

ESSAYS ON LABOR AND DEMOGRAPHIC ECONOMICS

By

Hsiu-Fen Hsu

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Economics—Doctor of Philosophy

2015

ABSTRACT

ESSAYS ON LABOR AND DEMOGRAPHIC ECONOMICS

By
Hsiu-Fen Hsu

This dissertation contains three self-contained chapters. The first chapter documents several changes that occurred in wage distribution in Taiwan between 1978 and 2012. For men, wage inequality narrowed initially, but then started widening. The declining wage inequality occurred evenly across the entire male wage distribution before the 1990s, when the economy was growing rapidly. Since the early 1990s, wage inequality among male workers has been rising, and the growth in inequality has been mainly due to expansion in upper-tail inequality. Around the same time, an increase in the college wage premium for male workers is also observed. Using a hybrid DFL reweighting approach, this study decomposes the changes in wage inequality into three main components: changes in the skill composition of the workforce, returns to skill, and residuals. The results show that for male workers, increases in returns to skill that arise from shifts in demand for skill play an important role in explaining the rising upper-tail wage inequality in the 1990s. By contrast, for female workers, changes in the skill composition of the workforce play an important role in explaining rising upper-tail inequality before the 1990s.

The second chapter investigates how children's educational attainment varies by birth order. In the literature, high-income and middle- and low-income countries have been shown to have opposite educational outcomes with regard to birth order. Studies using data from high-income countries usually find that later-born children have an educational disadvantage; in contrast, studies using data from middle- and low-income countries find that later-born children have an educational advantage over earlier-born children. This study, however, finds that birth order–educational attainment patterns in

high-income countries and Taiwan share some similarities: in smaller Taiwanese families, both later-born boys and girls have an educational disadvantage compared with their older siblings, a pattern typically found in high-income countries. This birth order pattern in smaller families also contradicts previous findings that later-born children receive more education in Taiwan.

The final chapter explores wage behavior over business cycles in Taiwan. The results show that real wages during the Great Recession are procyclical, whereas real wages in the recession of the early 2000s are somewhat acyclical. The finding that real wages are more procyclical in the Great Recession than in the recession of the early 2000s is consistent with that in the U.K. The analysis also finds that the responses of real wages to cyclical fluctuations in the 2000s are similar among gender, education, and age groups.

ACKNOWLEDGMENTS

I would like to sincerely thank my advisor, Gary Solon, for his invaluable guidance and support, both in terms of comments and suggestions on this dissertation and in my development as an economist. I will be forever grateful for his mentorship and support that kept me motivated and upbeat through the toughest moments. I am also grateful to the other members of my guidance committee: Steven Haider, Todd Elder, and Amita Chudgar. Each of them has provided helpful feedback on my research, and I am indebted to all of them for their advice. The papers comprising this dissertation also benefited greatly from helpful comments from other faculty and graduate students at Michigan State University including John Goddeeris, Scott Imberman, Leah Lakdawala, Jeff Wooldridge, and Yu-Wei Luke Chu, among many others. Their combined effort has helped immensely in the completion of this project. All remaining errors are my responsibility.

TABLE OF CONTENTS

LIST OF TABLES	vii
-----------------------------	------------

LIST OF FIGURES	viii
------------------------------	-------------

CHAPTER 1

DECOMPOSING CHANGES IN THE WAGE DISTRIBUTION IN TAIWAN.....1

1.1	Introduction.....	1
1.2	Data and Changes in Wage Inequality.....	6
1.2.1	The MS and MUS Data.....	6
1.2.2	Changes in Wage Inequality	9
1.3	Empirical Methodology	12
1.3.1	Hybrid Version of DFL Reweighting Approach	13
1.3.2	Estimation	20
1.4	Decomposition Results	21
1.4.1	Composition and Wage Structure Effects	21
1.4.2	The Role of Returns to Skill and the Role of Residuals	23
1.5	Conclusion	24
	APPENDICES.....	26
	APPENDIX A - FIGURES.....	27
	APPENDIX B - TABLES.....	30
	APPENDIX C - THE MS/MUS DATA, 1978-2012	32
	APPENDIX D - IMPUTATION.....	35
	APPENDIX E - ADDITIONAL FIGURES	38
	APPENDIX F - ADDITIONAL TABLES	40
	BIBLIOGRAPHY	42

CHAPTER 2

BIRTH ORDER AND EDUCATIONAL ATTAINMENT: EVIDENCE FROM

TAIWAN45

2.1	Introduction.....	45
2.2	Background.....	47
2.2.1	Theoretical and Empirical Background	47
2.2.2	The Taiwanese Context.....	50
2.3	Data and Methods	51
2.3.1	Data	51
2.3.2	Method	54
2.4	Results.....	55
2.4.1	Overall Birth Order Patterns	55
2.4.2	Changing Patterns Across Cohorts	58
2.5	Sensitivity Analysis	59
2.6	Conclusion	61
	APPENDICES.....	63
	APPENDIX A - FIGURE	64
	APPENDIX B - TABLES.....	65
	APPENDIX C - UNREPRESENTATIVE BIRTH ORDER.....	72
	BIBLIOGRAPHY	74

CHAPTER 3

WAGE ADJUSTMENT OVER THE BUSINESS CYCLE: EVIDENCE FROM

TAIWAN77

3.1	Introduction.....	77
3.2	Data	79
3.3	Empirical Methodology	82
3.4	Empirical Results.....	84
	3.4.1 Overall Wage Adjustment over the Business Cycle	84
	3.4.2 Group Heterogeneity.....	88
3.5	Conclusion	88
	APPENDICES.....	90
	APPENDIX A - FIGURES.....	91
	APPENDIX B - TABLES.....	97
	BIBLIOGRAPHY	102

LIST OF TABLES

Table 1.1	The Hybrid DFL Decomposition Results for Log Wages, Men.....	30
Table 1.2	The Hybrid DFL Decomposition Results for Log Wages, Women	31
Table 1.3	Descriptive Statistics, Men	40
Table 1.4	Descriptive Statistics, Women	41
Table 2.1	Descriptive Statistics: Means and Proportions	65
Table 2.2	Average of Years of Schooling by Family Size and Birth Order	66
Table 2.3	Fixed Effects Estimates by Family Size (Full Sample)	67
Table 2.4	Fixed Effects Estimates by Family Size (Girls)	68
Table 2.5	Fixed Effects Estimates by Family Size (Boys)	69
Table 2.6	Fixed-Effects Estimates by Birth Cohort (Families with Four or Less Children)	70
Table 2.7	Interval Regression Estimates (Pooled Maximum Likelihood Estimates with Family Means)	71
Table 2.8	Fixed-Effects Estimates (Families with Four or Less Children)	73
Table 3.1	Mean Log Real Hourly Wages by Gender and Year	97
Table 3.2	Men's Log Real Wages in the Recessions in the 2000s	98
Table 3.3	Women's Log Real Wages in the Recessions in the 2000s	99
Table 3.4	Mean Year-to-Year Changes in Log Real Wage by Gender from Longitudinally Matched MS/MUS Data	100
Table 3.5	Log Real Wage Changes in the Recessions in the 2000s	101

LIST OF FIGURES

Figure 1.1	Changes in Wage Inequality	27
Figure 1.2	Changes in Log Wage by Percentile	28
Figure 1.3	Changes in Log Wage by Percentile	37
Figure 1.4	Evolution of Log Wage	38
Figure 1.5	Cyclicalities in Measures of Wage Dispersion: 1978-2012	39
Figure 2.1	Average Years of Schooling by Year of Birth.....	64
Figure 3.1	Men's and Women's Mean Log Real Wages over the Business Cycle	91
Figure 3.2	Log Real Wages in the Recessions in the 2000s.....	92
Figure 3.3	Mean Year-to-Year Changes in Log Real Wage by Gender from Longitudinally Matched MS/MUS Data.....	93
Figure 3.4	Log Real Wage Changes in the Recessions in the 2000s	94
Figure 3.5	Log Real Wage Changes in the Recessions in the 2000s by Education, Age, and Sector, Men.....	95
Figure 3.6	Log Real Wage Changes in the Recessions in the 2000s by Education, Age, and Sector, Women	96

CHAPTER 1

DECOMPOSING CHANGES IN THE WAGE DISTRIBUTION IN TAIWAN

1.1 Introduction

Changes in wage inequality have been one of the topics that have been extensively researched in labor economics in recent decades. One reason for the interest for this topic is that the United States witnessed a steep rise in wage and earnings inequality during the 1980s (e.g., Bound and Johnson, 1992; Levy and Murnane, 1992; Murphy and Welch, 1992; Juhn, Murphy, and Pierce, 1993; Katz and Murphy, 1992; Acemoglu, 2002).¹

The change in the wage gap between more and less educated workers has been recognized as an important part of the change in overall wage inequality. For instance, Katz and Murphy (1992) and Bound and Johnson (1992) show that the college-high school wage gap increased sharply in the 1980s after declining during the 1970s. They propose a simple supply-and-demand explanation of this phenomenon, which later turned into the skill-biased technological change (SBTC) hypothesis in the literature.² However, this SBTC hypothesis has been challenged in more recent studies that argue that the surge of wage inequality in the 1980s is largely explained by nonmarket factors such as minimum wages (Lee, 1999; Card and DiNardo, 2002; Lemieux, 2006). As a result of the debate, the literature reached a broad consensus—that is, much of the surge of the U.S. wage inequality in the 1980s appears to be explained by shifts in the supply of and

¹ Other Anglo-Saxon countries, such as the United Kingdom (e.g., Gosling, Machin, and Meghir, 2000) and Canada (e.g., Boudarbat, Lemieux, and Riddell, 2006), witnessed a similar expansion in wage and earnings gaps in the 1980s.

