect (LATE), which allows the heterogeneous effect of the treatment among the different populations. In this analysis, I allow the returns of a master's degree obtained immediately after college to differ among master's degree holders. Therefore, I am interested in the average treatment effect of a recession-induced master's degree, i.e., the returns from a master's degree for the compliers. Hence, the parameter of interests can be defined as:

$$\tau_{LATE} = E[Y_1 - Y_0 | D_1 > D_0] \tag{3.1}$$

By Angrist et al. (1996), the two-stage least square (2SLS) estimator can be interpreted as the local average treatment effect (LATE). In my context, the estimator of the regression uses Z (whether graduated into a recession) as an instrumental variable for the treatment D (whether immediately enrolled in a master's program after college). The outcome variable is Y (the labor market outcomes). The exclusion restriction underlying IV estimator may be more likely to be valid after conditioning on covariates X in my context. Therefore, To interpret the 2SLS estimate as the local average treatment effect, i.e., the returns to a master's degree immediately obtained after college, induced by the recession, we need to satisfy the following identification assumptions[12]:

A.1 Independence of the instrument: Conditional on X, the random vector (Y_{00}, Y_{01}, Y_{10}, Y_{11}, D_0, D_1) is independent of Z

A.2 Exclusion restriction: $P(Y_{1d} = Y_{0d}|X) = 1$ for $d \in 0, 1$

A.3 First Stage: $0 < P(Z = 1|X) < 1$ and $P(D_1 = 1|X) > P(D_0 = 1|X)$

A.4 Monotonicity: $P(D_1 \geq D_0|X) = 1$

Assumption $A.1$ is also called "ignorability", meaning that Z is "as good as randomly" assigned once we condition on X. In this analysis, Z is the plausibly random recession indicator.

Assumption $A.2$ means that, once we condition on X, variation in the instrument does not change potential outcomes other than through the treatment D. Once the value of the treatment is fixed, the instrument has no direct effect on the outcome. Given this exclusion restriction, the potential outcomes for each treatment status only depend on the treatment, not the instrument, so we have $Y_0 = Y_{00} = Y_{10}$ and $Y_1 = Y_{01} = Y_{11}$. $A.1$ and $A.2$ together guarantee that the only effect of the instrument on the outcome is through variation in treatment status. In this analysis, this exclusion restriction requires that the recession at college graduation will not affect the future labor market outcome outside the effect on whether an individual immediately obtained a master's degree.

Assumption $A.3$ is related to the first stage, and it guarantees that Z and D are correlated conditional on X, and that the instrument affects the treatment. In addition, it implies that the support of X conditional on $Z = 1$ coincides with the support of X conditional on $Z = 0$. My analysis requires that graduating into a recession will affect the probability of graduate school attendance.

Monotonicity ($A.4$) is an assumption about the relationship between the instrument Z and treatment D to allow for heterogeneous effects. It states that no individuals would get the treatment when the instrument takes the value of zero but would not when the instrument takes the value of one, i.e., $D_1 - D_0 \geq 0$. In the present analysis, monotonicity means that those who attend post-graduate education when not graduating into a recession will also attend post-graduate education when graduating into a recession, holding everything else equal. Assumption $A.4$ rules out the existence of defiers, i.e., individuals whose graduate

[12]Since the exclusion restriction underlying IV estimator may be more likely to be valid after conditioning on covariates X, I assume that the assumptions of the LATE theorem in Angrist et al. (1996) hold conditional on X. If X is discrete with finite support, it is straightforward to produce estimators of $E[Y_1|X; D_1 > D0]$ and $E[Y_0|X; D_1 > D_0]$ (Abadie, 2003). The covariates are all (mostly) discrete and finite in this analysis; under $A1 - A4$, we can still interpret the 2SLS estimates with covariates as the LATE.

school decisions are procyclical. Hence, Assumption $A.4$ defines a population partition into always-takers (those with a master's degree regardless of whether they are caught by the recession), compliers (those recession-induced master's degree holders), and never-takers (those who will not obtain a master's degree regardless of a recession). Therefore, we can identify individual i with $D_i = 1$ and $Z_i = 0$ as an "always-taker", and with $D_i = 0$ and $Z_i = 1$ as a "never-taker".

Under $A.1 - A.4$, the 2SLS estimand identifies the average treatment effect for the compliers, or the local average treatment effect (LATE). In this analysis, the LATE represents the economic returns for individuals induced to attend post-graduate education when graduating into a recession.

3.5.1 Average Characteristics for Recession-Induced Master's Degree Attendees Immediately after Graduation

In our analysis, always-takers are individuals who choose to attend a master's program immediately, regardless of the economic condition at the time of college graduation. On the contrary, never-takers will never immediately enroll in a master's program. Compliers are those recession-induced individuals who immediately obtain a master's degree. Since we never observe both potential treatment assignments for the same individual, we can not identify individual units as compliers, always-takers, or never-takers. However, under the assumptions A2 (exclusion restriction), A3 (first-stage), and A4 (monotonicity), it is easy to identify the proportion of compliers (π_c), always-takers (π_{at}), and never-takers (π_{nt}), respectively, in the population:

$$\pi_c : \quad P(D_1 > D_0|X) = E[D|X, Z = 1] - E[D|X, Z = 0] \tag{3.2}$$

$$\pi_{at} : \quad P(D_1 = D_0 = 1|X) = E[D|X, Z = 0] \tag{3.3}$$

$$\pi_{nt} : \quad P(D_1 = D_0 = 0|X) = 1 - E[D|X, Z = 1] \tag{3.4}$$

Similarly, the proportion of compliers (recession-induced individuals) among the treated and the untreated can be identified. For example, the proportion of compliers among the treated would be as follows:

$$P(D_1 > D_0|X, D = 1) = \frac{P(Z = 1|X)(E[D|X, Z = 1] - E[D|X, Z = 0])}{P(D = 1|X)} \tag{3.5}$$

Therefore, the proportion of individuals in graduate school induced due to the recession is given by Equation (3.5) once the effect of a recession on the probability of graduate school attendance is identified.

Then, I can obtain the average pre-treatment characteristics of the always-takes, never-takers, and compliers. To obtain the average characteristics (or covariate means) of the always-takers and never-takers, we only need assumptions A.1 (the Independence of the instrument) and A.4 (Monotonicity). Assumption A.4 rules out defiers, and A.1 ensures that the characteristics we are looking at are independent of the instrument (graduate into a recession). Therefore, we can obtain the average characteristics of always-takers by looking at the observed always-takers who are not exposed to the treatment ($D = 1$, $Z = 0$). In our context, we are looking at individuals who immediately obtain a master's degree without graduating into a recession:

$$\mu_{at} = E[X|D_1 = D_0 = 1] = E[X|D = 1, Z = 0]. \tag{3.6}$$

The pre-treatment covariate means of the never-takers are based on the observed never-takers who do not immediately attend a master's program when graduating into a recession:

$$\mu_{nt} = E[X|D_1 = D_0 = 0] = E[X|D = 0, Z = 1]. \tag{3.7}$$

The intuition to obtain the average characteristics of the compliers is by subtracting the weighted mean of the observed always-takers and the observed never-takers from the mean of the entire sample, from which I can back out the covariate mean for compliers. Hence, by the Law of Iterated Expectations (LIE), we can decompose the population means of X into a linear combination of the weighted means of sub-population:

$$\begin{aligned} \mu = E[X] = E[D_1 > D_0]&P(D_1 > D_0) \\ + E[X|D_1 = D_0 = 1]&P(D_1 = D_0 = 1) \\ + E[X|D_1 = D_0 = 0]&P(D_1 = D_0 = 0). \end{aligned} \tag{3.8}$$

Under Assumptions A.1 and A.4, substitute Equation (3.6) and (3.7) into Equation (3.8), we can solve for the covariate means for the compliers:

$$\mu_c = E[X|D_1 > D_0] = \pi_c^{-1}(\mu - \mu_{at}\pi_{at} - \mu_{nt}\pi_{nt}), \tag{3.9}$$

since all terms on the right-hand-side are directly observed, the average characteristics of those recession-induced individuals are identified.

3.5.2 Assessment of Assumptions

In this subsection, I assess the assumptions in the context of analysing the returns of the master's degree induced by the recession.

Assumption A.1 is the random assignment of the instrument conditional on the covariates. In my context, this requires that the potential earnings with and without immediately attending a master's degree be independent of the recession at college graduation, conditional on individual characteristics. Since the macroeconomic condition is an exogenous shock for each individual, individual characteristics would not affect the instrument, which is "graduating into a recession". Therefore, the independence of the instrument assumption is plausible.

Assumption A.2 (exclusion restriction assumption) states that the recession at college graduation affects the labor market outcomes exclusively through an indicator of enrollment in the master's degree. In our context, the assumptions could be violated if the earnings of an individual who graduated from college into a recession are still under the "scarring effect." The earnings will still be affected by the recession at college graduation if we observe the earnings close to the time of college graduation. Prior research provides evidence that finishing college and starting work in the middle of a weak economy will have a hard time finding full-time work and receive lower hourly wages for their work (Rodríguez et al., 2020). This disadvantage can last for years. Therefore, if we observe the earnings of individuals who graduated into a recession close to graduation, the observed earnings will contain a component affected by the recession. This component stays even after conditioning on the covariate such as gender, race, potential experience, and occupations, i.e., the exclusion restriction will not be satisfied.

However, studies suggest that the negative effect of graduating into a recession declines over time. For example, Altonji et al. (2016) found that the recession graduates reported about 11% less annual earnings in their first year; after three years of labor market experience, the difference was only about 4%, and by year seven, the effect was no longer observed. Similarly, Schwandt and Von Wachter (2019) found the negative wage effect from a one percent increase in unemployment at graduation virtually disappeared within 6-7 years. Genda et al. (2010) found no effect after 4-6 years for workers with at least some college education. Therefore, it is reasonable to assume that the recession has no direct effect on an individual's observed income after six years of college graduation if individual graduates into a recession from college, regardless of whether an individual obtained a master's degree or not.[13] Table 3.3 tabulates the year of the first graduate degree and the time for the wage observation in our sample. It is clear that all the individuals in the sample are observed at least six years after college graduation, then the average number of years since graduation will surely be greater than six years. Therefore, conditional on the covariates, the exclusion restriction (A.2) are satisfied.

Assumption A.3 states that the instrument has a non-zero average effect on the treatment, i.e., graduating into recession has a non-zero average effect on the immediate obtainment of a master's degree. This is supported by Table 3.4. Two subgroups are used in the analysis: the first one contains those with only a bachelor's degree and those who immediately obtained a master's degree after graduation (shown in columns (2)-(4)); the second contains all those with a master's degree (shown in the last three columns). I use a univariate probit model to estimate the individual's probability of immediately attending a master's program shortly after the first bachelor's degree. I use two instrumental variables separately: the recession indicator and the annual national unemployment rate at the time of bachelor graduation. Estimation results in the tables present the average effects of graduating into a recession on the probability of immediately attending a master's program, or the marginal effects for the national unemployment rate at the time of college graduation. effect on the treatment, i.e.,

[13]However, Kahn (2010) found the negative effect can last for 17 years after graduation, and Oreopoulos et al. (2012) found young graduates entering the labor market in a recession suffer significant initial earnings losses that eventually fade after 8 to 10 years. On the one hand, Kahn (2010) examines the negative shock of the 1982 recession, and Oreopoulos et al. (2012) examines a similar issue using rich Canadian university–employer-employee matched data from 1982 to 1999. The 1982 recession might be particularly damaging and correlated with the recession after ten years, and it is reasonable to believe the scarring effect would be longer-lasting. Additionally, with the data constraint, I needed to track more individuals who had at least 17 years since graduation. Therefore, I rely on the analysis results based on the more recent recessions and choose to use "at least six years from college graduation" as the criteria.

graduating into recession has a non-zero average effect on the immediate obtainment of a master's degree for both gender.

Overall, graduating during a recession increases the probability of pursuing a graduate degree right after college by 4.08 percentage points. Given that the average probability of graduate attendance is 0.12, this represents a 33% increase in the probability of immediately obtaining a master's degree among full-time workers. The effect of the recession is heterogeneous between genders as shown in Table 3.5. For males, the increase in the probability of pursuing a graduate degree right after college is 0.03, and the average probability in the whole sample is 0.08, which is an overall 37% increase. For females, the increase in the probability of pursuing a graduate degree right after college is 0.03, and the average probability in the whole sample is 0.23, which is an overall 13% increase.

Individual-level weak monotonicity of the treatment in the instrument (Assumption A.4) is also needed. Although this is a conventional assumption of IV methods, it may be strong in my setting since the monotonicity is imposed at the individual level. Assumption A.4 requires that no individual enrolls in a master's program if not graduating into a recession but does not enroll if graduating into a recession. However, this assumption can be violated since some have found that the increase in the unemployment rate can affect graduate school enrollment in either way, depending on whether the budget constraint effect or the opportunity cost effect dominates. For example, Bedard and Herman (2008) found that enrollment in master's degrees is procyclical for males and that different majors diverge in response to the labor market condition. Therefore, I report the first stage analysis by the broad undergraduate majors in Table 3.6.

It is clear from Table 3.6 that for those with an undergraduate major in computer and mathematical sciences or in physical or related sciences, the probability for them to immediately attend a master's program statistically significantly decreases when graduating into a recession, and this is true for both males and females. Those in biology, agriculture, and environment life sciences also become more reluctant to immediately obtain a master's degree when facing a recession at the time of college graduation, even though the effect is not statistically significant. On the other hand, individuals in social sciences and non-S&E related fields are more willing to immediately attend the master's program when graduating from college into a recession. There is some evidence of a positive effect, but not statistically significant for those with an engineering or S&E-related major during college.

Therefore, for the rest of the paper, I only estimate the effect of graduating into a recession on the probability of an individual's attendance at a master's program right after college for a sub-sample. I exclude individuals who obtained their bachelor's degree in the computer and mathematical sciences, biology, agricultural and environment life sciences, and physical or related sciences. I call from now on this sub-sample the "non-STEM" sample[14].

Table 3.7 presents the first-stage estimation results based on the "non-STEM " sample. In this sub-sample, overall, the probability of immediately attending the master's program after graduation increases by 3.59 percentage points if an individual graduates from college during a recession year. The estimation shows an increase of 3.77 percentage points if we only focus on the individuals who are not currently in school and an increase of 4.65 percentage

[14]Detailed summary statistics for the non-STEM sample are provided in Table A4 and Table A5 in the Appendix.

points for those who are currently full-time employed. Therefore, within the "non-STEM" sample, it seems plausible to assume the weak monotonicity of the immediately attending a master's program in graduating into a recession.