² It is argued in the literature that much of the rise in the U.S. wage inequality evident in the 1980s reflects an ongoing and secular increase in the demand for skill, which is primarily due to skill-biased technological change resulting from the onset of the computer revolution, and slowdown in the growth of the relative supply of college-equivalent workers during the 1980s (Katz and Murphy, 1992; Autor, Katz, and Krueger, 1998; Card and Lemieux, 2001; Acemoglu, 2002).

demand for skills, combined with nonmarket factors (Autor, Katz, and Kearney, 2008).

Further, recent research has increasingly focused on changes in inequality at different parts of the wage distribution, in addition to the traditional overall wage inequality (i.e., the standard deviation and 90-10 gap of wages). For example, Autor, Katz, and Kearney (2008) show that in the United States, upper-tail inequality, measured as the 90-50 wage gap, increased during the 1990s at roughly the same pace as in the 1980s, whereas lower-tail inequality (the 50-10 gap) has been falling or flat since the late 1980s.³ Understanding changes across the entire distribution of wages helps deepen our understanding of the shifting nature of wage inequality, as we know that changes in inequality at different parts of the wage distribution tend to be explained by different factors.⁴

While the trend of changes in wage inequality in the United States has been extensively studied, research on the trend of changes in wage inequality in Taiwan is relatively limited. Furthermore, most previous studies focus on the evolution of measures of overall wage inequality, such as the Theil coefficient or wage differentials by education (Gindling and Sun, 2002; Lin and Orazem, 2003; Vere, 2005; Huang, 2011; Chen, 2013).⁵ No existing works explore how changes in inequality at different parts of the wage distribution evolve over time, while few studies have investigated the

³ In part motivated by the divergent development of the path of upper-tail and lower-tail inequality, Acemoglu and Autor (2011) refine the skill-biased technological change hypothesis, the leading explanation of wage inequality, and propose a task-based model to explain the change in wage inequality.

⁴ For example, Lemieux (2008) suggests several explanations for the continuing growth in upper-tail inequality in the United States. One of the suggested explanations is performance pay, which is considered to play a role in explaining the top-end wage inequality. On the other hand, the minimum wage is ruled out as an explanation for growing top-end inequality, but it is considered to be an important explanation for lower-tail wage inequality.

⁵ Chen (2002) examines the impact of minimum wages on the change in wage structure. The measure of inequality used in his paper is Gini and Theil coefficients, which are the measure of overall inequality.

underlying factors driving changes in wage inequality.⁶ In addition, exploration of changes in the wage distribution after the late 1990s is limited.⁷

The case of Taiwan is interesting given the enormous changes in the country over recent decades (e.g., expansion in higher education, trade liberalization, growth in the information and communication technology (ICT) industry). The expansion of higher education is expected to increase the relative supply of skilled workers and mitigate future inequality that stems from increases in relative demand for skilled workers due to factors such as changes in industry structure. Although increasing the proportion of college attendees is considered to be an appropriate public policy response to the phenomenon of increasing inequality, education may have a secondary effect on wage inequality. In other words, increasing the supply of high-educated workers exerts a pressure that decreases the wages of those workers. By contrast, if high-educated workers experience greater within-group wage dispersion, their increased supply may also lead to an increase in wage inequality.^{8,9} The net result of the so-called composition and price effects is certainly an empirical question, which constitutes the primary motivation for this paper.

This paper adds to the literature on wage distribution in several ways. First, to the best of my knowledge, it is the first paper to document the evolution of wages and

⁶ The one existing paper that attempts to analyze the underlying factors is Vere (2005). He proposes an approach to decompose the Theil coefficient, a measure of overall wage inequality, but he does not analyze how the factors considered affect inequality at different parts of the wage distribution, and his data only cover the years 1979 to 1998.

⁷ Vere (2005) studies overall wage inequality, but his data do not cover the 2000s. Huang (2011) and Chen (2013) extended the time period to 2008 and 2011, respectively. However, both studies focus on wage differentials by skills, such as education and experience.

⁸ Lemieux (2006) points out that without any underlying changes in market prices for skill, changes in the skill composition of the workforce can raise or lower wage inequality simply by altering the employment share of workers with higher or lower within-group wage dispersion.

⁹ It is also well known that composition effects tend to obscure the procyclicality of the level of real wages (Solon, Barsky, and Parker, 1994).

changes in inequality at different parts of the wage distribution in Taiwan over a long period (the 35 years from 1978 to 2012). A full understanding of the changes that have occurred in wage distribution requires disentangling the effect of changes in the skill composition of the workforce (i.e., composition effects) from the effect of changes in returns to observed skill (i.e., price effects). As a second and methodological contribution, this paper extends the hybrid version of the DFL (DiNardo, Fortin, and Lemieux (1996)) reweighting framework proposed by Lemieux (2002) to explore how these composition and price effects contribute to the observed changes in inequality at different parts of the wage distribution.

The original DFL reweighting approach proposed by DiNardo, Fortin, and Lemieux (1996) can be used to semi-parametrically decompose changes in wage inequality into two components: composition effects and wage structure effects. The limitation of this approach, however, is that wage structure effects include not only the contribution of returns to observed skill but also the contribution of residuals. To overcome this limitation, Lemieux (2002) suggests a simple approach to extend the DFL reweighting method. The main advantage of the hybrid DFL reweighting approach proposed by Lemieux (2002) is that it allows one to decompose changes in wage inequality into three components: composition effects, the role of returns to observed skill and the role of residuals.

However, one of the limitations of this hybrid approach is that the composition effects identified depend on a given model of wages and thus they may be sensitive to the choice of the functional forms of wages.¹⁰ To overcome this issue, I modify Lemieux's (2002) decomposition procedure. In the first step, I compute the composition effects semi-parametrically by using the original DFL reweighting approach. In the second step wage structure effects are further decomposed into the role of returns to observed skill

¹⁰ This limitation can be seen clearly in Table 2 in Lemieux (2002).

and the role of residuals in the spirit of the hybrid approach.

This paper sets out to document changes in the distribution of wages in Taiwan from 1978 to 2012 for male and female workers using microdata from the Manpower Survey (MS) and its May supplement, the Manpower Utilization Survey (MUS). The data reveal that there have been several changes in the wage distribution over these 35 years. First, for male workers, the wage distribution was narrowing before the 1990s, and the decline in inequality occurred evenly across the entire wage distribution. Together with the fact that all parts of the wage distribution grew dramatically during the same period, which was the fruit of the rapid economic growth, the declining wage inequality suggests that Taiwan was "growing together."¹¹

Second, during the 1990s, it is found that the changes in wage inequality reversed direction. Wage inequality among male workers started rising; the increase in overall wage inequality was mainly due to an increase in inequality at the upper tail of the male wage distribution. Around the same time an increase in the college wage premium for male workers is also observed, suggesting that rising returns to college education may have contributed to the widening of the upper half of the male wage distribution. Finally, while the picture of trends in female wage inequality is less clear, the impression is that there was a substantial increase in overall wage inequality before the 1990s, which was driven by rising upper-tail inequality.

The decomposition results show that for male workers, returns to skill (price effects) play an important role in explaining rising upper-tail wage inequality during the 1990s. They explain about half of the increase in the 90-50 log wage differential for male workers during this decade. As a substantial increase in returns to college education for male workers is observed during the same period, the decomposition results thus suggest that returns to college education play an important role in explaining the rising male

¹¹ A similar "growing together" was once observed in the United States, from the close of World War II to the 1970s (Goldin and Katz, 2007).

upper-tail inequality. Furthermore, together with the fact that the skill of the workforce increased in the 1990s, rising returns to skill suggest that the shifts in labor market demand must have outpaced those in supply.

For female workers, the decomposition results show that positive composition effects (i.e., changes in the skill composition of the workforce) play an important role in explaining the rise in inequality at the upper tail of the female wage distribution before the 1990s.

This paper is organized as follows. Section 1.2 provides a brief data description and documents the evolution of the wage distribution in Taiwan from 1978 to 2012. Section 1.3 describes the hybrid DFL decomposition method. Section 1.4 reports the decomposition results. The last section summarizes the empirical findings and draws conclusions.

1.2 Data and Changes in Wage Inequality

1.2.1 The MS and MUS Data

In this section, I briefly describe the data and how they are processed. Data and measurement issues are discussed in more detail in Appendix C.

The data sets are from the Manpower Survey (MS) and its May supplement, the Manpower Utilization Survey (MUS). The MS is conducted by the Directorate General of Budget, Accounting and Statistics (DGBAS) of Taiwan, and its survey design is similar to the U.S. Current Population Survey (CPS). This paper uses the MS and the MUS microdata for the years 1978 to 2012.

The MS is given to approximately 20,000 registered households, and there are nearly 60,000 civilians aged 15 and older in these sampled households. The MS is conducted monthly in the week right after the reference week covering the 15th of a month. The MS asks detailed questions on hours worked during the previous week (i.e.,

the reference week) and jobs held, in addition to demographic information such as educational attainment. The MUS is the May supplement to the MS, and it asks about monthly earnings at an individual's main job, which are a "point-in-time" measure of earnings in general.

Following most of the literature, this paper uses the hourly wage rate. As discussed in Lemieux (2006), the hourly wage rate pertains to theories of wage determination and represents the price of labor; by contrast, weekly, monthly, or annual earnings reflect the responsiveness of labor supply to changes in the price of labor. Since one of the goals of this paper is to examine the contribution of returns to skill, the hourly wage rate is the most appropriate measure. The earnings reported in the MUS, however, are monthly. To deal with this issue, I follow the procedure used in Card and DiNardo (2002) and Lemieux (2006) to convert monthly earnings into an hourly wage rate.¹²

There are a number of problems in the MS/MUS data, which also occur in many data sets used in the literature, such as the CPS. For one thing, the earnings of highly paid workers are top-coded at certain values. A second problem is that some workers refuse to answer the earnings questions in the MUS. To deal with these earnings issues, I impute the missing and top-coded earnings. A final problem is that some workers do not report hours worked in the previous week. To deal with this issue, the missing hours are imputed as well. The results reported in this paper are based on the imputed earnings obtained by the censored normal regression imputation method and the imputed hours of work obtained by the normal linear regression imputation method. Details about the imputations can be found in Appendix D.

I keep workers aged 15-64 with positive earnings and potential experience. Following Card and DiNardo (2002), I use data on hourly wages for all workers—men

¹² For example, Lemieux (2006) computes an hourly wage rate by dividing usual weekly earnings by usual hours of work. Details about how the hourly wage rate is constructed in this paper can be found in Appendix C.

and women, full-time and part-time workers. Details about the sample selection criteria can be found in Appendix C.

Wage measures used for all analyses are log real hourly wages.¹³ The MS/MUS sample weights are used throughout the empirical analysis. In the main analysis, I pool several years of data together to improve the precision of the estimates. The whole sample period (1978 to 2012) is divided into three periods. The first, second, and third periods run from 1978-80 to 1990-92, from 1990-92 to 2000-02, and from 2000-02 to 2010-12, respectively. These three periods are used to capture the changes that occurred during the 1980s, 1990s, and 2000s.

Tables 1.3 and 1.4 in Appendix F present the summary statistics for male and female workers, respectively. The average age and potential experience for male workers increased from 35 and 20 in 1978-80 to 40 and 21 in 2010-12. The changes in age and experience are relatively limited for male workers—an increase of 14% ($((40-35)/35 \approx 0.143)$) in age and 5% in experience. By contrast, there were greater changes in the female workforce over the 35 years studied. For female workers, the average age and potential experience increased from 27 and 13 in 1978-80 to 37 and 18 in 2010-12—that is, an increase of 37% in age and 38% in experience.

The average years of schooling for male workers increased from 9 in 1978-80 to 13 in 2010-12; the proportion of workers with at least 16 years of schooling (i.e., college or above) increased from 0.08 in 1978-80 to 0.28 in 2010-12. For female workers, the change in the proportion of workers with at least 16 years of schooling is more dramatic. It increased from 0.05 in 1978-80 to 0.33 in 2010-12.

Tables 1.3 and 1.4 also present the changes in log real hourly wages at the mean. For both gender groups, average log real hourly wages rose rapidly in the first period (1978-80 to 1990-92) by about 0.79. The 10th, 50th, and 90th percentiles of the log wage

¹³ Wages are deflated to 2011 real New Taiwanese dollars (NT\$) using the Consumer Price Index (CPI).

distribution also experienced remarkable wage growth, as shown in Figure 1.4 in Appendix E. In the second period (1990-92 to 2000-02), the wage growth at the means and the 10th, 50th, and 90th percentiles decelerated for both genders. For example, the average log wage for men and women increased by about 0.22 and 0.34, respectively. In the final period (2000-02 to 2010-12), the average log wage for men declined by about 0.07 while that for women increased slightly, by about 0.02.

In summary, there are two main messages from these two tables. First, both male and female workers became more educated and experienced. In other words, the workforce became more skilled. The other message is that the female workforce experienced larger changes in the distribution of observed skills than the male workforce.

1.2.2 Changes in Wage Inequality

In this section, I describe the major changes in wage inequality in Taiwan from 1978 to 2012. I focus on three inequality measures: overall wage inequality, summarized by the 90-10 wage gap; inequality in the upper and lower halves of the wage distribution, summarized by the 90-50 and 50-10 wage gaps (which are referred to as upper-tail and lower-tail inequality); and the college-high school wage premium.¹⁴ In order to reduce measurement error, I use the three-year average of the measure of wage inequality. For example, the 90-10 gap for 1980 plotted in Figure 1.1 is the arithmetic average of the gaps for 1979, 1980, and 1981. Each measure is computed separately by gender.

The 90-10 Gap of Log Wages. Figure 1.1 displays the evolution of the 90-10 gap of log wages from 1978 to 2012. For men, the 90-10 gap of log wages declined in the first period (1978-80 to 1990-92) and the main decline occurred between the mid-1980s to the

¹⁴ The 90-10 gap is the difference between the 90th and 10th percentiles of log real hourly wage and so on. The college-high school wage gap is the difference between the log real hourly wage of workers with at least 16 years of schooling and that of workers with 12 years of schooling conditional on experience.

early 1990s. The decline in inequality was followed by growth in inequality in the second period (1990-92 to 2000-02). The acceleration of inequality, however, did not last. A moderate decline was observed again in the final period (2000-02 to 2010-12). Over the 35 years studied, the overall wage inequality for male workers experienced ups and downs, and then reverted to an inequality level close to that of the early 1980s, which was relatively high. For women, the picture of the changes in the 90-10 gap is less clear. One impression is that female overall wage inequality rose substantially in the first period, from 1978-80 to 1990-92.

The Top Versus the Bottom. Figure 1.1 shows that from 1978-80 to 1990-92, both the male 90-50 and 50-10 log wage differentials declined. As shown in Figure 1.4 in Appendix E, during the same time period, the 10th, 50th, and 90th percentiles of the log wage distribution also experienced remarkable wage growth. This suggests that Taiwan was "growing together" during this period. However, the situation reversed dramatically in the subsequent period, 1990-92 to 2000-02. It is observed that there was a divergence in the development of upper-tail and lower-tail inequality—that is, the male 90-50 gap rose while the male 50-10 gap experienced almost no changes. This finding indicates that the expansion of the overall wage gap in the 1990s was due to rising upper-tail inequality.

Figure 1.2 illustrates the changes in the development of the lower and upper ends of the wage distribution in a different manner. It shows the change at each percentile of the log real hourly wage distribution for the three periods by gender. The changes shown are those between 3-year averages. The graphs are smoothed in order to minimize the effect of measurement error and facilitate the visual interpretation.

From 1978-80 to 1990-92, the lower end of the male wage distribution experienced greater wage growth, but the upper end of the male wage distribution had smaller wage growth. This difference in wage growth across the wage distribution led to the decline in male wage inequality. For female workers, the finding is opposite.

The situation reversed dramatically in the subsequent period, 1990-92 to 2000-02. In

this period, we can observe that the lower half of the male wage distribution continued to have a similar degree of wage growth, while the upper half of the male wage distribution experienced higher wage growth—and the higher the percentile, the greater the wage growth. As a result, male upper-tail wage inequality expanded sharply during this period, while lower-tail wage inequality changed little. The lower end of the female wage distribution (below the 20th percentile) had higher wage growth, leading to declining overall and lower-tail wage inequality.