3.6 Empirical Strategy

3.6.1 Probability of Employment and Full-time Employment

The analysis for the labor market outcome is based on individuals who are full-time employed and not self-employed. One concern is that the result might be biased due to the selection into employment and full-time employment. The selection into employment can vary depending on the sub-sample considered. Let us first consider the case by comparing those who are induced to immediately pursue a master's degree by the recession and those who graduate and enter the labor market without exposure to a recession and with only a bachelor's degree. Suppose individuals who are induced to obtain a master's degree immediately have higher underlying employment and full-time employment probabilities. In that case, it might be that the subset of full-time workers who directly entered the labor market without a recession is more positively selected than those recession-induced master's degree holders. On the other hand, suppose individuals who are induced to obtain a master's degree immediately have lower employment and full-time employment probabilities. In this case, the subset of full-time workers from those recession-induced master's degree holders is more positively selected than those who obtained a master's degree later in life. I investigate whether the employment status will still be affected by the immediately obtained master's degree after at least six years of college graduation for those who are recession-induced to obtain a master's degree immediately after college. I apply the following analysis to check whether positive selection into employment exists:

$$P(emp_{it}) = \alpha + \beta G_i^{im} + \theta unemp_t + \eta FMAJ_i + \gamma x_{it} + \kappa_c + \tau_t + \epsilon_{it} \tag{3.10}$$

where emp_{it} is a dummy representing whether an individual i observed in year t is employed, and α is a constant term. G_i^{im} is a dummy representing whether an individual attending a master's program immediately after college. $unemp_t$ is the annual average unemployment rate at the time an individual's employment status is observed. $FMAJ_i$ is the field of study of individual i during the highest degree (either bachelor's or master's), x_{it} is a set of individual-specific characteristics, and κ_c captures the college graduate year c fixed effect. τ_t controls for the year fixed effect when observing the labor market outcome, and ϵ_{it} is the error term.

The estimation of the probability of full-time employment is conditional on employment, and the analysis is specified as follows:

$$P(fulltime_{it}) = \alpha + \beta G_i^{im} + \theta unemp_{jt} + \delta Occ_i + \gamma x_{it} + \eta_s + \tau_t + \epsilon_{it} \tag{3.11}$$

where $fulltime_{it}$ is a dummy representing whether an employed individual i observed in year t is full-time employed, and α is a constant term. G_i^{im} is a dummy representing whether an individual attending a master's program immediately after college. $unemp_{jt}$ is the annual unemployment rate in the employment location at the time an individual's full-time employment status is observed. Occ_i is the occupation an individual is employed in, x_{it} is a set of individual-specific characteristics, and η_s captures the employment sector s fixed effect. An individual can belong to either an Education Institution, Government or Industry Sector. τ_t controls for the year fixed effect when observing the labor market outcome, and ϵ_{it} is the error term.

β in both equations is the coefficient of interest, which captures the effect of a master's degree obtained immediately after college on the full-time employment probability after at least six years past college graduation. Educational attainment is affected by labor market entry conditions because of the changes in the opportunity cost of remaining in school and seeking further education. Both the trigger of the treatment (whether an individual graduated into a recession from college), the treatment (whether immediately attending the master's program), and the outcome (whether employed/full-time employed) are binary.

3.6.2 Benchmark Analysis: Returns of the Master's Degree

In this paper, I am interested in the returns from the master's education for those who are induced to immediately attend the master's program by a recessionary labor market at the time of college graduation. Therefore, the analysis defines a cohort by the year of college graduation. The potential experience is defined as the years since college graduation. Therefore, I cannot simultaneously identify the graduation cohort effects and calendar year effects; instead, I can simultaneously identify the calendar year effects, potential experience, and tenure effects. This is because not all graduates start their current principal jobs simultaneously. Hence, among individuals of the same observed tenure at the observed principal jobs at time t, there is a variation in the college graduation cohorts they belong. The variation stemmed from the fact that people start their observed principal job at different times, i.e., there is variation in the potential experience for individuals with the same length of tenure in the same survey year. Using the NSCG data gives me the advantage of accessing accurate information on when each individual obtained each degree.

My benchmark estimation takes on the following form:

$$ln(w_{it}) = \alpha + \beta G_i^{im} + \delta exp_{it} + \theta unemp_{jt} + \gamma x_{it} + \kappa_j + \eta_s + \tau_t + \epsilon_{it} \tag{3.12}$$

where $ln(w_{it})$ is the log real annualized salary as the dependent variable for an individual i in full-time employment (excluding the self-employed) observed in year t, and α is a constant term. G_i^{im} is a dummy representing whether I observe an individual attend the master's program immediately after college. exp_{it} is a vector containing up to the quadratic term of tenure in the principal job and up to the quadratic term of potential experience of an individual i at the time t. $unemp_{jt}$ is the measure of the macroeconomic condition at the time the annual earnings of the individual employed in the census division j are observed, including the national unemployment rate and the unemployment rate in the census division of employment. x_{it} is a set of individual-specific characteristics, including race, gender, employed occupations, working time (weeks per year and hours per week), whether married or living in a marriage-like relationship, and the number of kids under age six living in the household. κ_j represents the employment location fixed effect, η_s represents the employment sector fixed effect, τ_t controls for the year fixed effect when observing the labor market outcome, and ϵ_{it} is the error term. In all the analyses, observations are weighted using person weights provided in the dataset.

β is the coefficient of interest, which captures returns from a master's degree that an individual obtained immediately after graduation. However, educational attainment is affected by labor market entry conditions. Since the opportunity cost of staying in school for further education decreases when an individual graduates into a recessionary labor market, this individual becomes more likely to enroll in a master's program immediately after graduation. I therefore have an endogenous dummy variable in my primary analysis.

I apply a two-step 2SLS method suggested by Wooldridge (2010). The first step is to estimate the binary response model $P(G^{im} = 1|x, z) = G(x, z)$ by the maximum likelihood method and obtain the fitted probability $\hat{G}_i$. The second step is to estimate the benchmark equation using the fitted probability $\hat{G}_i$ as the IV for the actual immediate master program attendance G_i^{im}.

After controlling for the current economic condition, including the national unemployment rate and the unemployment rate in the census division of employment, the identification of β is driven solely by cross-cohort differences in outcomes that were systematically related by whether the immediate attendance of graduate school happened during a recession or not. One concern is that graduating into a recession might affect an individual's current labor market outcome through other channels outside the changes in the decision to attend a master's program immediately. The effect of graduating into a recession on one's labor market outcome could be long-lasting and potentially indirectly alter an individual's labor market choice. By including the current macroeconomic condition, the location of employment fixed effect, and the employed occupation, I would ideally capture all the potential variation that a recession at college graduation could cause. Hence, in my benchmark analysis, the identification of β is driven solely by cross-cohort differences in outcomes that were systematically related by whether the immediate attendance of graduate school happened during a recession or not.

3.6.3 The Average Characteristics for the Recession-Induced Individuals who Obtained a Master's Degree Immediately After College Graduation

As before, let D represent whether an individual immediately obtained a master's degree after the first bachelor's, and Z represent whether an individual graduated into a recession from college. Under Assumptions A.1 to A.4, I can identify the average characteristics for the different subpopulations of individuals defined by the potential treatment indicators given by the combination of $\{D, Z\}$. The average characteristics for each subpopulation can be identified from the observed mean of those characteristics for the four groups defined in Table 3.2. Each of them is a weighted average of the mean characteristics of different subpopulation as shown in Equation (3.2)-(3.4) in Section 5.1. Following Chen et al. (2018), let $\overline{x_k}$ denote the expectation of a scalar variable for a specific subpopulation k. Note that the assumptions used in Chen et al. (2018) are the random assignment of the instrument and weak monotonicity, where they assume the instrument is randomly assigned without conditioning on the covariates. In this analysis, the instrument is whether an individual graduated into a recession. Since I believe the macroeconomic condition is exogenous, it seems plausible to assume the random assignment of the instrument even without conditioning on the covariates, when estimating the average pre-treatment characteristics.

Therefore, I estimate the following moment function for the average characteristics:

$$g\left(\{\bar{x}_k\}\right) = \begin{bmatrix} \left(x - \bar{x}_{at}\right)(1-Z)D \\ \left(x - \bar{x}_{nt}\right)Z(1-D) \\ \left(x - \bar{x}_c \frac{\pi_c}{p_{1|1}} - \bar{x}_a \frac{\pi_{at}}{p_{1|1}}\right) ZD \\ \left(x - \bar{x}_c \frac{\pi_c}{p_{0|0}} - \bar{x}_n \frac{\pi_{nt}}{p_{0|}}\right)(1-Z)(1-D) \\ x - \sum_k \pi_k \bar{x}_k \end{bmatrix} \tag{3.13}$$

where $\{\bar{x}_k\} = \{\bar{x}_{at}, \bar{x}_{nt}, \bar{x}_c\}$. By Law of Iterated Expectations, $E[g\left(\{\bar{x}_k\}\right)] = 0$ when evaluated at the true value of $\{\bar{x}_k\}$. Therefore, I first estimate the proportions of all the subpopulations, and then estimate all the average characteristics given the estimated proportions. For each variable in $g\left(\{\bar{x}_k\}\right)$, there are five equations to identify three means, i.e. $\{\bar{x}_k\}$. Since the standard errors obtained from this GMM model do not take into account the fact that the proportions for each sub-population are also estimated, I employed a 100-repetition bootstrap to calculate the standard errors of the estimated average characteristics.

3.7 Results

3.7.1 Probability of Employment and Full-time Employment

In this study, the analysis of the returns from a master's degree obtained within a short time frame after college graduation is based on those who are full-time non-self-employed individuals. Hence, it is important first to understand whether the induced education will also increase the employment probability after at least six years after college graduation. Table 3.8 presents the estimation results for the effect on employment probability based on individuals who are not currently in school from the non-STEM sample. Panel A reports the estimation based on individuals who obtained a master's degree immediately after college or those with only a bachelor's degree. Panel B reports the estimation based on individuals with a master's degree. In Table 3.8, columns (1)-(4) report the estimation based on the whole sample. Column (1) reports the OLS estimation of the effect on employment probability from an immediately obtained master's degree, and column (2) reports the same estimation based on a probit model. Column (3) reports the estimation using the standard 2SLS model, while column (4) reports the result after implementing the two-step 2SLS method in Wooldridge (2010). Columns (5)-(8) report the corresponding set of estimations based on males, and the last three columns report the corresponding estimations for females.

Accompanying the 2SLS results, I also report the Cragg-Donald statistic (Cragg and Donald, 1993), which can be thought of as the matrix-analog of the first stage F-statistic. The critical value for the Cragg-Daniels statistic is based on Stock and Yogo (2002). The critical value is selected to represent the case when the bias from 2SLS is greater than 10% of the bias from OLS estimation. Then, if the Cragg-Donald statistic is less than the critical value, we cannot reject the null hypothesis that instruments are weak; on the other hand, if the statistic is higher than the critical value, we conclude that instruments are not weak. We have sufficient statistical evidence to reject the null hypothesis that instruments are weak as the F-statistics are significantly higher than the critical value in the 2SLS analysis in Table 3.8.

OLS and probit estimation show no statistically significant effect on the employment probability after at least six years post-graduation from an immediately-obtained master's degree both for the whole sample and for females. Neither do the 2SLS estimations find any statistically significant effect in either Panel A or B. However, there is evidence for a positive effect from the immediately obtained master's degree on the employment probability compared to individuals with only a bachelor's degree even after at least six years of college graduation for males by OLS and probit estimation (Table 3.8 Panel A column (5) and (6)). The increase in the employment probability is 2.99 - 4.41 percentage points. However, endogeneity exists in OLS and probit due to the selection in the unobserved ability. The estimated increase in the employment probability may be due to biases.

The 2SLS estimation implementing the two-step 2SLS method in Wooldridge (2010) also finds statistically significant evidence for a positive effect for 10.63 percentage points (Table 3.8 Panel A column (8)). Therefore, compared to their peers with only a bachelor's degree without exposure to a recession at college graduation, the recession-induced males who immediately obtained a master's degree have a higher employment probability at least six years after graduation. There is no evidence for a statistically significant effect compared to the peers who obtained a master's degree later in life without graduating into a recessionary labor market (Panel B).

Table 3.9 reports the corresponding estimations for the full-time employment probability based on employed individuals who are not currently in school from the non-STEM sample. OLS and probit estimations show statistically significant evidence for a positive effect of an immediately obtained master's degree. Compared to peers who obtained a master's degree later in life, an immediately obtained master's degree will increase the full-time employment probability by 4.86 percentage points (Panel B column(1)-(2)). For males, an immediately obtained master's degree will lead to an 8.32 - 9.36 percentage point increase in the full-time employment probability (Panel B column(5)-(6)) after at least six years since graduation. The 2SLS estimations find no such statistically significant evidence.

On the other hand, the 2SLS estimation implementing the two-step 2SLS method in Wooldridge (2010) finds statistically significant evidence for a negative effect in the whole sample (Table 3.9 Panel A column (4)). Compared to their peers with only a bachelor's degree and without being exposed to a recession at college graduation, the recession-induced individuals who immediately obtained a master's degree have a lower full-time employment probability at least six years after graduation, conditional on being employed. The immediately-obtained master's degree decreases the full-time employment probability by 8.08 percentage points. There is no such evidence separately for the sub-samples of males (Panel A column (8)) or females (Panel A column (12)).

To summarize, after at least six years past college graduation, there is some statistically significant evidence that the immediately-obtained master's degree will positively affect the employment probability for the recession-induced male degree holders. At the same time, there is no statistically significant effect on the full-time employment probability conditional on being employed. Therefore, those recession-induced male master's degree holders are more likely to be full-time employed than individuals who directly entered the labor market without a recession with only a bachelor's degree. Therefore, the estimated return from a recession-induced master's degree for males in the benchmark analysis provides a lower-bound estimate of the returns since individuals with only a bachelor's degree and without graduating into a recession from college are more positively selected in the sample of males.

3.7.2 Benchmark Results

The benchmark estimation uses log real annualized salary for the sample of individuals in full-time nonself-employed employment. Table 3.10 presents the estimated returns. Panel A reports the estimation based on individuals who obtained a master's degree immediately after college or those with only a bachelor's degree. Panel B reports the estimation based on individuals with a master's degree.

Columns (1), (3), and (5) report the OLS estimation for the whole sample, males and for females, respectively. The OLS estimated coefficient on the immediate master's program enrollment is positive and statistically significant(12-14%) for the whole sample, males and females with only a bachelor's degree or who immediately attend the master's program. There are no statistically significant returns on earnings with samples including only individuals with a master's degree, except for females. The estimation show 4% annual earnings for those who immediately obtained the master's degree. However, unobserved ability may be correlated with whether and when to obtain graduate education, and the OLS estimate might be biased.