The rise in male overall wage inequality observed in 1990-92 to 2000-02 may be in part due to differences in macroeconomic conditions, since the unemployment rate in 2000-02, 4.2 percent, is greater than the unemployment rate of 1.6 percent in 1990-92.¹⁵ However, the fact that the 50-10 log wage differential did not exhibit much change during this period is somewhat surprising, since recessions are typically believed to have a particularly adverse impact on the bottom end of the distribution of wages (e.g., the 10th percentile). As it turns out, wage inequality does not exhibit much of a cyclical pattern. This can be seen in the case of the 90-50 and 50-10 log wage differentials for both men and women in Figure 1.5 in Appendix E. This suggests that the role of macroeconomic conditions in explaining the key inequality changes documented in this paper is relatively limited.

College-High School Log Wage Gap. Figure 1.1 plots the college/high-school log wage differential for the years 1978 to 2012 by gender. It plots estimated coefficients of a college education dummy. These estimates are obtained by regressing log real hourly wage on a dummy for college education and an unrestricted set of dummies for years of experience. The regression models are estimated separately by gender and year using samples of people with either a high school diploma or a college degree (observations of those with a postcollege degree are also used). Survey sample weights are used in the

¹⁵ There were two recessions in the 2000s. One was in 2001-02 and the other was in 2008-09.

regressions.

For men, the college/high school log wage differential rose by 0.1 over the 35 years and the main increase, about 0.13, occurred between the mid-1990s and the early 2000s. For women, the college wage premium rose slightly over the 35 years. Further, unlike the United States, where the college/high school log wage gap has been trending upward since the 1980s, the gap in Taiwan has actually declined since the early 2000s for both gender groups.

In summary, the data from the MS/MUS reveal several changes in the wage distribution over the 35 years studied. First, for male workers, wage inequality was decreasing between 1978-80 and 1990-92, and this decline in wage inequality occurred evenly across the entire wage distribution. Second, it is found that the decline in male wage inequality was followed by a sharp rise from 1990-92 to 2000-02, and this growth in wage inequality was mainly due to an increase in inequality at the upper tail of the male wage distribution. This rising male upper-tail inequality coincided with an increase in the college/high school wage gap for male workers (see Figure 1.1), suggesting that rising returns to college education may have contributed to the widening of the upper half of the male wage distribution. Finally, for female workers, the patterns of change in wage distribution are less clear, but an impression is that overall and upper-tail inequality rose substantially before the 1990s.

1.3 Empirical Methodology

The data discussed in the previous section reveal different patterns of change in wage distribution in Taiwan over the 35 years studied. They also identify changes in the distribution of skills, in particular for female workers, and a substantial increase in returns to education for male workers. Are the changes in wage inequality explained by changes in workforce composition (i.e., the distribution of skills), or do they reflect

changes in skill prices?

Why is it important to account for compositional changes in the workforce? Lemieux (2006) points out that if within-group wage inequality (i.e., wage inequality among workers with the same characteristics such as education and experience) is higher for more educated and experienced workers and the employment share of these workers also increases over time, these shifts in the workforce (i.e., changes in the distribution of educational attainment or labor market experience of workers in the workforce) will lead to a rise in wage dispersion even if skill prices do not change.¹⁶ In other words, without any underlying change in market prices for skills, changes in the skill composition of the workforce can raise or lower wage inequality simply by altering the employment share of workers with higher or lower within-group wage dispersion.

1.3.1 Hybrid Version of DFL Reweighting Approach

One of the influential decomposition methods in the literature is the reweighting method proposed by DiNardo, Fortin, and Lemieux (1996). The advantage of the DFL reweighting approach is that it provides a simple way to compute composition effects for any distributional statistics. The decomposition can be easily computed by running a single probability model (logit or probit) for group membership and using standard packages to compute distributional statistics with a reweighting factor as weights.

However, one of the limitations of this approach is that it is unable to calculate the contribution of returns to observed skill, because the wage structure effects computed include both returns to observed skills (i.e., regression coefficients on observed skills, such as education and experience) and returns to unobserved skills (or measurement error).¹⁷ Lemieux (2002) suggests a simple approach to extend the DFL reweighting

¹⁶ Lemieux (2006) shows that composition effects play an important role in the rise in residual wage inequality between 1973 and 2003 in the United States.

¹⁷ The wage structure effects are the difference between overall changes and composition

method and in the process overcome the above limitation. The approach suggested by Lemieux (2002) allows one to further decompose changes in wage inequality into three components: composition effects, the role of returns to observed skill and the role of residuals (i.e., returns to unobserved skills and measurement error). For instance, changes in overall wage inequality, the 90-10 wage differential, between times t and s can be decomposed into

$$\underbrace{\Delta_o^{90-10}}_{\text{overall changes in 90-10 wage gap}} = \underbrace{\Delta_x^{90-10}}_{\text{composition effects}} + \underbrace{\overbrace{\Delta_\beta^{90-10}}^{\text{the role of returns to observed skills}} + \overbrace{\Delta_u^{90-10}}^{\text{the role of residuals}}}_{\text{wage structure effects}}. \quad (1.1)$$

However, one of the limitations of the approach suggested by Lemieux (2002) is that the composition effects identified depend on a given model of wages and thus they may be sensitive to the choice of the functional forms of wages. To overcome this issue, I modify Lemieux's (2002) decomposition procedure. To compute the composition effects that do not depend on a given model of wages, I use the DFL reweighting approach in the first step to obtain composition effects semi-parametrically. For instance, the changes in the 90-10 wage gap between times t and s can be decomposed into

$$\underbrace{\Delta_o^{90-10}}_{\text{overall changes in 90-10 wage gap}} = \underbrace{\Delta_x^{90-10}}_{\text{composition effects}} + \underbrace{\Delta_w^{90-10}}_{\text{wage structure effects}}. \quad (1.2)$$

In the second step, I further decompose the wage structure effects into the role of returns to skill and the role of residuals in the spirit of the hybrid DFL reweighting approach. For example, the wage structure effects of changes in the 90-10 wage gap between times t and s can be decomposed into

effects under the DFL approach.

$$\Delta_w^{90-10} = \underbrace{\Delta_\beta^{90-10}}_{\text{the role of returns to observed skills}} + \underbrace{\Delta_u^{90-10}}_{\text{the role of residuals}}. \quad (1.3)$$

A. The DFL Reweighting Approach and Composition Effects

The composition effects contributing to changes in wage inequality can be computed by comparing a reweighted distribution of wages in time s and an actual distribution of wages in time s . For instance, the composition effects of changes in the 90-10 wage differential between times t and s are computed as follows.¹⁸

$$\begin{aligned} \Delta_x^{90-10} &= \underbrace{[Q_{s,9}^{reweighted} - Q_{s,1}^{reweighted}]}_{\text{the 90-10 gap in a reweighted distribution of wages}} - \underbrace{[Q_{s,9} - Q_{s,1}]}_{\text{the 90-10 gap in the actual distribution of wages}} \\ &= \underbrace{[Q_{s,9}^{reweighted} - Q_{s,9}]}_{\text{the composition effect in a decomposition of the 90th percentile}} - \underbrace{[Q_{s,1}^{reweighted} - Q_{s,1}]}_{\text{the composition effect in a decomposition of the 10th percentile}}, \end{aligned} \quad (1.4)$$

where $Q_{s,9}^{reweighted}$ is the 90th percentile of a reweighted (unconditional) distribution of wages in time s and $Q_{s,9}$ is the 90th percentile of a (actual and unconditional) distribution of wages in time s .¹⁹ The reweighted distribution of wages is asking what the distribution of wages in time s would look like if the workers' skill distribution in time s were the same as in time t , holding the conditional distribution of wages in time s fixed. Thus, the difference between $Q_s^{reweighted}$ and Q_s is explained by changes in workers' characteristics (i.e., composition effects).

¹⁸ Autor, Katz, and Kearney (2008) and Dustmann, Ludsteck, and Schonberg (2009) use this aggregate decomposition method (i.e., the DFL reweighting approach) to analyze the role of composition effects and wage structure effects. They apply the DFL reweighting procedure to both actual wages and wage residuals.

¹⁹ Various statistics from the counterfactual distribution of wages, such as the 10th, 50th, and 90th percentile, can be computed using actual wages with the reweighting factor as weights.

Constructing the reweighted distribution of wages in time s simply requires calculating a reweighting factor, $\psi(x)$, defined by DFL.²⁰ The observed (actual) densities of wages y at times t and s are:^{21 22}

$$f_{y_t}(y) = \int f_{y_t|x_t}(y|x) dF_{x_t}(x) \quad (1.5)$$

$$f_{y_s}(y) = \int f_{y_s|x_s}(y|x) dF_{x_s}(x). \quad (1.6)$$

As DFL shows, the reweighted density that would prevail in time s if workers in time s had the observed skill distribution (i.e., the distribution of x) in time t can be written as

$$f_{y_s}^{reweighted}(y) = \int f_{y_s|x_s}(y|x) dF_{x_t}(x). \quad (1.7)$$

By manipulating equation (1.7),

$$f_{y_s}^{reweighted}(y) = \int f_{y_s|x_s}(y|x) \psi(x) dF_{x_s}(x) \quad (1.8)$$

where $\psi(x) = \frac{dF_{x_t}(x)}{dF_{x_s}(x)}$. In practice, the reweighting factor is usually constructed using

a substitution that follows from Bayes' rule:

$$\psi(\mathbf{x}) = \frac{\Pr(D_t = 1 | \mathbf{x}) / \Pr(D_t = 1)}{\Pr(D_t = 0 | \mathbf{x}) / \Pr(D_t = 0)} \quad (1.9)$$

²⁰ Survey sample weights are used throughout the paper.

²¹ For simplicity, the individual subscript is left out in density functions.

²² Throughout the paper, time s refers to beginning years and time t refers to end years for each period. For example, time t stands for 1990-92 and time s stands for 1978-80 for the period 1978-80 to 1990-92.

where the dummy variable, D_t , is equal to one if time = t and zero if time = s ; $\Pr(D_t = 1)$ is the unconditional probability that an observation is in time t (the share of the pooled sample that is in time t); and $\Pr(D_t = 1 | \mathbf{x})$ is the conditional probability that an observation is in time t conditional on observed skills, $\mathbf{x}$.²³ The reweighting factor can be computed by estimating a logit model for $\Pr(D_t = 1 | \mathbf{x})$ applied to the pooled data from times s and t .²⁴ Using the predicted probabilities, $\hat{\Pr}(D_t = 1 | \mathbf{x})$, we then can compute the reweighting factor $\psi(\mathbf{x})$ for each observation in time s . This reweighting procedure follows Firpo et al. (2007) and Fortin et al. (2011).²⁵

The wage structure effects are then computed as the difference between overall changes and composition effects,

$$\Delta_w^{90-10} = \Delta_o^{90-10} - \Delta_x^{90-10}. \quad (1.10)$$

B. The Hybrid DFL Reweighting Approach and Decomposing Wage Structure Effects

To decompose the wage structure effects into the contribution of returns to observed skill and the contribution of unobserved skills (i.e., residuals), we need to model the wage measure.²⁶ Consider a regression model,²⁷

$$y_{is} = \mathbf{x}_{is}\boldsymbol{\beta}_s + u_{is} \quad (1.11)$$

where i indexes the individual and s indexes time s ; y is the wage measure, $\mathbf{x}$ is a $1 \times k$ vector of covariates (i.e., observed skills such as education and experience) with

²³ $\Pr(D_t = 0) = 1 - \Pr(D_t = 1)$ and $\Pr(D_t = 0 | \mathbf{x}) = 1 - \Pr(D_t = 1 | \mathbf{x})$

²⁴ Survey sample weights are used in regressions.

²⁵ In the Fortin et al. (2011) decomposition, for example, workers in 1983-85 (time s) were reweighted to look like workers in 2003-05 (time t).

²⁶ Resorting to a parametric model is necessarily restrictive, but this weakness buys some additional information.

²⁷ Assuming a linear model is necessarily restrictive. However, in practice we would never know what the true model is and the linear model is the leading case in the literature.

$x_{1,is}$ being unity (i.e., a constant), β_s is a $k \times 1$ vector of parameters (i.e., returns to observed skills such as the return to education), and u_{is} is the error term and assumed to have a zero conditional mean.²⁸

Applying least squares regression to equation (1.11), the estimated regression equation is

$$y_{is} = \mathbf{x}_{is}\hat{\beta}_s + \hat{u}_{is}, \quad (1.12)$$

where $\hat{\beta}_s$ is the estimate of β_s , and $\hat{u}_{is}$ is the regression residual in time s .²⁹ Under the assumption made, the estimates represent the effects of explanatory variables on mean wages.³⁰

To measure the role of returns to observed skill, I transform each observation of y_{is} into a counterfactual wage y_{is}^C by replacing $\hat{\beta}_s$ with $\hat{\beta}_t$:

$$y_{is}^C = \mathbf{x}_{is}\hat{\beta}_t + \hat{u}_{is}, \quad (1.13)$$

where $\hat{\beta}_t$ represents estimated returns to observed skill in time t . The counterfactual wage y_{is}^C can now be used to generate a reweighted distribution of the wages that would have prevailed in time s if returns to observed skill were the same as in time t . As before, these counterfactual wages are combined with the reweighting factor $\psi(\mathbf{x})$ to control also for changes in the skill distribution. Accordingly, this reweighted distribution of wages is asking what the distribution of wages in time s would look like if the skill distribution of and returns to skill for workers were the same as in time t .

Utilizing the reweighted distribution of counterfactual wages described above, the

²⁸ The zero conditional mean assumption is restrictive and certainly does not hold in practice. However, since decomposition methods are an accounting exercise, not "causal inference," I follow the decomposition literature and maintain this assumption throughout this paper.

²⁹ The regression equation is estimated separately by year and gender. Survey sample weights are used in regressions.

³⁰ There is no heterogeneity in the effects as well.

wage structure effects can be decomposed into two components: the role of returns to observed skill and the role of residuals. For example, the role of returns to observed skill can be obtained by

$$\Delta_{\beta}^{90-10} = \underbrace{\left[Q_{s,9}^{reweighted, y^c} - Q_{s,9}^{reweighted} \right]}_{\substack{\text{the role of returns to skill} \\ \text{in a decomposition of} \\ \text{the 90th percentile}}} - \underbrace{\left[Q_{s,1}^{reweighted, y^c} - Q_{s,1}^{reweighted} \right]}_{\substack{\text{the role of returns to skill} \\ \text{in a decomposition of} \\ \text{the 10th percentile}}}, \quad (1.14)$$

where $Q_{s,9}^{reweighted, y^c}$ is the 90th percentile of reweighted (unconditional) distribution of counterfactual wages y_{is}^c . In other words, the distributional statistics are computed using reweighted wages y_{is}^c with the reweighting factor $\psi(\mathbf{x})$ as weights. As described above, $Q_s^{reweighted}$ is obtained by using y_{is} with the reweighting factor $\psi(\mathbf{x})$ as weights. Thus, the difference between $Q_s^{reweighted, y^c}$ and $Q_s^{reweighted}$ is explained by changes in returns to skill (i.e., β).

The role of residuals is defined as

$$\Delta_u^{90-10} = \underbrace{\left[Q_{t,9} - Q_{s,9}^{reweighted, y^c} \right]}_{\substack{\text{the role of residuals} \\ \text{in a decomposition of} \\ \text{the 90th percentile}}} - \underbrace{\left[Q_{t,1} - Q_{s,1}^{reweighted, y^c} \right]}_{\substack{\text{the role of residuals} \\ \text{in a decomposition of} \\ \text{the 10th percentile}}}, \quad (1.15)$$

where $Q_{t,9}$ is the 90th percentile of (actual and unconditional) distribution of wages in time t . Since $Q_s^{reweighted, y^c}$ is obtained by using y_{is}^c with the reweighting factor $\psi(\mathbf{x})$ as weights, the difference between Q_t and $Q_s^{reweighted, y^c}$ is explained by changes in residuals (i.e., u).

For example, changes in the 90-10 wage gap between 1990-92 (time s) and 2000-02 (time t) can be decomposed into³¹

$$\begin{aligned}
\Delta_o^{90-10} &= \underbrace{\left[Q_{00/02,.9} - Q_{00/02,.1} \right]}_{\text{90-10 gap in 00/02}} - \underbrace{\left[Q_{90/92,.9} - Q_{90/92,.1} \right]}_{\text{90-10 gap in 90/92}} \\
&= \underbrace{\left[Q_{00/02,.9} - Q_{90/92,.9} \right]}_{\text{wage changes at the 90th percentile}} - \underbrace{\left[Q_{00/02,.1} - Q_{90/92,.1} \right]}_{\text{wage changes at the 10th percentile}} \\
&= \underbrace{\left[Q_{00/02,.9} - Q_{90/92,.9}^{reweighted, y^c} \right]}_{\Delta_u^{90-10}, \text{ the role of residuals}} - \underbrace{\left[Q_{00/02,.1} - Q_{90/92,.1}^{reweighted, y^c} \right]}_{\Delta_\beta^{90-10}, \text{ the role of returns to skill}} \\
&\quad + \underbrace{\left[Q_{90/92,.9}^{reweighted, y^c} - Q_{90/92,.9}^{reweighted} \right]}_{\Delta_x^{90-10}, \text{ composition effects}} - \underbrace{\left[Q_{90/92,.1}^{reweighted, y^c} - Q_{90/92,.1}^{reweighted} \right]}_{\Delta_x^{90-10}, \text{ composition effects}}
\end{aligned}$$

1.3.2 Estimation

The same set of covariates is used to estimate the wage equation and the logit model used to construct the reweighting factor.³³ These covariates include four education dummies and six potential experience dummies.^{34,35} I decompose the changes in wage inequality during three periods: 1978-80 to 1990-92, 1990-92 to 2000-02, and 2000-02 to 2010-12. The beginning and end years of each period include observations from three years. For

³¹ The same decomposition procedure can be implemented for the 90-50 and 50-10 wage differentials.