Columns (2), (4), and (6) report the estimated returns implementing the two-step 2SLS method from Wooldridge (2010) with the recession indicator as the IV. In Table 3.10, I also report the Cragg-Donald statistic (Cragg and Donald, 1993), which shows sufficient statistical evidence to reject the null hypothesis that instruments are weak for all the estimations of returns to a master's degree.

Column (2) of Table 3.10 reports the estimations based on the total population. The recession-induced master's degree holders are those who enroll in a master's program immediately after college when facing a recessionary labor market but otherwise would not enroll. The result in Panel A indicates that compared to peers who graduate without exposure to a recession and hold a bachelor's degree, the recession-induced master's degree holders, on average, have a master's degree earnings premium of 23.28% after college graduation for at least six years. The recession-induced substitutors are individuals who intertemporally substitute for their master's education. In other words, they change the timing for their education at the master's degree level by immediately pursuing the master's degree shortly after graduation; otherwise, they will pursue the master's degree later in life. Hence, for those individuals, their lifetime human capital accumulation does not change. The result in Panel B shows that compared to peers who graduate without exposure to a recession and gain a master's degree later in life, the recession-induced substitutors, on average, have no earnings benefit after graduating from college for at least six years. Therefore, the return from a recession-induced master's degree can be interpreted as the return for a master's degree for the whole sample.

Columns (4) and (6) in Table 3.10 report the estimations based on males and females, respectively. The results in Panel A indicate that compared to peers who graduate without being exposed to a recession and hold a bachelor's degree, the recession-induced master's degree holders, on average, have a positive advantage in earnings at least six years after college graduation. The earnings premium is 33.34% for males and 17.59% for females. While compared to peers who graduate without being exposed to a recession and gain a master's degree later in life, the recession-induced substitutors, on average, have no earnings benefit at least six years after college graduation for either males or females (Panel B). Therefore, I can interpret the return from a recession-induced master's degree as the return for a master's degree for both genders.

In a nutshell, there is a statistically significant positive return from a recession-induced master's degree. The earnings advantages differ in magnitude between males and females after at least six years from college graduation.

3.7.3 Average Characteristics for Individuals who Induced to Obtain a Master's Degree Immediately by the Recession

Who are those individuals switching their master's degree decision when graduating into a recessionary labor market? This section characterizes those recession-induced master's degree holders and those who intertemporally substitute their master's education when graduating into a recession.

Recall that, in our analysis, always-takers are individuals who will attend graduate school immediately after college graduation regardless of the recession; never-takers are individuals who choose not to attend graduate school immediately regardless of exposure to the recession. "Compliers" are individuals who will not choose to attend a graduate school when the recession does not exist; however, when they graduate under exposure to the recession, they will choose to attend graduate school. Table 3.11 displays the sample proportions of always-takers, compliers, and never-takers for each sub-sample. Among individuals who are either with only a bachelor's degree or immediately obtained a master's degree, the sample proportion of always-takers, compliers, and never-takers are 13.68%, 3.83%, and 82.49%; the corresponding estimated proportions are 36.59%, 10.05%, and 53.36% among all individuals with a master's degree. The estimated proportions for each sub-sample vary over gender. Among individuals with only a bachelor's degree or who immediately obtained a master's degree, the sample proportions of always-takers, compliers, and never-takers are 9.22%, 3.49%, and 78.25%. In contrast, the corresponding proportions for females are 17.32%, 4.43%, and 78.25%. On the other hand, for males with a master's degree, the sample proportions of always-takers, compliers, and never-takers are 32.64%, 9.42%, and 57.94%, while for females, the corresponding proportions are 38.61%, 20.81%, and 50.58%.

Given the estimated proportions for always-takers, compliers, and never-takers, I can now estimate all the average pre-treatment characteristics for each subpopulation. The baseline characteristics include gender, race, age when obtaining the first bachelor's degree, categories of the institution that received the first bachelor's degree,[15] parental education level, and

[15] Categories of the institution where individuals received the first bachelor degree are based on the Carnegie classifications (1994) and Barron's selectivity categories. Tier 1 includes Private Research I and II universities in Carnegie classification, Tier 2 includes Liberal Arts I college, Tier 3 includes Public Research

the field of study for the first bachelor's degree.[16] Several relevant differences emerge.

Table 3.12 reports the average baseline characteristics and the corresponding 95% confidence intervals for always-takers, compliers, and never-takers based on the individuals who either with only a bachelor's degree or those who immediately obtained a master's degree after college graduation. In this case, the compliers are individuals who immediately enrolled in a master's program when graduating into a recessionary labor market and will not enroll otherwise. Never-takers are individuals who will not obtain a master's degree regardless of whether graduating into a recession. On the contrary, always-takers will immediately obtain a master's degree regardless of whether they are exposed to a recession when they graduate from college.

Results in Table 3.12 show that compared to never-takers, the recession-induced master's degree holders (compliers) are statistically significantly younger when they received their first bachelor's degree (21.37 vs. 21.76 years old). They also seem more likely to be non-white females from less research-active institutions for their bachelor's degrees and less likely to have parents with at least a bachelor's degree, but these differences are not statistically significant. When compared with always-takers, on the other hand, compliers are statistically significantly less likely to have a BA degree in "other STEM" field (2.8% vs. 16.8%) but more likely to be in "other majors" (59.8% vs. 32.8%) for the bachelor's degree. I do not find any statistically significant difference between compliers and always-takers, nor between compliers and never-takers for males (Tabel 3.13). However, I find that female compliers are statistically significantly younger than never-takers when they received their first bachelor's degree (21.44 vs. 22.07 years old), and they are less likely to have parents with a graduate degree (11.8% vs. 29.8%) than never-takers (Tabel 3.14).

Table 3.15 reports the average baseline characteristics and the corresponding 95% confidence intervals for always-takers, compliers, and never-takers based on the individuals with a master's degree. In this case, the compliers are individuals who immediately enrolled in a master's program when graduating into a recessionary labor market and will otherwise enroll in a master's degree later in life. Never-takers are individuals who will not immediately obtain a master's degree regardless of whether graduating into a recession. On the contrary, always-takers will immediately obtain a master's degree regardless of whether they are exposed to a recession when they graduate from college.

Among individuals with a master's degree, compared to never-takers, I find that compliers are statistically significantly younger when they receive their first bachelor's degree (21.44 vs. 21.99 years old). Compliers are more likely to come from a family where neither parent has a bachelor's degree (13.4% vs. 1.5%), and they are less likely to study in other-STEM fields (0.4% vs. 7.8%) but more likely to study in other Majors (56.5% vs. 37.6%) for their bachelor's degrees than the never-takers. Similarly, individuals who intertemporally substitute their master's education (compliers) are more likely to have parents whose highest

I, and Tier 4 are the remaining 4-year colleges and universities excluding specialized institutions which focus on a narrow curriculum (Hersch, 2019). Research Universities are those classified as Research I & II and Doctoral I & II universities.

[16] Four broad categories for the field of study are reported. BA Engineering is the engineering field. BA Social Sciences includes economics, political science, and other humanities majors. BA Other STEM fields include Architecture/Environmental Design. BA Other Majors include non-STEM fields such as English/Languages/Literature and Fine/Performing Arts.

educational attainment is at the high school level than always-takers (13.4% vs. 1.9%). Additionally, compliers are less likely to study in other-STEM fields (0.4% vs. 16.8%) but more likely to study in other Majors (56.5% vs. 32.9%) for their bachelor's degrees than the never-takers. I do not find any statistically significant difference between compliers and always-takers, nor between compliers and never-takers for males (Tabel 3.16). However, I find female compliers are statistically significantly younger when they received their first bachelor's degree (21.39 vs. 21.84 years old) than never-takers (Tabel 3.17).

Therefore, younger females are generally more sensitive to the master's education decision when graduating from college in a recessionary labor market. Specifically, those who changed their decision when facing a recession usually have a bachelor's degree in a major such as English. Additionally, those individuals are more likely to obtain their bachelor's degree from less research-active institutions, and they are more likely to have parents without a bachelor's degree. This finding is consistent with the previous literature that those who go directly to graduate school are academically and economically advantaged relative to those who do not (Altonji and Zhong, 2021).

3.8 Discussion and Conclusion

This paper estimates the labor market returns to a master's degree. To control for the selection of unobserved abilities and preferences in graduate education, I use whether an individual graduated into a recession from college as an instrumental variable (IV). Graduating during a recession increases the probability of pursuing a graduate degree right after college by 4 percentage points. Given that the average probability of graduate attendance is 0.12, this represents an overall more than 30% increase in the probability of immediately obtaining a master's degree among full-time workers. The effect of the recession is heterogeneous between genders. For males, the increase in the probability of pursuing a graduate degree right after college is 0.03, and the average probability in the whole sample is 0.08, which is an overall 34% increase. Even though the percentage point increase is relatively the same but slightly higher for females, the average probability is 0.23 for females, which results in a 17% increase in the probability.

Individuals who intertemporally substitute their master's education when graduating in a recessionary labor market postpone their entrance to the labor market without changing their lifetime human capital accumulation.[17] They may benefit from the "timing effect" of attending the master's education immediately right after the college education. Those recession-induced master's holders benefit from both the "timing effect" and "human capital effect," which is the accumulation of additional human capital through a master's degree.

The estimated results suggest a 23.38% return for the pooled sample, 33.34% for males, and 17.59% for females from a recession-induced master's degree for full-time non-self-employed individuals after at least six years since graduation.

[17]However, due to the construction of the sample, we could not compare the lifetime human capital for cohorts who graduated into the recession with those lucky cohorts. The longest span for the unlucky cohort is 18 years. Furthermore, for those who graduated during the 2008 - 2009 recession, the span is only 12 years. Even though it is less common for individuals to obtain a master's degree after age 30, this paper captures a short- to mid-term effect.

At the same time, the estimated results suggest no evidence of earning advantage for the master's education substitutors. This result suggests that the returns through the delayed entry into the labor market are negligible by analyzing the annual earnings after graduation for at least six years. These estimation results are consistent with the exclusion restriction assumption we imposed to identify the local average treatment effect for individuals induced to obtain a master's degree by the recession. Since after six years of graduating into a recession, there appears to be no effect for workers with at least a college education (Genda et al., 2010, Schwandt and Von Wachter, 2019 and Altonji et al., 2016), for individuals who were caught by the recession and college-graduates who are affected by the scarring effect, after at least six years of college graduation, they can go back to the "original" wage distribution as if they had never been affected by the negative shock from the economic condition at the time of college graduation. As a result, the shift in the wage distribution for those compliers is only the result of the additional human capital accumulation through a master's degree, which they would not obtain if graduating into a good economic condition from college. Therefore, the estimated returns for the recession-induced master's degree holders can be interpreted as the return of the master's degree.

The estimated returns for a master's degree are large in terms of returns from education; however, those estimates are still in line with the previous literature scrutinizing the returns for a graduate degree. For example, Titus (2007) found a 20% private returns of a master's degree, while Altonji and Zhong (2021) found the returns for a master's degree is in the range of 10 - 27%. One potential explanation is that I am looking at the economic returns for the marginal individuals induced to obtain a master's degree by the recession, and the returns for those types of individuals could be comparatively large. Therefore, this paper enriched the surprisingly understudied returns to a master's degree by providing a new estimation of the returns on the recession-induced master's degree holders.

In addition, this paper provides a complement to the finding that "more competitive students"[18] choose to delay the labor market entrance by staying in the undergraduate studies (Finamor, 2022). This paper provides a missing side of the story for the "less competitive students". This paper finds that the "less competitive students" would be more likely to delay the labor market entrance by obtaining a master's degree. Specifically, I find that younger females with a bachelor's education in "other majors" from less research-active universities and who come from families with neither parent holding a bachelor's degree are more sensitive to the master's education decision when graduating into a recession. Therefore, the marginal individuals in my sample are more likely to be from a non-Science or Engineering background. The economic returns of obtaining a master's degree for them appear to be relatively larger than for individuals from other educational backgrounds during college, regardless of their curriculum at the master's level (Altonji and Zhong, 2021).

This paper conveys important information about graduate school returns that individuals can rely on and insight for policymakers and universities interested in helping unlucky cohorts who faced adverse economic conditions during a recession. I find evidence for strong returns of a recession-induced master's degree, and this return diverges between males and females. For future studies, it would be interesting to use individual panel data to track

[18]The source of determining whether a student is competitive or not depending on gender, the major of study during undergrads, family background and types of school obtained the bachelor's degree.

the employment history to explore the mechanism of this divergence. Additionally, future research can go beyond identifying the local average treatment effects and estimate the marginal treatment effects (MTEs) to derive more relevant treatment parameters and explore the underlying self-selection into education behavior, especially for females.

Figures and Tables

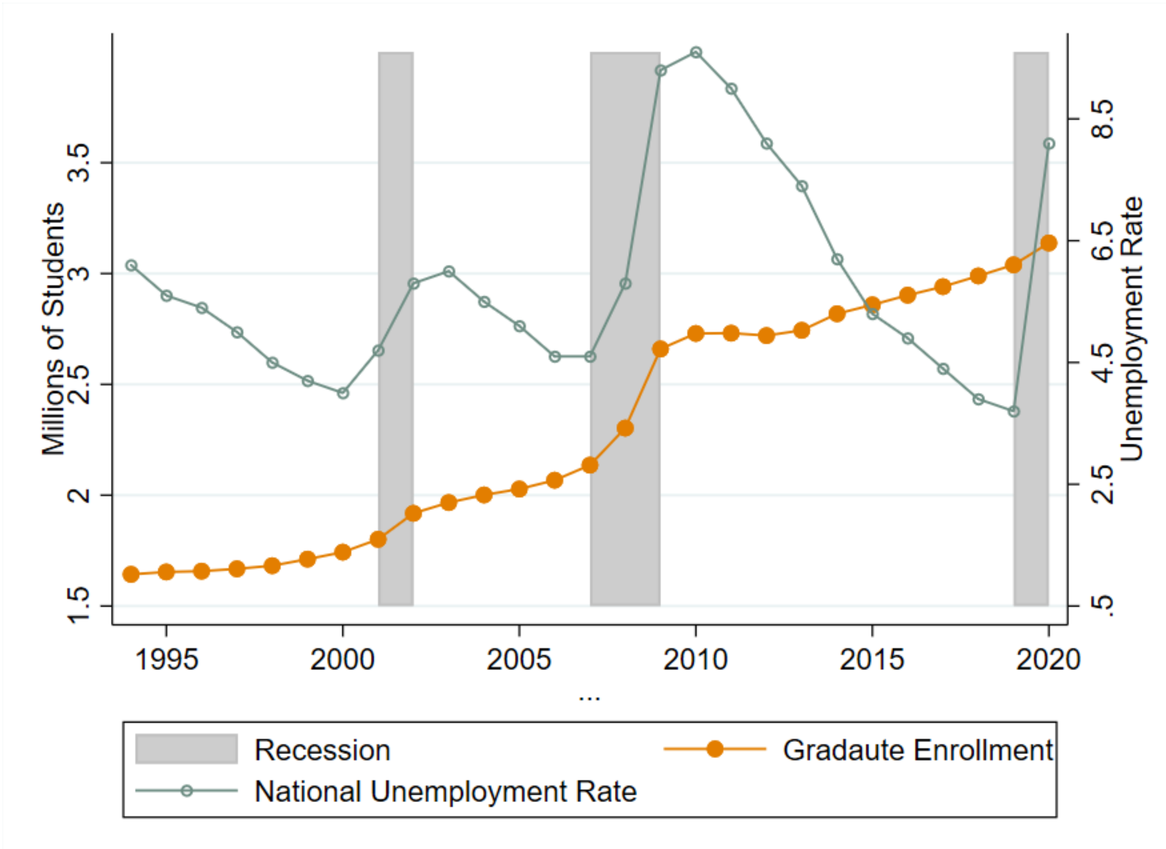

Figure 3.1: Graduate School Enrollment and National Unemployment Rate

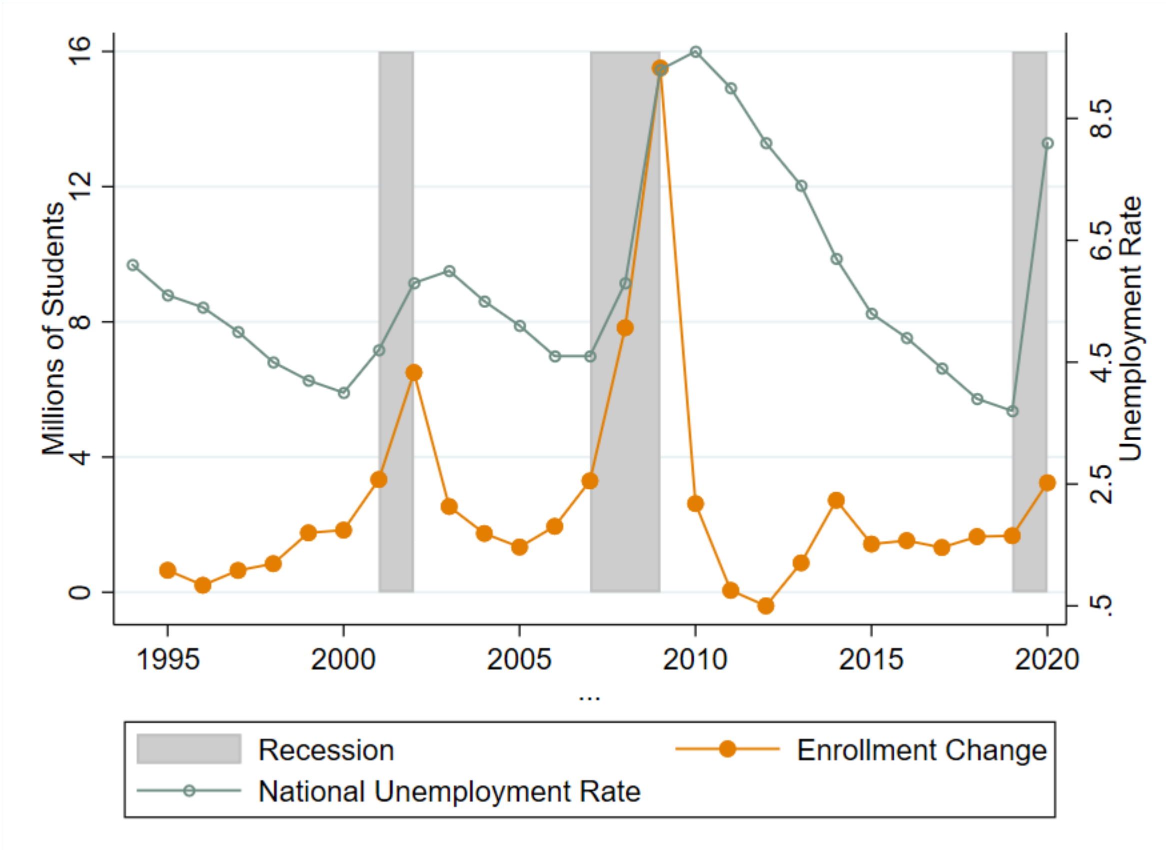

Figure 3.2: Percent Change in Graduate School Enrollment and National Unemployment Rate

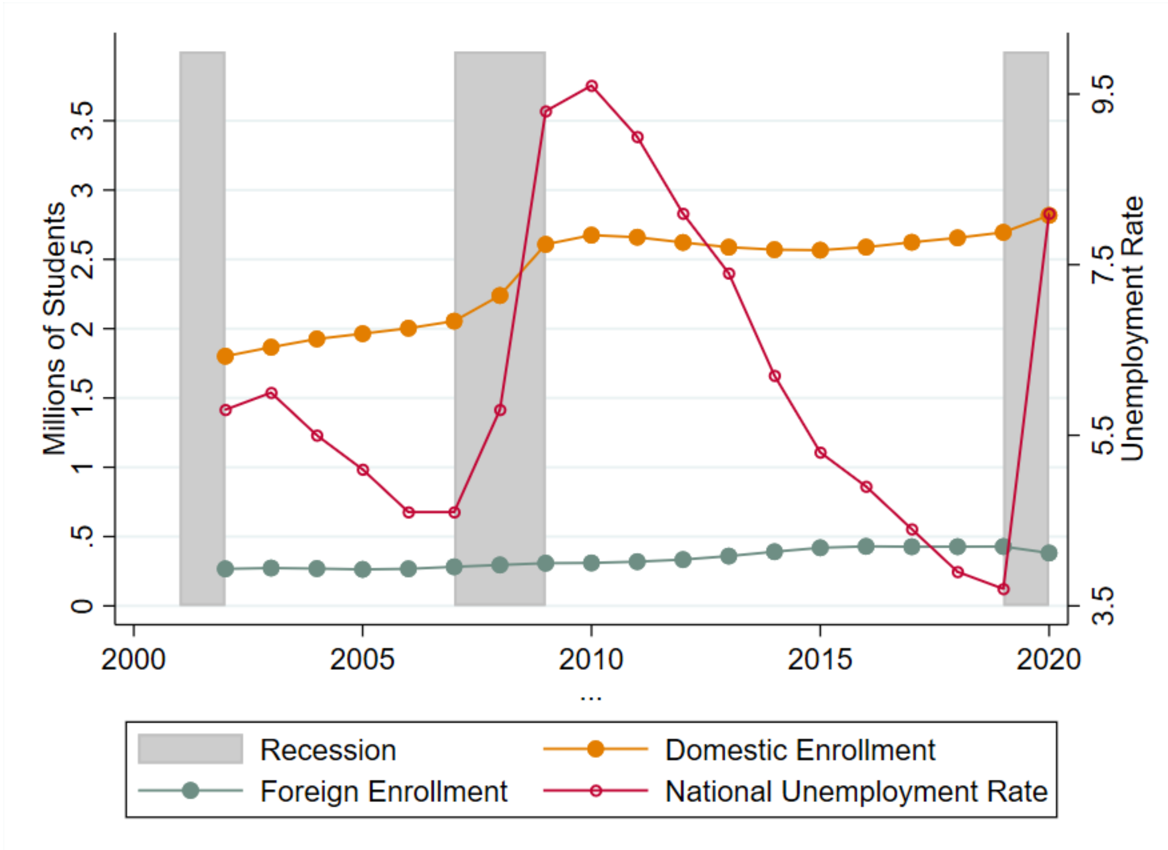

Figure 3.3: Graduate School Enrollment and National Unemployment Rate by Domestic or Foreign Students: 2002 - 2020

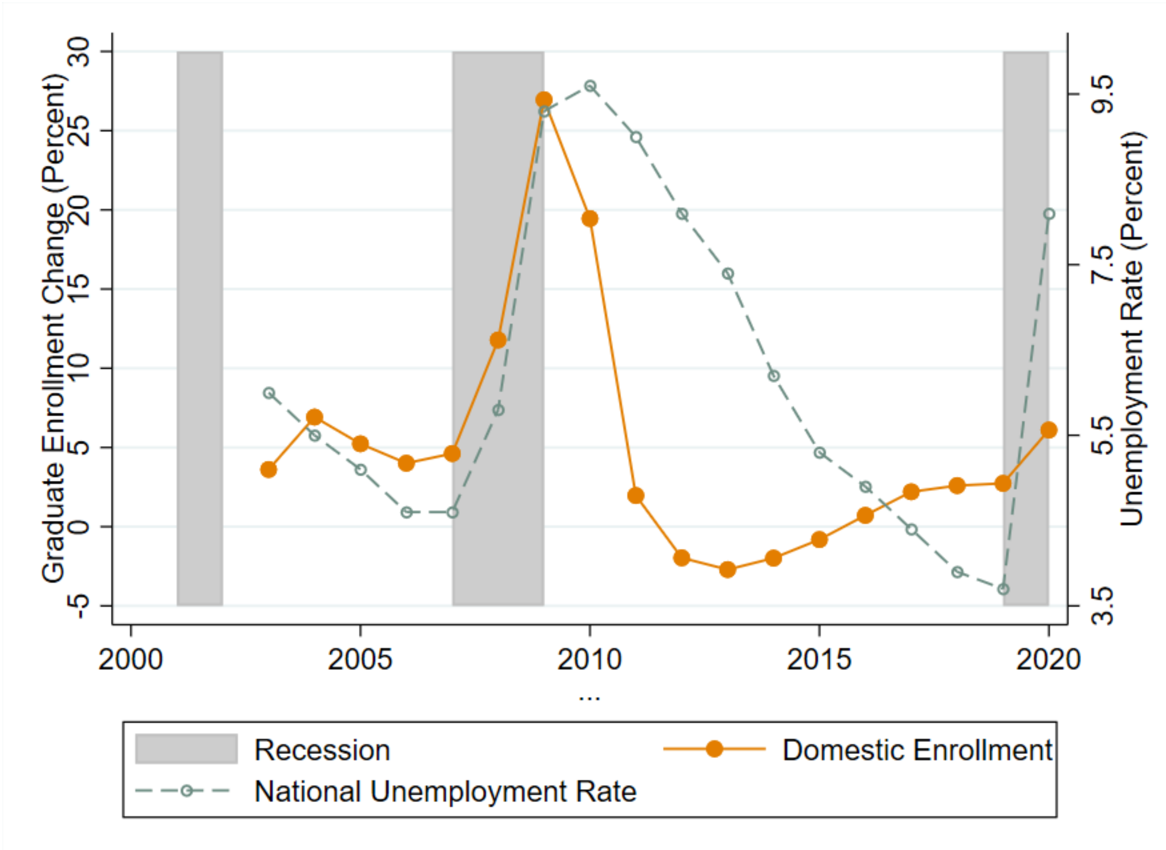

Figure 3.4: Percent Change Graduate School Enrollment for Domestic Students and National Unemployment Rate Foreign Students: 2003 - 2020

Table 3.3: Year of Wage Observation and College Graduation Year

BA Year	Survey Year				
	2010	2013	2015	2017	2019
1995	410	460	352	322	326
1996	414	471	354	333	321
1997	426	522	424	337	325
1998	408	487	375	309	296
1999	385	494	407	333	325
2000	460	579	470	403	395
2001	480	721	569	450	408
2002	491	802	688	525	466
2003	560	882	819	602	540
2004	572	997	893	696	668
2005		1216	1167	839	758
2006		1389	1271	886	859
2007		1501	1559	1000	1070
2008			1971	1105	1149
2009			1640	1207	1247
2010				1088	1334
2011				917	1329
2012					1289
2013					1087

Note: The sample contains full-time employed individuals who are not in school and not self-employed, who got their first bachelor's degree from a US institution during 1995 - 2017 at age 20 - 24, and who graduated from college for at least six years. Each cell represents the number of individuals observed in a specific survey year who received a bachelor's degree in a particular BA year. Full-time employment is defined as working at least 40 weeks per year and at least 35 hours per week.