³³ The regression equations are estimated separately by year and gender using WLS with the survey sample weight. I also weight the observations with the survey sample weight when estimating the logit model.

³⁴ Tables 1.3 and 1.4 in Appendix F give the details of the education and experience categories used. High school and 20 to 24 years of experience are the omitted categories.

³⁵ Following Lemieux (2006), I only use education and experience as a proxy for observed skills. This specification allows me to focus on measures of skills, which are arguably "pure."

instance, for the first period 1978-80 to 1990-92, years 1978 to 1980 are pooled for the beginning years (i.e., time s mentioned above) and years 1990 to 1992 are pooled for the end years (i.e., time t). Pooled observations are employed to improve precision, as the sample size in each year is relatively small. Standard errors are bootstrap estimates, and bootstrap samples are taken independently within each town in each year.

1.4 Decomposition Results

1.4.1 Composition and Wage Structure Effects

Tables 1.1 and 1.2 report the hybrid DFL reweighting decomposition results for men and women, respectively. Panel A of each table provides the decomposition results obtained with the DFL reweighting approach. Overall changes in wage inequality are decomposed into composition and wage structure effects. Panel B of each table presents the decomposition results of wage structure effects. In Panel B, wage structure effects are decomposed into the role of returns to (observed) skill and the role of residuals using the WLS coefficient estimates of returns to skill. Further, Tables 1.1 and 1.2 report the decomposition results for men and women, respectively; each table presents the decomposition results for changes in wage inequality for each of the three periods mentioned above. The 90-10 log wage differential is used as a measure of overall wage inequality; the 90-50 and 50-10 log wage differentials are used as measures of upper-tail and lower-tail wage inequality, respectively.

Starting with the DFL decomposition results in the first period, 1978-80 to 1990-92, the first three columns of Table 1.1 show that, consistently with the changes observed in Figures 1.1 and 1.2, male overall wage inequality (the 90-10 gap) declined by about 0.14. This decline is due to evenly declining inequality at both the upper and lower ends of the male wage distribution. The 90-50 and 50-10 log wage differentials declined by about 0.07, respectively. All changes in inequality are statistically significant. The

decomposition results indicate that the decrease in the 90-50 gap is entirely attributable to wage structure effects, which account for more than 100% of the net decline, since composition effects are negligible and go in the opposite direction. For the 50-10 gap, both composition and wage structure effects contribute to the decline and they are equally important in explaining the decrease in inequality.

By contrast, the first three columns of Table 1.2 show that female overall wage inequality increased by about 0.08. This increase is due to rising upper-tail inequality.³⁶ The decomposition results indicate that the increase in overall and upper-tail inequality is entirely attributable to composition effects, since wage structure effects go in the opposite direction or are insignificant.

The middle three columns of Table 1.1 present the results for men for 1990-92 to 2000-02. In contrast to the decline in wage inequality in the previous period, the 90-10 gap in this period increased by about 0.09. Although upper-tail and lower-tail inequality experienced similar decline from 1978-80 to 1990-92, the changes in upper-tail and lower-tail inequality diverged in the period 1990-92 to 2000-02. While there is no significant change in the 50-10 gap, the 90-50 gap increased sharply, by about 0.09, and this increase accounts for all of the increase in the overall inequality. The decomposition results indicate that wage structure effects (0.084 with s.e.=0.009) account for over 90% of the increase in the 90-50 gap. For women, the middle three columns of Table 1.2 show that during the same period, female overall wage inequality declined, and this decline is due to the compression in the lower end of the female wage distribution, which is attributable to wage structure effects.

The last three columns of Table 1.1 show that for the final period, male overall wage inequality declined slightly between 2000-02 and 2010-12. This moderate decline is attributable to the declining 50-10 gap, which is entirely due to wage structure effects.

³⁶ Changes in the 50-10 log wage differential are negligible and insignificant.

There is no significant change in the 90-50 gap during this period since positive composition effects are offset by negative wage structure effects. Similarly, female overall wage inequality declined during this period, and this moderate decline is attributable to declining upper-tail and lower-tail inequality, which is entirely due to wage structure effects.

1.4.2 The Role of Returns to Skill and the Role of Residuals

The DFL decomposition results discussed above suggest that most of the observed changes in the 90-10 and 90-50 wage differentials for male workers before the 2000s are attributable to wage structure effects. However, the wage structure effects computed using the DFL reweighting approach express the difference between total changes and composition effects, and thereby include not only the contribution of returns to skill but also the contribution of residuals. Utilizing the hybrid version of the DFL reweighting approach, I separate the role of returns to skill from wage structure effects. The results are presented in Panel B of Table 1.1.³⁷

Panel B in Table 1.1 shows that the residuals obtained with the WLS estimates account for about 68% $(-0.047/-0.069)$ of wage structure effects for the male 90-50 gap in 1978-80 to 1990-92. Therefore, they constitute the most important component in explaining the declining 90-50 wage differential. In the second period, 1990-92 to 2000-02, the decomposition results show that residuals and returns to skill are equally important in explaining the rising male 90-50 wage gap and returns to skill account for

³⁷ The picture of changes in wage inequality is less clear for female workers, but an impression is that there is a substantial rise in female overall wage inequality in the 1980s and the rise is entirely due to the rising upper-tail inequality that is attributable to composition effects. Therefore, in this section I focus on the decomposition of wage structure effects for male workers. The decomposition results for female workers can be found in Panel B of Table 1.2. One thing worth noting is that returns to observed skill also contribute to the rising female 90-50 wage gap in a nontrivial way in the 1980s (see Panel B in Table 1.2), but are offset by the residuals.

about half of the rising male upper-tail inequality.

In summary, the decomposition results show that for male workers the decline in wage inequality between 1978-80 and 1990-92 is accounted for by wage structure effects, in particular for overall and upper-tail inequality. The role of residuals constitutes the most important component in explaining the declining 90-50 wage differential. This decline is followed by a rise in the subsequent period, 1990-92 to 2000-02. This rising male wage inequality is entirely due to the widening upper end of the wage distribution, which is attributable to wage structure effects. Returns to skill explain about half of the rise in the male 90-50 log wage differential in the 1990s. For female workers, the picture of changes in wage inequality is less clear, but an impression is that there is a substantial rise in female overall wage inequality in the 1980s and that this rise is entirely due to rising upper-tail inequality, which is mostly attributable to composition effects.

1.5 Conclusion

This paper documents several changes in the distribution of wages in Taiwan from 1978 to 2012. The data reveal that for male workers, the wage distribution was narrowing before the 1990s, and the decline in wage inequality occurred evenly across the entire wage distribution. The decline, however, was followed by a rise during the 1990s, and the increase in overall wage inequality was mainly due to the widening of the upper half of the male wage distribution. It is also observed that around the same time there was an increase in the college wage premium for male workers. The picture of trends in female wage inequality is less clear, but an impression is that there was a substantial increase in overall wage inequality, which was driven by the rising upper-tail inequality before the 1990s.

The decomposition results show that for male workers, returns to (observed) skill

play an important role in explaining the rise in the upper-tail wage inequality during the 1990s. They explain about half of the increase in the 90-50 log wage differential for male workers during the 1990s. As a substantial increase in returns to college education for male workers is observed during the same time period, the decomposition results suggest that returns to college education play an important role in explaining the rising male upper-tail inequality.

Together with the fact that the skill of the workforce increased in the 1990s, the rising returns to skill suggest that the shifts in labor market demand must have outpaced the shifts in supply. What caused the increase in the relative demand for more skilled workers between 1990-92 and 2000-02? While more research is needed on this issue, the timing implies that it may have been the consequence of growth in the information and communication technology (ICT) industry, which created demand for engineers (skilled workers).