Table 3.4: First Stage: The Probability of Immediately Attending a Master's Program: (NSCG 10 - 19)

	All	BA and Im. Grad	Grad only
A. Not in School Sample			
Recession Indicator	0.0183***	0.0200***	0.0536***
	(0.0063)	(0.0075)	(0.0175)
Unemp Rate at BA graduation	0.0096***	0.0085***	0.0410***
	(0.0015)	(0.0018)	(0.0043)
Observations	97,939	75,683	43,265
B. Non-self Full-time Employed			
Recession Indicator	0.0408***	0.0476***	0.0938***
	(0.0081)	(0.0101)	(0.0203)
Unemp Rate at BA graduation	0.0117***	0.0101***	0.0442***
	(0.0020)	(0.0024)	(0.0051)
Observations	59,438	44,936	28,157

Note: Outcome: the probability of immediately obtaining a master's degree after graduation, which refers to enroll a master's program within two years of college graduation and obtaining the degree within the average time for full-time students. Coefficients are the average treatment effect for whether graduating into a recession.The controls include age, gender,race,age received the first bachelor's degree, the field of study for the bachelor's degree, the classification of the institution that received the first bachelor's degree, parental education level. The estimation is based on individuals who are not in school and who got their first bachelor's degree from a US institution during 1995 - 2017 at age 20 - 24 and who graduated from college for at least six years. NSCG individual weights are used. Standard errors that appear in the parentheses are the robust standard errors. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 3.5: First Stage: The Probability of Immediately Attending a Master's Program by Gender

	Males			Females		
	All	BA and Im. Grad	Grad only	All	BA and Im. Grad	Grad only
A. Not in School Sample						
Recession Indicator	0.0186**	0.0212***	0.0634**	0.0166*	0.0162	0.0470**
	(0.0083)	(0.0097)	(0.0275)	(0.0086)	(0.0104)	(0.021)
Unemp Rate at BA graduation	0.0092***	0.0096**	0.0370***	0.0097***	0.0072***	0.0426***
	(0.0021)	(0.0024)	(0.0068)	(0.0021)	(0.0025)	(0.0055)
Observations	47,544	37,776	17,563	50,395	37,907	25,702
B. Non-self Full-time Employed						
Recession Indicator	0.0345***	0.0410***	0.0975***	0.0420***	0.0468***	0.0878***
	(0.0110)	(0.0133)	(0.0330)	(0.0109)	(0.0137)	(0.0244)
Unemp Rate at BA graduation	0.0104***	0.0108***	0.0387***	0.0124***	0.0084**	0.0464***
	(0.0027)	(0.0033)	(0.0081)	(0.0027)	(0.0033)	(0.0065)
Observations	29,550	23,065	11,587	29,888	21,871	16,570

Note: Outcome: the probability of immediately obtaining a master's degree after graduation, which refers to enroll a master's program within two years of college graduation and obtaining the degree within the average time for full-time students. Coefficients are the average treatment effect for whether graduating into a recession.The controls include age, race,age received the first bachelor's degree, the field of study for the bachelor's degree, the classification of the institution that received the first bachelor's degree, parental education level. The estimation is based on individuals who are not in school and who got their first bachelor's degree from a US institution during 1995 - 2017 at age 20 - 24 and who graduated from college for at least six years. NSCG individual weights are used. Standard errors that appear in the parentheses are the robust standard errors. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table 3.6: First Stage: The Probability of Immediately Attending a Master's Program by Filed of Study during Bachelor's Degree

	Pooled Sample	BA and Im. Grad			Grad only		
	All	All	Males	Female	All	Males	Female
Computer and Mathematical Sciences	-0.0650*** (0.0128)	-0.0711*** (0.0153)	-0.0597*** (0.0154)	-0.1070*** (0.0404)	-0.1994*** (0.0414)	-0.1633*** (0.0447)	-0.2064*** (0.0661)
Obs	6,690	5,214	3,696	1,518	2,770	1,639	1,131
Bio,Agr,and Env Life Sciences	-0.0217 (0.0184)	-0.0344 (0.0225)	0.0246 (0.0272)	-0.0686** (0.0322)	0.0124 (0.0418)	0.1567** (0.0696)	-0.0346 (0.0484)
Obs	8,831	6,762	2,796	3,966	4,023	1,302	2,721
Physical and Related Sciences	-0.0757** (0.0383)	-0.1288** (0.0476)	-0.1322*** (0.0450)	-0.1138 (0.0704)	-0.0146 (0.0694)	-0.1229 (0.0825)	0.0510 (0.0765)
Obs	3,732	2,929	1,681	1,248	1,686	895	791
Social and Related Sciences	0.0314** (0.0123)	0.0359** (0.0157)	0.0001 (0.0176)	0.0601*** (0.0141)	0.0605** (0.0254)	0.0147 (0.0394)	0.0854*** (0.0313)
Obs	18,546	13,089	4,766	8,323	9,900	2,856	7,044
Engineering	0.0216** (0.0110)	0.0181 (0.0135)	0.0309** (0.0133)	-0.0337 (0.0362)	0.0932** (0.0281)	0.0949*** (0.0296)	0.0934 (0.0613)
Obs	18,923	15,047	11,829	3,218	8,041	5,849	2,192
S & E Related Fields	0.0054 (0.0196)	0.0137 (0.0198)	0.0188 (0.0049)	0.0074 (0.0284)	-0.0334 (0.0360)	0.0255 (0.0557)	-0.0482 (0.0410)
Obs	7,822	6,406	1,787	4,619	3,972	787	3,185
Non - S & E Related Fields	0.0507*** (0.0112)	0.0601*** (0.0138)	0.0493*** (0.0181)	0.0573*** (0.0186)	0.1250*** (0.0325)	0.1188** (0.0536)	0.1161*** (0.0385)
Obs	14,147	10,394	4,683	5,711	6,244	2,095	4,149

Note: Outcome: the probability of immediately obtaining a master's degree after graduation, which refers to enroll a master's program within two years of college graduation and obtaining the degree within the average time for full-time students. Coefficients are the average treatment effect for whether graduating into a recession.The controls include age, gender,race,age received the first bachelor's degree, the classification of the institution that received the first bachelor's degree, parental education level. The estimation is based on individuals who are not in school and who got their first bachelor's degree from a US institution during 1995 - 2017 at age 20 - 24 and who graduated from college for at least six years. NSCG individual weights are used. Standard errors that appear in the parentheses are the robust standard errors. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Table 3.7: First Stage: The Probability of Immediately Attending a Master's Program Excluding by Gender(non-STEM)

	All	BA and Im. Grad	Grad only
A. Non-self Full-time Employed			
Recession Indicator	0.0310***	0.0355***	0.0752***
	(0.0074)	(0.0091)	(0.0184)
Unemp Rate at BA graduation	0.0115***	0.0098***	0.0443***
	(0.0018)	(0.0022)	(0.0045)
Observations	78,691	58,841	36,636
B. Males			
Recession Indicator	0.0261***	0.0310***	0.0762***
	(0.0098)	(0.0117)	(0.0291)
Unemp Rate at BA graduation	0.0100**	0.0103***	0.0386***
	(0.0024)	(0.0029)	(0.0070)
Observations	39,784	31,238	15,423
C. Females			
Recession Indicator	0.0316**	0.0337***	0.0712***
	(0.0100)	(0.0126)	(0.0223)
Unemp Rate at BA graduation	0.0124***	0.0086***	0.0468***
	(0.0024)	(0.0030)	(0.0058)
Observations	38,907	28,603	21,213

Note: Outcome: the probability of immediately obtaining a master's degree after graduation, which refers to enroll a master's program within two years of college graduation and obtaining the degree within the average time for full-time students. Coefficients are the average treatment effect for whether graduating into a recession.The controls include age, gender, race,age received the first bachelor's degree, the field of study for the bachelor's degree, the classification of the institution that received the first bachelor's degree, parental education level. The estimation is based on the non-STEM subsample with individuals who are not in school and who got their first bachelor's degree from a US institution during 1995 - 2017 at age 20 - 24 and who graduated from college for at least six years. NSCG individual weights are used. Standard errors that appear in the parentheses are the robust standard errors. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$.

Table 3.8: The Effect of Immediately Obtained Master's Degree Induced by a Recession at College Graduation on the Probability of Employment (NSCG 10 - 19)

			Pr(Emp)				Pr(Emp)				Pr(Emp)	
	(1) OLS	(2) Probit	(3) 2SLS	(4) 2SLS	(5) OLS	(6) Probit	(7) 2SLS	(8) 2SLS	(9) OLS	(10) Probit	(11) 2SLS	(12) 2SLS
	For the Whole Sample				**Males**				**Females**			
A. BA vs Im. Grad												
	0.0243	0.0528	-0.0315	-0.0093	0.0299***	0.0441**	-0.0616	0.1063**	0.0352	0.0351	-0.1585	-0.0209
	(0.0202)	(0.0227)	(0.3073)	(0.0356)	(0.0099)	(0.0193)	(0.2735)	(0.0457)	(0.0290)	(0.0336)	(0.5421)	(0.0412)
CD Wald F-stat	——-	——-	50.397	3895.797	——-	——-	41.00	1361.745	——-	——-	17.58	2564.919
Stock-Yogo Critical Value	——-	——-	16.38	16.38	——-	——-	16.38	16.38	——-	——-	16.38	16.38
Observations	56,102				27,593				28,509			
B. Grads												
	-0.0176	-0.0152	0.0313	-0.0346	-0.0103	-0.0089	-0.0574	-0.0123	-0.0172	-0.0120	0.0568	-0.0630
	(0.0124)	(0.0127)	(0.1114)	(0.0392)	(0.0095)	(0.0096)	(0.1374)	(0.0193)	(0.0184)	(0.0185)	(0.1514)	(0.0520)
CD Wald F-stat	——-	——-	149.39	1209.13	——-	——-	60.96	584.38	——-	——-	92.33	928.24
Stock-Yogo Critical Value	——-	——-	16.38	16.38	——-	——-	16.38	16.38	——-	——-	16.38	16.38
Observations	29,992				11,734				18,258			

Note: The estimation is based on the non-STEM subsample with individuals who are not self-employed nor in school and who obtained their first bachelor's degree from a US institution during 1995 - 2017 at age 20 - 24 and who graduated from college for at least six years. The controls include age, gender, race, years since graduation, and years since the most recent degree. The estimation also controls for the field of study for the most recent degree, the classification of the institution that received the first bachelor's degree, the current national unemployment rate, marital status, the number of kids under age six in the household, and the survey year fixed effect. NSCG individual weights are used. Standard errors that appear in the parentheses are the robust standard errors. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$. Cragg-Donald statistics(Cragg and Donald, 1993) and the critical value(Stock and Yogo, 2002) for weak-iv testing are also reported along with the 2SLS results.

Table 3.9: The Effect of Immediately Obtained Master's Degree Induced by a Recession at College Graduation on the Probability of Full-Time Employment (NSCG 10 - 19)

			Pr(Full-time)				Pr(Full-time)				Pr(Full-time)	
	(1) OLS	(2) Probit	(3) 2SLS	(4) 2SLS	(5) OLS	(6) Probit	(7) 2SLS	(8) 2SLS	(9) OLS	(10) Probit	(11) 2SLS	(12) 2SLS
	For the Whole Sample				**Males**				**Females**			
A. BA vs Im. Grad												
	-0.0215	-0.0220	0.2373	-0.0808*	-0.0075	-0.0091	0.1477	0.0020	-0.0278	-0.0339	0.3277	-0.0572
	(0.0274)	(0.0229)	(0.1752)	(0.0454)	(0.0248)	(0.0226)	(0.2143)	(0.0477)	(0.0405)	(0.0359)	(0.2534)	(0.0560)
CD Wald F-stat	——-	——-	131.196	2134.77	——-	——-	54.24	843.30	——-	——-	68.62	1375.263
Stock-Yogo Critical Value	——-	——-	16.38	16.38	——-	——-	16.38	16.38	——-	——-	16.38	16.38
Observations	44,815				23,052				21,763			
B. Grads												
	0.0486**	0.0485**	0.0999	0.0347	0.0936***	0.0832***	0.0210	0.1121	0.0210	0.0191	0.1670	-0.024
	(0.0238)	(0.0233)	(0.1468)	(0.0705)	(0.0310)	(0.0269)	(0.1685)	(0.0749)	(0.0184)	(0.0324)	(0.2211)	(0.0964)
CD Wald F-stat	——-	——-	24.245	1137.366	——-	——-	98.27	483.363	——-	——-	103.175	670.405
Stock-Yogo Critical Value	——-	——-	16.38	16.38	——-	——-	16.38	16.38	——-	——-	16.38	16.38
Observations	25,603				11,734				18,258			

Note: The estimation is based on the non-STEM subsample with employed individuals who are not self-employed nor in school and who obtained their first bachelor's degree from a US institution during 1995 - 2017 at age 20 - 24 and who graduated from college for at least six years. The controls include years since college graduation, the employment type, the size of the employer, the geographical region of the employer, unemployment rate at the employed region, occupation, race, gender, marital status, number of kids under age six in the household and the survey year fixed effect. NSCG individual weights are used. Standard errors that appear in the parentheses are the robust standard errors. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. Cragg-Donald statistics(Cragg and Donald, 1993) and the critical value(Stock and Yogo, 2002) for weak-iv testing are also reported along with the 2SLS results.

Table 3.10: Main Results: The Returns in Annual Earning for Full-Time Workers who Immediately Obtained a Master's Degree Induced by a Recession at College Graduation (NSCG 10 - 19)

	All Sample		**Males**		**Females**	
	OLS (1)	Use Rec Indicator (2)	OLS (3)	Use Rec Indicator (4)	OLS (5)	Use Rec Indicator (6)
A. BA only + Im Grad						
	0.1241***	0.2328***	0.1229***	0.3334**	0.1352***	0.1759*
	(0.0147)	(0.0792)	(0.0232)	(0.1514)	(0.0187)	(0.0958)
CD Wald F-stat	——-	1462.373	——-	593.914	——-	836.468
Stock-Yogo Critical Value	——-	16.38	——-	16.38	——-	16.38
Observations:	37,325		19,903		17,422	
B. Grad only						
	-0.019	0.058	0.019	0.063	-0.043*	0.1103
	(0.017)	(0.083)	(0.026)	(0.100)	(0.0223)	(0.1028)
CD Wald F-stat	——-	834.279	——-	495.766	——-	541.51
Stock-Yogo Critical Value	——-	16.38	——-	16.38	——-	16.38
Observations:	20,244		9,167		11,077	

Note: Earnings are measured in 2010 dollars. The estimation is based on the non-STEM subsample with non-schooler full-time non-self-employed individuals who obtained their first bachelor's degree from a US institution during 1995 - 2017 at age 20 - 24 and who graduated from college for at least six years. Full-time employment is defined as working at least 40 weeks per year and at least 35 hours per week. The controls include years since college graduation, the employment type, the size of the employer, the geographical region of the employer, unemployment rate at the employed region, occupation, race, gender, marital status, number of kids under age six in the household and the survey year fixed effect. NSCG individual weights are used. Standard errors that appear in the parentheses are the robust standard errors. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$. Cragg-Donald statistics(Cragg and Donald, 1993) and the critical value(Stock and Yogo, 2002) for weak-iv testing are also reported along with the 2SLS results.

Table 3.11: Stratum Proportions (Under Assumption A1 and A4)

	BA only + $Grad^{IM}$			Grads		
	All	Males	Females	All	Males	Females
π_{at}	0.1368***	0.0922***	0.1732***	0.3659***	0.3264***	0.3861***
	(0.0037)	(0.0051)	(0.0042)	(0.0083)	(0.0141)	(0.0093)
π_c	0.0383***	0.0349**	0.0443***	0.1005***	0.0942**	0.1081***
	(0.0112)	(0.0140)	(0.0119)	(0.0228)	(0.0373)	(0.0275)
π_{nt}	0.8249***	0.8729***	0.7825***	0.5336***	0.5794***	0.5058***
	(0.0112)	(0.0129)	(0.0113)	(0.0188)	(0.0324)	(0.0245)

Note: BA only + $Grad^{IM}$ sample contains 37,325 individuals with a bachelor's degree. Grads sample has 20,244 master's degree holders. π_{at},π_c, and π_{nt} represent the proportion of always-takers, compliers, and never-takers, respectively. Always-takers are individuals who will attend graduate school regardless of the recession. Compliers are individuals who are induced to attend graduate school by recessions. "Compliers" are individuals who are induced to attend a graduate school by recessions. Never-takers choose not to attend graduate school regardless of exposure to economic downturns. Standard errors that appear in the parentheses are the bootstrapped standard errors.

Table 3.12: Average Characteristics for Subpopultions (BA only + Grad^{IM})

Variable	at	nt	c	nt - c	c-at	nt- at
Female	0.696***	0.521***	0.589***	-0.068	-0.107	-0.174***
	(0.013)	(0.007)	(0.116)	(0.119)	(0.123)	(0.013)
White	0.851***	0.852***	0.905***	-0.053	0.054	0.001
	(0.010)	(0.006)	(0.110)	(0.112)	(0.113)	(0.011)
Age Obtained BA	21.76***	22.21***	21.37***	0.840**	-0.397	0.443***
	(0.026)	(0.018)	(0.017)	(0.337)	(0.335)	(0.030)
BA in Research University	0.514***	0.487***	0.518***	0.005	-0.027	0.063*
	(0.013)	(0.007)	(0.154)	(0.157)	(0.015)	(0.040)
Tire 3 BA	0.240***	0.221***	0.382***	-0.161	0.142	-0.019
	(0.011)	(0.006)	(0.128)	(0.130)	(0.130)	(0.012)
Tire 4 BA	0.626***	0.648***	0.665***	-0.016	0.038	0.022
	(0.015)	(0.007)	(0.141)	(0.909)	(0.145)	(0.015)
Parents with Highest High School Degree	0.020***	0.020***	0.061	-0.041	0.041	0.000
	(0.004)	(0.002)	(0.040)	(0.041)	(0.041)	(0.004)
Either Parent with a Bachelor's Degree	0.676***	0.587***	0.517***	0.070	-0.159	-0.089***
	(0.012)	(0.008)	(0.017)	(0.179)	(0.179)	(0.011)
Either Parent with a Grad Degree	0.407***	0.300***	0.147	0.153	-0.259	-0.106***
	(0.011)	(0.008)	(0.172)	(0.177)	(0.176)	(0.012)
BA Engineering	0.090***	0.083***	0.040	0.043	-0.050	-0.007*
	(0.004)	(0.003)	(0.036)	(0.038)	(0.039)	(0.004)
BA Other STEM	0.168***	0.095***	0.028	0.067	-0.139**	-0.073***
	(0.008)	(0.003)	(0.062)	(0.063)	(0.064)	(0.007)
BA Social Sciences	0.422***	0.279***	0.330***	-0.051	-0.092	-0.143***
	(0.014)	(0.006)	(0.119)	(0.121)	(0.124)	(0.015)
BA Other Majors	0.328***	0.547***	0.598***	-0.051	0.270**	0.219***
	(0.016)	(0.007)	(0.104)	(0.105)	(0.108)	(0.016)

Note: This analysis is based on 37,325 individuals with a bachelor's degree.Averages are estimated with the overidentified nonparametric GMM procedure described in the Identification section. Computations use individual weights provided by NSCG. Numbers in parentheses are standard errors. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$. Categories of the institution that received the first Bachelor's degree are based on the Carnegie classifications(1994) and Barron's selectivity categories. Tier 1 includes Private Research I and II universities in Carnegie classification, Tier 2 includes Liberal Arts I college, Tier 3 includes Public Research I, and Tier 4 are the remaining 4-year colleges and universities excluding specialized institutions which focus on a narrow curriculum. (Hersch, 2019) Research Universities are those classified as Research I & II and Doctoral I II universities. BA Other STEM fields include Architecture/environmental design etc. BA Other Majors include non-STEM fields such as English/Languages/Literature, Fine/Performing arts, etc.

Table 3.13: Average Characteristics for Subpopultions (BA only + Grad^{IM}, Males)

	at	nt	c	nt - c	c-at	nt- at
White	0.874***	0.869***	0.988	-0.119	0.114	-0.005
	(0.016)	(0.007)	(0.796)	(0.769)	(0.798)	(0.015)
Age Obtained BA	21.97***	22.36***	21.41***	0.949	-0.558	0.391***
	(0.064)	(0.028)	(0.921)	(0.925)	(0.938)	(0.067)
BA in Research University	0.602***	0.501***	0.518	-0.017	-0.085	-0.102***
	(0.027)	(0.012)	(0.477)	(0.482)	(0.488)	(0.024)
Tire 3 BA	0.297***	0.228***	0.446	-0.218	0.150	-0.068***
	(0.023)	(0.010)	(0.829)	(0.830)	(0.832)	(0.020)
Tire 4 BA	0.573***	0.642***	0.577	0.064	0.004	0.068***
	(0.023)	(0.010)	(0.433)	(0.436)	(0.441)	(0.022)
Parents with Highest High School Degree	0.021***	0.014***	0.003	0.010	-0.018	-0.007
	(0.007)	(0.002)	(0.066)	(0.067)	(0.068)	(0.007)
Either Parent with a Bachelor's Degree	0.674***	0.611***	0.520	0.091	-0.154	-0.063**
	(0.023)	(0.011)	(0.769)	(0.771)	(0.773)	(0.025)
Either Parent with a Grad Degree	0.394***	0.302***	0.192	0.110	-0.202	-0.092
	(0.022)	(0.010)	(0.874)	(0.876)	(0.887)	(0.023)
BA Engineering	0.214***	0.141***	0.119	0.022	-0.095	-0.073***
	(0.015)	(0.004)	(0.543)	(0.543)	(0.549)	(0.015)
BA Other STEM	0.109***	0.067***	0.046	0.021	-0.064	-0.042***
	(0.011)	(0.004)	(0.190)	(0.191)	(0.193)	(0.010)
BA Social Sciences	0.315***	0.236***	0.237	-0.001	-0.078	-0.079***
	(0.022)	(0.009)	(0.362)	(0.367)	(0.363)	(0.025)
BA Other Majors	0.365***	0.560***	0.609	-0.048	0.244	0.195***
	(0.027)	(0.011)	(0.437)	(0.439)	(0.443)	(0.031)

Note: This analysis is based on 19,903 individuals with a bachelor's degree.Averages are estimated with the overidentified nonparametric GMM procedure described in the Identification section. Computations use individual weights provided by NSCG. Numbers in parentheses are standard errors. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$. Categories of the institution that received the first Bachelor's degree are based on the Carnegie classifications(1994) and Barron's selectivity categories. Tier 1 includes Private Research I and II universities in Carnegie classification, Tier 2 includes Liberal Arts I college, Tier 3 includes Public Research I, and Tier 4 are the remaining 4-year colleges and universities excluding specialized institutions which focus on a narrow curriculum. (Hersch, 2019) Research Universities are those classified as Research I & II and Doctoral I II universities. BA Other STEM fields include Architecture/environmental design etc. BA Other Majors include non-STEM fields such as English/Languages/Literature, Fine/Performing arts, etc.

Table 3.14: Average Characteristics for Subpopultions (BA only + Grad^{IM}, Females)

	at	nt	c	nt - c	c-at	nt- at
White	0.840***	0.838***	0.878***	0.041	-0.038	0.002
	(0.012)	(0.008)	(0.114)	(0.119)	(0.118)	(0.013)
Age Obtained BA	21.68***	22.07***	21.40***	0.676**	-0.282	0.394***
	(0.034)	(0.027)	(0.322)	(0.335)	(0.343)	(0.034)
BA in Research University	0.474***	0.473***	0.509	-0.036	0.035	-0.001
	(0.016)	(0.016)	(0.157)	(0.163)	(0.163)	(0.019)
Tire 3 BA	0.214***	0.213***	0.304**	-0.091	0.090	-0.001
	(0.013)	(0.010)	(0.120)	(0.126)	(0.125)	(0.014)
Tire 4 BA	0.652***	0.657***	0.732***	-0.075	0.080	0.005
	(0.014)	(0.012)	(0.135)	(0.143)	(0.139)	(0.017)
Parents with Highest High School Degree	0.017***	0.020***	0.085	-0.065	0.068	0.003
	(0.004)	(0.003)	(0.067)	(0.068)	(0.067)	(0.004)
Either Parent with a Bachelor's Degree	0.677***	0.566***	0.520***	0.045	-0.157	-0.112***
	(0.014)	(0.011)	(0.174)	(0.182)	(0.178)	(0.014)
Either Parent with a Grad Degree	0.412***	0.298***	0.118	0.179***	-0.293	-0.114***
	(0.016)	(0.011)	(0.181)	(0.188)	(0.187)	(0.019)
BA Other STEM	0.193***	0.120***	0.026	0.094	-0.168*	-0.073***
	(0.009)	(0.006)	(0.096)	(0.100)	(0.100)	(0.010)
BA Social Sciences	0.468***	0.316***	0.415***	-0.098	-0.054	-0.152***
	(0.015)	(0.010)	(0.156)	(0.161)	(0.161)	(0.018)
BA Other Majors	0.312***	0.536***	0.566***	-0.029	0.254*	0.224***
	(0.016)	(0.011)	(0.146)	(0.153)	(0.152)	(0.019)

Note: This analysis is based on 17,422 females with a bachelor's degree.Averages are estimated with the overidentified nonparametric GMM procedure described in the Identification section. Computations use individual weights provided by NSCG. Numbers in parentheses are standard errors. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$. Categories of the institution that received the first Bachelor's degree are based on the Carnegie classifications(1994) and Barron's selectivity categories. Tier 1 includes Private Research I and II universities in Carnegie classification, Tier 2 includes Liberal Arts I college, Tier 3 includes Public Research I, and Tier 4 are the remaining 4-year colleges and universities excluding specialized institutions which focus on a narrow curriculum. (Hersch, 2019) Research Universities are those classified as Research I & II and Doctoral I II universities. BA Other STEM fields include Architecture/environmental design etc. BA Other Majors include non-STEM fields such as English/Languages/Literature, Fine/Performing arts, etc.

Table 3.15: Average Characteristics for Subpopultions (Grads)

Variable	at	nt	c	nt - c	c-at	nt- at
Female	0.693***	0.623***	0.689***	-0.066	-0.004	-0.070***
	(0.014)	(0.021)	(0.115)	(0.131)	(0.120)	(0.022)
White	0.853***	0.829***	0.855***	-0.027	0.002	-0.024
	(0.010)	(0.017)	(0.090)	(0.103)	(0.094)	(0.018)
Age Obtained BA	21.76***	21.99***	21.44***	0.544**	-0.323	0.221***
	(0.033)	(0.048)	(0.223)	(0.257)	(0.239)	(0.046)
BA in Research University	0.513***	0.476***	0.532***	-0.056	0.019	−0.037
	(0.012)	(0.021)	(0.119)	(0.137)	(0.121)	(0.023)
Tire 3 BA	0.242***	0.230***	0.296***	-0.067	0.054	-0.013
	(0.010)	(0.016)	(0.097)	(0.109)	(0.100)	(0.018)
Tire 4 BA	0.627***	0.572***	0.638***	-0.066	0.011	-0.055***
	(0.014)	(0.020)	(0.111)	(0.128)	(0.117)	(0.021)
Parents with Highest High School Degree	0.019***	0.015***	0.134***	-0.119**	0.115**	-0.004
	(0.004)	(0.006)	(0.049)	(0.053)	(0.050)	(0.006)
Either Parent with a Bachelor's Degree	0.673***	0.610***	0.606***	0.004	-0.067	-0.063***
	(0.014)	(0.023)	(0.126)	(0.145)	(0.134)	(0.023)
Either Parent with a Grad Degree	0.393***	0.327***	0.564***	-0.237	0.171	-0.066***
	(0.014)	(0.023)	(0.132)	(0.149)	(0.138)	(0.024)
BA Engineering	0.088***	0.081***	0.079***	0.002	-0.009	-0.007
	(0.004)	(0.005)	(0.027)	(0.031)	(0.028)	(0.005)
BA Other STEM	0.168***	0.078***	0.004	0.074*	-0.165***	-0.091***
	(0.008)	(0.007)	(0.034)	(0.038)	(0.027)	(0.010)
BA Social Sciences	0.422***	0.482***	0.344***	0.138	-0.077	0.060**
	(0.014)	(0.022)	(0.113)	(0.130)	(0.118)	(0.024)
BA Other Majors	0.329***	0.376***	0.565***	-0.189*	0.236**	0.047*
	(0.014)	(0.023)	(0.099)	(0.113)	(0.103)	(0.025)

Note: This analysis is based on 20,244 master's degree holders.Averages are estimated with the overidentified nonparametric GMM procedure described in the Identification section. Computations use individual weights provided by NSCG. Numbers in parentheses are standard errors. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. Categories of the institution that received the first Bachelor's degree are based on the Carnegie classifications(1994) and Barron's selectivity categories. Tier 1 includes Private Research I and II universities in Carnegie classification, Tier 2 includes Liberal Arts I college, Tier 3 includes Public Research I, and Tier 4 are the remaining 4-year colleges and universities excluding specialized institutions which focus on a narrow curriculum. (Hersch, 2019) Research Universities are those classified as Research I & II and Doctoral I II universities. BA Other STEM fields include Architecture/environmental design etc. BA Other Majors include non-STEM fields such as English/Languages/Literature, Fine/Performing arts, etc.