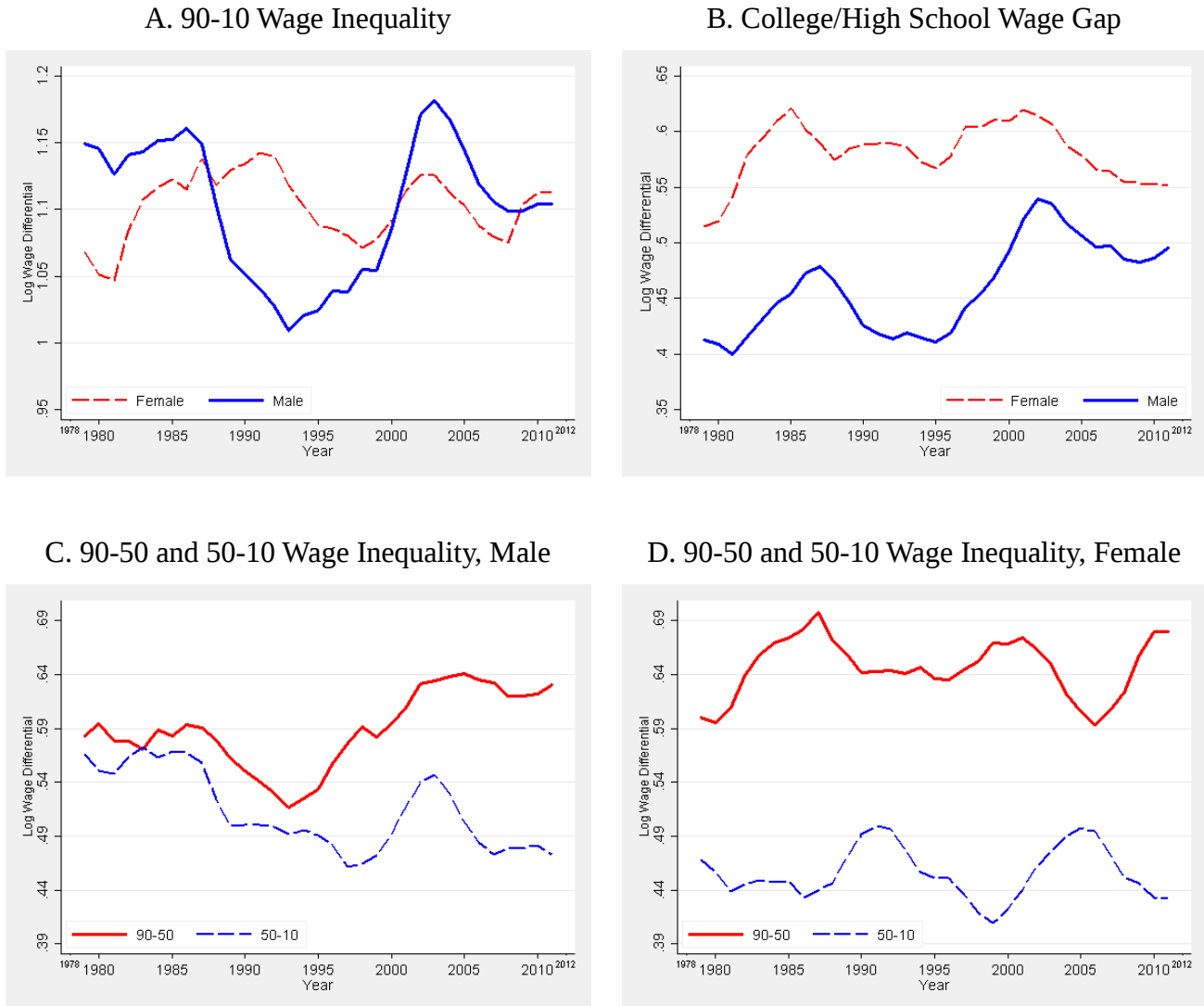
For female workers, the decomposition results show that positive composition effects (i.e., changes in the skill composition of the workforce) play an important role in explaining the rise in inequality at the upper-tail of the female wage distribution before the 1990s.

It is well known that decomposition is useful for quantifying the contribution of various factors to changes in wage inequality, but it may not necessarily pin down the mechanism that explains the relationship between the factors and changes in wage inequality. For instance, even if decomposition results suggest that changes in returns to observable skill account for a large fraction of the change in wage inequality, we still have no information about what force is driving the changes in returns to observable skill. That being said, quantifying the importance of factors provides useful indications of particular explanations to be pursued in more detail.

APPENDICES

APPENDIX A - FIGURES

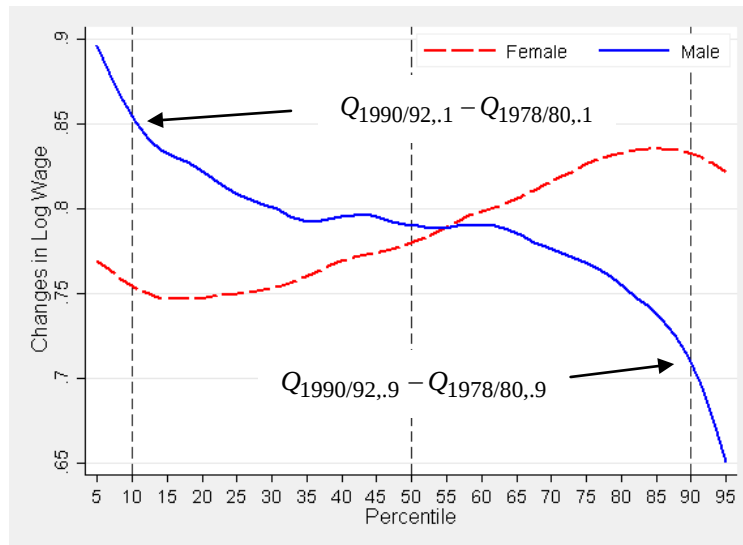
Figure 1.1 Changes in Wage Inequality



Notes: For the college/high school wage gap, the figure plots estimated coefficients of a college education dummy. These estimates are obtained from regressing log real hourly wage on a dummy for college education and an unrestricted set of dummies for years of experience. The regression models are estimated separately by gender and year using samples of people with either a high school diploma or a college degree (observations with a postcollege degree are also used). Survey sample weights are used in the regressions.

Figure 1.2 Changes in Log Wage by Percentile

A. 1978/80 to 1990/92



B. 1990/92 to 2000/02

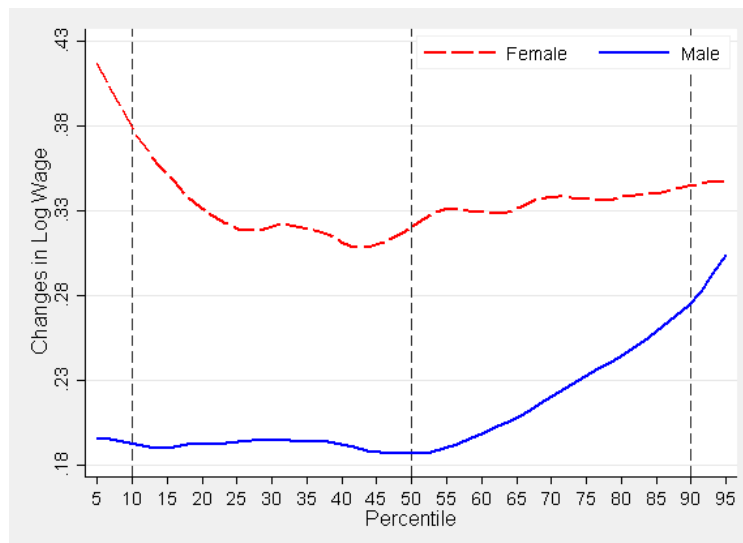
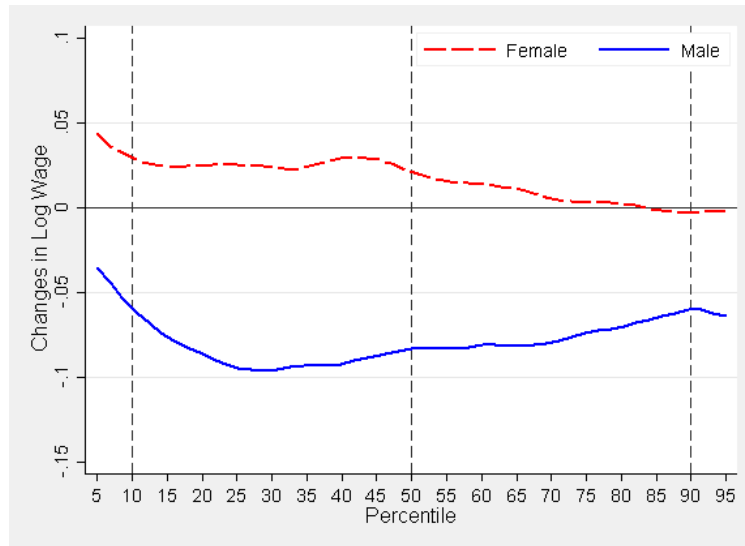


Figure 1.2 (cont'd)

C. 2000/02 to 2010/12



Notes: $Q_{1990/92,.1} - Q_{1978/80,.1}$ indicates wage changes at the 10th percentile between 1978-80 and 1990-92. Changes in the 90-10 log wage differential between 1978-80 and 1990-92 can be calculated as follows:

$$\Delta_o^{90-10} = (Q_{1990/92,.9} - Q_{1978/80,.9}) - (Q_{1990/92,.1} - Q_{1978/80,.1})$$

.