Table 3.16: Average Characteristics for Subpopultions (Grads, Males)

	at	nt	c	nt - c	c-at	nt- at
White	0.885***	0.875***	0.860*	0.015	- 0.024	-0.010
	(0.012)	(0.020)	(0.448)	(0.458)	(0.449)	(0.022)
Age Obtained BA	21.94***	22.21***	21.74***	0.469	-0.202	0.267***
	(0.078)	(0.090)	(0.919)	(0.967)	(0.955)	(0.088)
BA in Research University	0.589***	0.476***	0.926*	-0.450	0.337	-0.113***
	(0.026)	(0.035)	(0.500)	(0.502)	(0.503)	(0.043)
Tire 3 BA	0.292***	0.226***	0.697	-0.471	0.404	-0.067**
	(0.025)	(0.023)	(1.634)	(1.634)	(1.634)	(0.035)
Tire 4 BA	0.578***	0.560***	0.422	0.138	-0.156	-0.018
	(0.027)	(0.025)	(0.702)	(0.704)	(0.703)	(0.037)
Parents with Highest High School Degree	0.020***	0.010**	0.213	-0.203	-0.193	-0.009
	(0.006)	(0.004)	(0.371)	(0.372)	(0.371)	(0.008)
Either Parent with a Bachelor's Degree	0.668***	0.605***	0.705	-0.101	0.037	-0.063**
	(0.0234	(0.025)	(1.091)	(1.09)	(1.093)	(0.028)
Either Parent with a Grad Degree	0.378***	0.305***	0.758	-0.453	0.380	-0.073**
	(0.023)	(0.023)	(1.604)	(1.607)	(1.610)	(0.029)
BA Engineering	0.208***	0.162***	0.243	-0.080	0.035	-0.045**
	(0.015)	(0.014)	(0.663)	(0.666)	(0.666)	(0.019)
BA Other STEM	0.105***	0.063***	0.107	-0.044	0.002	-0.042**
	(0.012)	(0.011)	(0.378)	(0.382)	(0.378)	(0.017)
BA Social Sciences	0.316***	0.364***	0.177	0.187	-0.139	0.048
	(0.023)	(0.025)	(0.367)	(0.377)	(0.370)	(0.032)
BA Other Majors	0.369***	0.418***	0.538	-0.120	0.168	0.048
	(0.029)	(0.027)	(0.694)	(0.705)	(0.696)	(0.037)

Note: This analysis is based on 9,167 male master's degree holders.Averages are estimated with the overidentified nonparametric GMM procedure described in the Identification section. Computations use individual weights provided by NSCG. Numbers in parentheses are standard errors. $^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$. Categories of the institution that received the first Bachelor's degree are based on the Carnegie classifications(1994) and Barron's selectivity categories. Tier 1 includes Private Research I and II universities in Carnegie classification, Tier 2 includes Liberal Arts I college, Tier 3 includes Public Research I, and Tier 4 are the remaining 4-year colleges and universities excluding specialized institutions which focus on a narrow curriculum. (Hersch, 2019) Research Universities are those classified as Research I & II and Doctoral I II universities. BA Other STEM fields include Architecture/environmental design etc. BA Other Majors include non-STEM fields such as English/Languages/Literature, Fine/Performing arts, etc.

Table 3.17: Average Characteristics for Subpopultions (Grads, Females)

	at	nt	c	nt - c	c-at	nt- at
White	0.841***	0.810***	0.839***	-0.029	-0.003	- 0.032
	(0.011)	(0.021)	(0.093)	(0.110)	(0.097)	(0.022)
Age Obtained BA	21.68***	21.84***	21.39***	0.441**	-0.286	0.155***
	(0.029)	(0.056)	(0.269)	(0.303)	(0.279)	(0.057)
BA in Research University	0.480***	0.480***	0.333**	0.147	-0.147	-0.000
	(0.016)	(0.023)	(0.149)	(0.167)	(0.152)	(0.026)
Tire 3 BA	0.221***	0.229***	0.127	-0.093	0.009	-0.201
	(0.012)	(0.020)	(0.089)	(0.089)	(0.024)	(0.155)
Tire 4 BA	0.650***	0.573***	0.774***	-0.201	0.124	-0.077**
	(0.013)	(0.030)	(0.132)	(0.155)	(0.135)	(0.031)
Parents with Highest High School Degree	0.018***	0.022***	0.064	-0.042	0.046	0.004
	(0.004)	(0.008)	(0.048)	(0.053)	(0.049)	(0.008)
Either Parent with a Bachelor's Degree	0.676***	0.613***	0.574***	0.039	-0.102	-0.063***
	(0.013)	(0.024)	(0.136)	(0.154)	(0.142)	(0.022)
Either Parent with a Grad Degree	0.399***	0.345***	0.443***	-0.097	0.044	-0.054*
	(0.015)	(0.028)	(0.146)	(0.168)	(0.154)	(0.028)
BA Engineering	0.033***	0.030***	0.010	0.021	-0.024	-0.003
	(0.003)	(0.004)	(0.019)	(0.023)	(0.020)	(0.004)
BA Social Sciences	0.468***	0.554***	0.421***	0.133	-0.048	0.086***
	(0.016)	(0.028)	(0.148)	(0.167)	(0.156)	(0.025)
BA Other Majors	0.311***	0.351***	0.570***	-0.219	0.258	0.039
	(0.017)	(0.029)	(0.1151)	(0.171)	(0.158)	(0.026)

Note: This analysis is based on 11,077 female master's degree holders.Averages are estimated with the overidentified non-parametric GMM procedure described in the Identification section. Computations use individual weights provided by NSCG. Numbers in parentheses are standard errors. $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$. Categories of the institution that received the first Bachelor's degree are based on the Carnegie classifications(1994) and Barron's selectivity categories. Tier 1 includes Private Research I and II universities in Carnegie classification, Tier 2 includes Liberal Arts I college, Tier 3 includes Public Research I, and Tier 4 are the remaining 4-year colleges and universities excluding specialized institutions which focus on a narrow curriculum. (Hersch, 2019) Research Universities are those classified as Research I & II and Doctoral I II universities. BA Other Majors include non-STEM fields such as English/Languages/Literature, Fine/Performing arts, etc.

Appendix

Analyses in this paper rely on 2010 - 2019 sample from the National Survey of College Graduates(NSCG). NSCG is part of the Scientists and Statistical Data System (SESTAT), and it is conducted by the National Center for Science and Engineering Statistics (NCSES) within the National Science Foundation (NSF). The NSCG has been a biannual- survey since 1993; however, unlike previous waves, from 2010 on, NSCG employs a new rotating sampling strategy. The NSCG 2010 is drawn from respondents to the 2009 American Community Survey (ACS).The sample for the NSCG 2013 and the 2015 surveys combine a subsample of the interviewees from the 2010 and 2013 waves of NSCG, and a subsample if interviewees with post secondary education from the 2011 and 2013 waves of the ACS. The NSCG 2017 and the 2019 survey sample combines a subsample of the interviewees from the 2010, 2013, 2015, 2017 NSCG, and a subsample of interviewees with post-secondary education from the 2015 and 2017 waves of the ACS.

Table A1 presents the summary statistics for the whole sample. Females are slightly more representative in the sample of people with a master's degree, either immediately obtained (70%) or obtained later in life (64%). Females only count 58% of individuals with only a bachelor's degree. The mean age for the individuals is 34.89. The group of people who immediately obtained a master's degree are, on average, slightly younger (33.81 years old) compared to those with only a bachelor's degree (34.92 years old) and those who obtained a master's degree later in life (35.48 years old) in the sample. Similarly, compared to those with only a bachelor's degree and those who obtained a master's degree later in life, those immediate-master-program-goers are, on average, younger when they obtained their first bachelor's degree at age 21.77, compared to age 22.19 for those only bachelor's degree holders and 21.92 for those obtained a master's degree later in life. The annual average national unemployment rate and the probability of graduating from college during a recession are slightly higher for those who attend the master's program immediately after the first bachelor's degree.

When compared to the field of major an individual studied for the bachelor's degree, the proportion of those who majored in computer and mathematical sciences or non-S&E related fields is lower among individuals who gained a master's degree compared to those with only a bachelor's degree. The proportion is higher for individuals who immediately enrolled in a master program for those with a bachelor's degree in Biological, agricultural and environmental life sciences; physical and related sciences and S&E-related fields. The proportion of individuals with a bachelor's degree in social science major is higher among individuals with a master's degree than those with only a bachelor's degree. However, the proportions among those who immediately attend the master's program or the master's program later in life are about the same, with the latter slightly higher.

Over 80% of the sample are white, 6.4% of those with a bachelor's degree are black, the black proportion is slightly higher among those with a master's program, which is 6.7% among those immediately attend the master's program, and 8.3% among those who attend the master's program later. About 5.7% of the individuals are Asian in the sample, and this number is 5.8%, 5.0%, and 5.8% among individuals with only a bachelor's degree, immediately attend the master's program and attend the master's program later in life respectively. In addition, the proportion of individuals with a family that both parents with a graduate degree is higher among individuals who go to the master's program immediately after the first bachelor's degree. To better understand an individual's educational background from the college, I classified all universities into five categories. Universities are grouped into tiers 1 - 4 by Carnegie classification, which is categorized by Barron's as most or highly competitive. Tier 1 institutions are private Research I and private Research II universities; tier 2 institutions are private Liberal Arts I colleges; tier 3 are public Research I universities; and tier 4 are the remaining four-year colleges and universities with Carnegie classification available, excluding specialized institutions which focus on a narrow curriculum and professional schools (Hersch, 2019). Compared to individuals with only a bachelor's degree or those who obtained a master's degree later in life, individuals who went directly for a master's degree are more likely to have studied in more research-active institutions. On average, individuals who choose to attend a master's program immediately after graduating from college are more likely to be young white females who obtained an S& E major from a research university and who graduated into a relatively worse economic and whose parents with relatively higher education. Table A2 provide more detailed statistics for males and females separately. Table A4 and Table A5 provide the summary statistics for the "non- STEM" sample and by gender.

Table A1: Summary Statistics for Main Variables: NSCG 2010 - 19 Full

	A. All Samples	B. BA only	C.Grad$_{IM}$	D.Grads
Female	0.577	0.543	0.695	0.635
	(0.494)	(0.498)	(0.460)	(0.481)
Age	34.89	34.92	33.81	35.48
	(4.79)	(4.87)	(4.68)	(4.43)
Age obtained the first BA	22.10	22.19	21.77	21.92
	(1.15)	(1.17)	(1.04)	(1.10)
Unemployment Rate at graduation	5.613	5.625	5.862	5.406
	(1.506)	(1.518)	(1.675)	(1.304)
Graduated During a Recession	0.157	0.157	0.181	0.145
	(0.364)	(0.364)	(0.385	(0.352)
Stay in the Same Major	0.897		0.677	0.635
	(0.304)		(0.468)	(0.482)
Categories of the Institution Received the First Bachelor's Degree				
Tire1	0.054	0.049	0.060	0.073
	(0.049)	(0.215)	(0.237)	(0.260)
Tire2	0.051	0.042	0.061	0.080
	(0.220)	(0.201)	(0.240)	(0.271)
Tire3	0.235	0.232	0.250	0.238
	(0.424)	(0.422)	(0.433)	(0.426)
Tire4	0.628	0.642	0.614	0.581
	(0.483)	(0.479)	(0.487)	(0.493)
Tire_Specialized	0.032	0.036	0.015	0.029
	(0.176)	(0.186)	(0.122)	(0.168)
Field of Study for the first Bachelor's Degree				
Computer and Mathematical Sciences	0.047	0.048	0.038	0.047
	(0.211)	(0.214)	(0.190)	(0.211)
Bio, Agri and Env Sciences	0.061	0.060	0.076	0.058
	(0.240)	(0.237)	(0.265)	(0.234)
Physical and Related Sciences	0.014	0.012	0.022	0.017
	(0.119)	(0.110)	(0.146)	(0.130)
Social and Related Sciences	0.168	0.146	0.222	0.217
	(0.373)	(0.353)	(0.416)	(0.412)
Engineering	0.067	0.067	0.069	0.067
	(0.250)	(0.249)	(0.254)	(0.251)
S & E- Related Field	0.080	0.077	0.134	0.057
	(0.271)	(0.267)	(0.341)	(0.232)
Non S & E- Related Field	0.563	0.590	0.439	0.536
	(0.496)	(0.492)	(0.496)	(0.499)
White	0.839	0.841	0.845	0.823
	(0.368)	(0.362)	(0.362)	(0.382)
Black	0.067	0.064	0.067	0.083
	(0.251)	(0.244)	(0.250)	(0.275)
Asian	0.057	0.058	0.050	0.058
	(0.232)	(0.233)	(0.218)	(0.234)
Obtained the BA from a Research University	0.492	0.491	0.521	0.479
	(0.500)	(0.500)	(0.500)	(0.500)
Parent's Education				
at most High School	0.023	0.023	0.021	0.028
	(0.151)	(0.149)	(0.144)	(0.164)
either parent with a grad degree	0.318	0.292	0.395	0.371
	(0.466)	(0.455)	(0.489)	(0.483)
Employed	0.902	0.890	0.917	0.938
	(0.298)	(0.276)	(0.276)	(0.241)
Self-Employed	0.140	0.165	0.091	0.074
	(0.347)	(0.371)	(0.288)	(0.262)
Non-self Full-time Employed	0.753	0.764	0.827	0.663
	(0.431)	(0.424)	(0.378)	(0.473)
Observations	97,941	54,674	21,009	22,258

Table A2: Summary Statistics for Main Variables: NSCG 2010 - 19 Full by Gender

	Males			Females		
	A. BA only	B.Grad$_{IM}$	C.Grads	A. BA only	B.Grad$_{IM}$	C.Grads
Age	35.13	33.72	35.71	34.74	33.85	35.35
	(4.90)	(4.83)	(4.41)	(4.84)	(4.62)	(4.44)
Age obtained the first BA	22.36	21.96	22.18	22.06	21.69	21.78
	(1.18)	(1.19)	(1.15)	(1.15)	(0.96)	(1.05)
Unemployment Rate at graduation	5.625	5.956	5.470	5.625	5.820	5.369
	(1.533)	(1.766)	(1.379)	(1.505)	(1.632)	(1.258)
Graduated During a Recession	0.163	0.201	0.161	0.151	0.172	0.136
	(0.370)	(0.401)	(0.367)	(0.358)	(0.378)	(0.343)
Stay in the Same Major		0.720	0.592		0.658	0.660
		(0.449)	(0.492)		(0.474)	(0.474)
Categories of the Institution Received the First Bachelor's Degree						
Tire1	0.053	0.073	0.081	0.045	0.053	0.068
	(0.225)	(0.261)	(0.272)	(0.207)	(0.225)	(0.252)
Tire2	0.037	0.034	0.070	0.046	0.074	0.085
	(0.190)	(0.180)	(0.256)	(0.210)	(0.261)	(0.279)
Tire3	0.245	0.323	0.280	0.220	0.218	0.214
	(0.430)	(0.468)	(0.449)	(0.415)	(0.413)	(0.410)
Tire4	0.630	0.547	0.545	0.651	0.644	0.601
	(0.483)	(0.498)	(0.498)	(0.477)	(0.479)	(0.490)
Tire_Specialized	0.034	0.023	0.078	0.037	0.012	0.033
	(0.181)	(0.151)	(0.269)	(0.190)	(0.107)	(0.177)
Field of Study for the first Bachelor's Degree						
Computer and Mathematical Sciences	0.079	0.069	0.080	0.023	0.024	0.028
	(0.270)	(0.254)	(0.271)	(0.148)	(0.153)	(0.164)
Bio, Agri and Env Sciences	0.058	0.067	0.046	0.061	0.080	0.065
	(0.234)	(0.251)	(0.210)	(0.239)	(0.271)	(0.246)
Physical and Related Sciences	0.014	0.040	0.025	0.011	0.014	0.012
	(0.118)	(0.197)	(0.157)	(0.103)	(0.116)	(0.111)
Social and Related Sciences	0.131	0.167	0.187	0.158	0.246	0.235
	(0.337)	(0.373)	(0.390)	(0.365)	(0.431)	(0.424)
Engineering	0.117	0.166	0.142	0.024	0.027	0.025
	(0.321)	(0.372)	(0.349)	(0.154)	(0.162)	(0.155)
S & E- Related Field	0.053	0.086	0.055	0.097	0.155	0.059
	(0.223)	(0.281)	(0.228)	(0.296)	(0.362)	(0.235)
Non S & E- Related Field	0.548	0.404	0.465	0.625	0.454	0.578
	(0.498)	(0.491)	(0.499)	(0.484)	(0.498)	(0.494)
White	0.851	0.866	0.841	0.834	0.836	0.812
	(0.356)	(0.340)	(0.366)	(0.373)	(0.370)	(0.391)
Black	0.056	0.043	0.062	0.070	0.077	0.094
	(0.230)	(0.203)	(0.241)	(0.255)	(0.267)	(0.292)
Asian	0.060	0.062	0.067	0.056	0.045	0.053
	(0.237)	(0.241)	(0.250)	(0.230)	(0.207)	(0.224)
Obtained the BA from a Research University	0.510	0.598	0.523	0.476	0.487	0.453
	(0.500)	(0.490)	(0.499)	(0.499)	(0.500)	(0.498)
Parent's Education						
at most High School	0.020	0.031	0.028	0.025	0.017	0.028
	(0.139)	(0.174)	(0.165)	(0.157)	(0.128)	(0.164)
either parent with a grad degree	0.303	0.391	0.377	0.284	0.396	0.368
	(0.459)	(0.488)	(0.485)	(0.451)	(0.489)	(0.482)
Employed	0.959	0.981	0.981	0.832	0.888	0.913
	(0.198)	(0.135)	(0.135)	(0.374)	(0.315)	(0.282)
Self-Employed	0.179	0.095	0.088	0.153	0.089	0.066
	(0.384)	(0.294)	(0.283)	(0.360)	(0.285)	(0.249)
Non-self Full-time Employed	0.791	0.876	0.779	0.742	0.806	0.597
	(0.407)	(0.330)	(0.415)	(0.438)	(0.395)	(0.491)
Observations	29,981	7,795	9,768	24,693	13,214	12,490

Table A3: Parental Education Levels by Education

	All Sample			Full_time Employed		
	A.Bachelor's Only	B. Grad School Immediately	C.Grad School Later	A.Bachelor's Only	B. Grad School Immediately	C.Grad School Later
Mother's Educational Attainment						
Less than High School	0.047	0.037	0.053	0.045	0.042	0.050
	(0.212)	(0.190)	(0.224)	(0.208)	(0.201)	(0.219)
High School	0.263	0.213	0.218	0.267	0.208	0.231
	(0.440)	(0.410)	(0.413)	(0.442)	(0.406)	(0.422)
Some College	0.272	0.261	0.272	0.269	0.247	0.260
	(0.445)	(0.439)	(0.445)	(0.443)	(0.431)	(0.439)
College	0.266	0.267	0.234	0.263	0.268	0.241
	(0.442)	(0.443)	(0.423)	(0.440)	(0.443)	(0.428)
Graduate Degree	0.151	0.221	0.223	0.156	0.235	0.217
	(0.358)	(0.415)	(0.416)	(0.362)	(0.424)	(0.412)
Father's Educational Attainment						
Less than High School	0.049	0.044	0.062	0.046	0.049	0.060
	(0.216)	(0.205)	(0.241)	(0.209)	(0.216)	(0.237)
High School	0.245	0.188	0.183	0.252	0.193	0.196
	(0.430)	(0.391)	(0.387)	(0.434)	(0.395)	(0.397)
Some College	0.223	0.207	0.237	0.224	0.213	0.245
	(0.416)	(0.405)	(0.425)	(0.417)	(0.409)	(0.430)
College	0.267	0.285	0.247	0.264	0.281	0.234
	(0.442)	(0.451)	(0.431)	(0.441)	(0.450)	(0.424)
Graduate Degree	0.151	0.221	0.223	0.156	0.235	0.217
	(0.358)	(0.415)	(0.416	(0.362)	(0.424)	(0.412)
Observation	55,078	21,060	22,344	29,132	12,359	12,239

Table A4: Summary Statistics for Main Variables: NSCG 2010 - 19 (non-STEM)

	A. All Samples	B. BA only	C.Grad$_{IM}$	D.Grads
Female	0.592	0.559	0.710	0.647
	(0.492)	(0.497)	(0.454)	(0.478)
Age	34.89	34.93	33.76	35.45
	(4.80)	(4.88)	(4.66)	(4.42)
Age obtained the first BA	22.09	22.19	21.77	21.92
	(1.15)	(1.17)	(1.05)	(1.10)
Unemployment Rate at graduation	5.615	5.625	5.873	5.408
	(1.503)	(1.516)	(1.675)	(1.294)
Graduated During a Recession	0.154	0.152	0.187	0.141
	(0.361)	(0.359)	(0.390	(0.348)
Stay in the Same Major	0.911		0.721	0.681
	(0.285)		(0.449)	(0.466)
Categories of the Institution Received the First Bachelor's Degree				
Tire1	0.053	0.048	0.055	0.073
	(0.225)	(0.214)	(0.229)	(0.260)
Tire2	0.048	0.040	0.053	0.074
	(0.213)	(0.197)	(0.224)	(0.261)
Tire3	0.229	0.225	0.246	0.233
	(0.420)	(0.417)	(0.431)	(0.423)
Tire4	0.636	0.648	0.630	0.590
	(0.481)	(0.478)	(0.483)	(0.492)
Tire_Specialized	0.034	0.038	0.016	0.031
	(0.182)	(0.192)	(0.124)	(0.172)
Field of Study for the first Bachelor's Degree				
Social and Related Sciences	0.191	0.166	0.257	0.247
	(0.393)	(0.372)	(0.437)	(0.432)
Engineering	0.076	0.076	0.080	0.077
	(0.266)	(0.265)	(0.271)	(0.266)
S & E- Related Field	0.091	0.087	0.155	0.065
	(0.288)	(0.283)	(0.362)	(0.247)
Non S & E- Related Field	0.642	0.671	0.507	0.611
	(0.480)	(0.470)	(0.500)	(0.488)
White	0.845	0.848	0.852	0.828
	(0.362)	(0.359)	(0.355)	(0.377)
Black	0.068	0.064	0.070	0.082
	(0.251)	(0.244)	(0.255)	(0.275)
Asian	0.051	0.052	0.040	0.054
	(0.219)	(0.221)	(0.196)	(0.226)
Obtained the BA from a Research University	0.487	0.485	0.523	0.475
	(0.500)	(0.500)	(0.499)	(0.499)
Parent's Education				
at most High School	0.023	0.022	0.023	0.030
	(0.151)	(0.146)	(0.149)	(0.170)
either parent with a grad degree	0.315	0.291	0.392	0.363
	(0.465)	(0.454)	(0.488)	(0.481)
Employed	0.900	0.887	0.917	0.939
	(0.300)	(0.317)	(0.275)	(0.240)
Self-Employed	0.144	0.170	0.093	0.076
	(0.351)	(0.375)	(0.290)	(0.264)
Non-self Full-time Employed	0.750	0.757	0.826	0.655
	(0.435)	(0.429)	(0.380)	(0.475)
Observations	73,804	40,651	16,104	17,049

Table A5: Summary Statistics for Main Variables: NSCG 2010 - 19 by Gender (non-STEM)

	Males			Females		
	A. BA only	B.Grad$_{IM}$	C.Grads	A. BA only	B.Grad$_{IM}$	C.Grads
Age	35.16	33.66	35.68	34.75	33.80	35.33
	(4.91)	(4.83)	(4.40)	(4.84)	(4.59)	(4.43)
Age obtained the first BA	22.36	21.97	22.18	22.06	21.69	21.78
	(1.17)	(1.21)	(1.15)	(1.15)	(0.96)	(1.05)
Unemployment Rate at graduation	5.624	5.987	5.471	5.627	5.827	5.375
	(1.530)	(1.781)	(1.373)	(1.504)	(1.627)	(1.249)
Graduated During a Recession	0.159	0.210	0.157	0.146	0.178	0.132
	(0.366)	(0.407)	(0.364)	(0.353)	(0.383)	(0.338)
Stay in the Same Major		0.767	0.640		0.702	0.704
		(0.423)	(0.480)		(0.457)	(0.457)
Categories of the Institution Received the First Bachelor's Degree						
Tire1	0.052	0.072	0.081	0.045	0.049	0.069
	(0.222)	(0.259)	(0.272)	(0.207)	(0.215)	(0.253)
Tire2	0.036	0.023	0.065	0.044	0.066	0.078
	(0.186)	(0.149)	(0.247)	(0.205)	(0.247)	(0.268)
Tire3	0.236	0.315	0.278	0.220	0.218	0.208
	(0.425)	(0.465)	(0.448)	(0.412)	(0.413)	(0.406)
Tire4	0.639	0.565	0.552	0.655	0.656	0.611
	(0.480)	(0.496)	(0.497)	(0.475)	(0.475)	(0.487)
Tire_Specialized	0.037	0.025	0.024	0.040	0.012	0.034
	(0.188)	(0.155)	(0.154)	(0.195)	(0.109)	(0.181)
Field of Study for the first Bachelor's Degree						
Social and Related Sciences	0.154	0.203	0.221	0.175	0.279	0.262
	(0.361)	(0.403)	(0.415)	(0.380)	(0.449)	(0.440)
Engineering	0.138	0.201	0.167	0.027	0.031	0.028
	(0.344)	(0.401)	(0.373)	(0.162)	(0.172)	(0.164)
S & E- Related Field	0.062	0.105	0.065	0.108	0.176	0.065
	(0.241)	(0.306)	(0.247)	(0.310)	(0.381)	(0.247)
Non S & E- Related Field	0.646	0.491	0.548	0.691	0.514	0.645
	(0.478)	(0.500)	(0.498)	(0.462)	(0.500)	(0.479)
White	0.860	0.875	0.849	0.838	0.843	0.817
	(0.347)	(0.331)	(0.358)	(0.368)	(0.364)	(0.387)
Black	0.056	0.046	0.063	0.070	0.080	0.093
	(0.230)	(0.210)	(0.243)	(0.255)	(0.271)	(0.290)
Asian	0.052	0.053	0.061	0.052	0.035	0.050
	(0.221)	(0.223)	(0.239)	(0.221)	(0.183)	(0.218)
Obtained the BA from a Research University	0.501	0.601	0.523	0.472	0.491	0.449
	(0.500)	(0.490)	(0.500)	(0.499)	(0.500)	(0.497)
Parent's Education						
at most High School	0.018	0.036	0.031	0.025	0.018	0.029
	(0.133)	(0.185)	(0.174)	(0.156)	(0.132)	(0.168)
either parent with a grad degree	0.298	0.385	0.357	0.285	0.395	0.367
	(0.457)	(0.487)	(0.479)	(0.451)	(0.489)	(0.482)
Employed	0.959	0.980	0.983	0.830	0.892	0.915
	(0.198)	(0.139)	(0.129)	(0.376)	(0.311)	(0.279)
Self-Employed	0.187	0.096	0.093	0.156	0.091	0.066
	(0.390)	(0.294)	(0.290)	(0.363)	(0.288)	(0.249)
Non-self Full-time Employed	0.782	0.874	0.774	0.738	0.806	0.590
	(0.413)	(0.332)	(0.418)	(0.440)	(0.396)	(0.492)
Observations	22,106	5,751	7,381	18,545	10,353	9,668

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Rui Xu

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Department of Economics
Syracuse University
110, Eggers Hall
Syracuse, NY 13244

Phone: (254) 292-8342
Email: rxu101@syr.edu
Website: https://sites.google.com/view/ruixu

Education

Ph.D., Economics **2023**
Syracuse University
Dissertation: "Essays on the Gender Wage Gap in China and the Returns to Higher Education in the United States"
Committee: Alfonso Flores-Lagunes(advisor), Hugo Jales, Maria Zhu

M.A., Economics **2017**
University of Texas at Austin

B.A., Mathematics, Philosophy and Economics(minor) **2016**
Baylor University

B.A.,Philosophy **2015**
Sichuan University

Research Fields

Primary Fields: Labor Economics

Secondary Fields: Economics of Education

Research Experience

Syracuse University Center for Policy Research **August 2022 - May 2023**
Research Assistant to Prof. Abdulaziz Shifa **2020**

Working Papers

The Returns to a Master's Degree: Evidence from Recession-Induced Graduate Degree Enrollment (Job Market Paper)

Gender Wage Differentials in China from 1995 to 2018: Distributional Evidence Accounting for Employment Composition using Partial Identification (with Xintong Wang and Alfonso Flores-Lagunes)

Gender Wage Gap in Urban China: Change and Decomposition

Working in Progress

Overeducation, Major Mismatch, and Returns to Higher Education

The Effect of Two- and Three-Child Policy on Female Labor Market Outcomes

Presentations

2023 Liaoning University

2022 Syracuse University Labor Group Seminar, Syracuse University Applied Micro Seminar, Syracuse University Graduate Student Workshop, Asian Meeting of the Econometric Society

2021 Syracuse University Labor Group Seminar, Syracuse University Graduate Student Workshop, Southern Economics Association Annual Meeting

Awards

Graduate Assistantship, Syracuse University

Skills & Languages

Programming	Stata, Python, R, LaTeX, MATLAB, ArcGIS
Languages	Mandarin (native), English (fluent)

Teaching

Intermediate Mathematical Microeconomics (undergrad, Syracuse University)
Teaching Assistant to Prof. Carmen Carrión-Flores **2023**
Teaching Assistant to Prof. Leyla D. Karakaş **2020 - 22**

Environmental and Resource Economics (undergrad, Syracuse University) **2022**
Teaching Assistant to Prof. Carmen Carrión-Flores

Game Theory and Economic Strategy (undergrad, Syracuse University) **2021**
Teaching Assistant to Prof. Leyla D. Karakaş

Economic Growth (undergrad, Syracuse University) **2020 - 22**
Teaching Assistant to Prof. Abdulaziz Shifa

Urban Economics (undergrad, Syracuse University) **2020**
Teaching Assistant to Prof. Alexander Rothenberg

Labor Economics (undergrad, Syracuse University) **2019**
Teaching Assistant to Prof. Hugo B. Jales

Economic Statistics (undergrad, Syracuse University) **2019**
Teaching Assistant to Prof. Hugo B. Jales

Economic Ideas and Issues (undergrad, Syracuse University) **2017 - 2019**
Teaching Assistant to Prof. Jerry Evensky