APPENDIX B - TABLES

Table 1.1 The Hybrid DFL Decomposition Results for Log Wages, Men

Inequality Measure:	1978/80 - 1990/92			1990/92 - 2000/02			2000/02 - 2010/12		
	90-10	90-50	50-10	90-10	90-50	50-10	90-10	90-50	50-10
A. DFL Decomposition									
Total Change	-0.136 (0.012)	-0.068 (0.010)	-0.068 (0.007)	0.092 (0.010)	0.092 (0.008)	0.000 (0.006)	-0.023 (0.011)	0.005 (0.007)	-0.028 (0.008)
Composition	-0.033 (0.011)	0.002 (0.009)	-0.034 (0.009)	0.029 (0.009)	0.008 (0.006)	0.021 (0.007)	0.077 (0.008)	0.063 (0.009)	0.014 (0.009)
Wage Structure	-0.104 (0.015)	-0.069 (0.013)	-0.034 (0.008)	0.063 (0.013)	0.084 (0.009)	-0.021 (0.010)	-0.100 (0.009)	-0.058 (0.008)	-0.042 (0.010)
B. Decomposition of Wage Structure									
Return to Skill (reg. coef.)	-0.062 (0.011)	-0.023 (0.008)	-0.040 (0.007)	0.040 (0.009)	0.043 (0.006)	-0.003 (0.006)	0.012 (0.012)	-0.016 (0.011)	0.028 (0.009)
Residual	-0.041 (0.009)	-0.047 (0.008)	0.005 (0.005)	0.023 (0.011)	0.041 (0.008)	-0.019 (0.008)	-0.112 (0.011)	-0.042 (0.010)	-0.070 (0.007)

Notes: Bootstrapped standard errors are in parentheses.

Table 1.2 The Hybrid DFL Decomposition Results for Log Wages, Women

Inequality Measure:	1978/80 - 1990/92			1990/92 - 2000/02			2000/02 - 2010/12		
	90-10	90-50	50-10	90-10	90-50	50-10	90-10	90-50	50-10
A. DFL Decomposition									
Total Change	0.084 (0.013)	0.088 (0.010)	-0.004 (0.010)	-0.032 (0.011)	0.017 (0.008)	-0.049 (0.008)	-0.035 (0.011)	-0.015 (0.008)	-0.019 (0.008)
Composition	0.123 (0.015)	0.077 (0.014)	0.046 (0.010)	0.116 (0.011)	0.030 (0.010)	0.086 (0.005)	0.165 (0.011)	0.015 (0.010)	0.151 (0.005)
Wage Structure	-0.039 (0.018)	0.011 (0.016)	-0.050 (0.010)	-0.148 (0.012)	-0.012 (0.010)	-0.136 (0.008)	-0.200 (0.012)	-0.030 (0.010)	-0.170 (0.008)
B. Decomposition of Wage Structure									
Returns to Skill (reg. coef.)	0.031 (0.014)	0.042 (0.014)	-0.012 (0.007)	0.015 (0.011)	0.026 (0.010)	-0.011 (0.006)	-0.067 (0.011)	-0.022 (0.010)	-0.045 (0.006)
Residual	-0.070 (0.014)	-0.031 (0.015)	-0.039 (0.008)	-0.163 (0.012)	-0.038 (0.011)	-0.125 (0.009)	-0.133 (0.012)	-0.008 (0.011)	-0.125 (0.009)

Notes: Bootstrapped standard errors are in parentheses.

APPENDIX C - THE MS/MUS DATA, 1978-2012

C1. Measurement Issues and Variable Description

Earnings

In the MUS, monthly earnings were censored at NT\$99,999 from 1978 to 1990, and at NT\$999,999 from 1991 to 2012. Further, the data also have a missing data problem. For some reason, certain workers refuse to answer the earnings questions in the MUS. Only a handful of workers, however, have top-coded or missing monthly earnings throughout the sample period. The DGBAS does not impute earnings for the non-respondents based on the response for a sample person with similar demographic characteristics. Instead, 0 is imputed as the earnings for the non-respondents.

The earnings measure comes from the following question in the MUS:

"How much are your monthly earnings at your main job (excluding the earnings at the secondary job)?"

According to the Report on the Manpower Utilization Survey (May, 2012), the term "earnings" indicates the profits earned through industrial or commercial activities, net income of farm workers, and employees' *regular* earnings such as salary, bonus, commission, overtime pay, tips, etc. *Irregular* pay such as maternity compensation or children's education subsidies is excluded.

Once again according to the Report on the Manpower Utilization Survey (May, 2012), the timing of the monthly earnings is defined as follows. First, workers with stable monthly earnings report their last month's earnings. Since the MUS is conducted in the week right after the reference week covering May 15th, the last month's earnings indicate the monthly earnings in April. Second, workers who were newly hired or just transferred to their current job in May report the estimate of their earnings based on the negotiation with employers. Finally, workers whose monthly earnings are unstable or seasonally fluctuating report their average monthly earnings. The reported monthly earnings can be

viewed as a point-in-time measure of earnings for the first two types of workers.

Hours of work

The measure of hours of work comes from the question in the MS that asks how many hours a worker worked last week (the reference week). The survey also asks workers to report hours of work for their main job and secondary job separately. Hours worked last week at a main job are used as the hours of work measure. Similarly to earnings, hours of work also have a missing data problem. That is, for some reason, certain workers do not report hours worked last week.

The estimated hourly wage

To construct hourly wage measures, I first convert the monthly earnings to an estimated weekly earnings by dividing by 4.29 ($\approx 30/7$) and then convert the weekly earnings to an estimated hourly wage by dividing by hours worked last week at a main job. Since both hours and earnings measures used are for main jobs, the estimated hourly wage is the wage for a main job. Hourly wages are deflated by Consumer Price Indices (base year = 2011). Wage measures used for all analyses are log real hourly wages.

Educational attainment

The survey reports each individual's highest educational qualification but not years of schooling. Furthermore, before 2007 it did not ask whether a worker graduated. It is therefore possible that the worker may either be in school, a dropout, or a graduate. To check if there is a large discrepancy between reported highest educational qualification and actual educational attainment, I use the data from 2007-2012 surveys to calculate the graduation rate, the dropout rate, and the in-school rate.¹ For the whole sample (all individuals in the data sets), the graduation, dropout, and in-school rates are about 82%, 5%, and 13% each year, respectively. The in-school rate seems nontrivial. However,

¹ Starting in 2007, the MS provides information on whether an individual is either in school, a dropout, a graduate, or not schooled. In-school rates, dropout rates, and graduation rates are calculated by dividing by the sum of dropouts, graduates, and those in-school.

when the data are limited to workers (i.e., those with jobs), the in-school rate declines substantially from 13% to 2%, and the graduation rate increases from 82% to 95%. Since the latter sample is of interest and the graduation rate is high in this sample, using the reported highest educational qualification as a proxy for the actual educational attainment (and skill) is not likely to be a severe issue.²

Weighting

For the sake of national representativeness, all the analyses use the provided sampling weights. Several papers, like DiNardo et al. (1996), Lemieux (2006), and Autor, Katz and Kearney (2008), also weight the observations by weekly hours of work. However, that type of weighting is not suitable for this paper since the conceptual object of interest for this paper is the distribution of wages that workers' skills command in the labor market. Therefore, following Acemoglu and Autor (2011), I only use the provided sampling weights to calculate statistics.

C2. Sample Selection Criteria

All samples include individuals between the ages of 15 and 64 with positive earnings and potential experience.³ Female and male workers (all the analyses are done separately by gender) and full- and part-time workers are included in the samples. Following the literature, all samples use wage and salary workers.⁴

² Since the ratios in 2007-2012 are quite constant over this sample period, it would be reasonable to assume that the graduation rate is also high before 2007.

³ Potential experience is defined as age minus 6 minus the years of schooling.

⁴ I exclude one observation that reports an unreasonable number of hours of weekly work. The observation reported 500 hours for hours worked last week, which is greater than the total number of hours in a week, 168 (=24*7), and clearly misreported.

APPENDIX D - IMPUTATION

D1. Imputation of Earnings

As discussed in Appendix C, some workers' earnings are either top-coded or missing. I impute the earnings by several imputation methods. Since most of the imputation methods assume normality, I model the log of (nominal) monthly earnings so that normality is more closely approximated. For each imputation method, log earnings regression models are estimated separately by year and gender. Each regression model includes a set of dummies for age, education, industry, and occupation.¹

The first imputation method, labeled "linear," is the normal linear regression imputation method. The second method, labeled "pmm," is the predictive mean matching imputation method. The third method, labeled "cnreg_1," is the censored normal regression imputation method. The final method, labeled "cnreg_2," imputes log earnings in a manner similar to "cnreg_1," but the log earnings regression models are further estimated separately for four education groups: primary, high school, junior college, and college or above.² The first and second methods only deal with missing earnings while the other methods deal with both top-coded and missing earnings. Except for the second method, the imputation methods all assume normality, and the imputed log earnings are simulated from the normal distribution.

¹ An unrestricted set of age dummies is included. The category of education varies by year due to the change in the survey design, so the dummies for these variables also vary by year. For instance, between 1978 and 1987, there are 8 education categories, while between 1995 and 2012 there are 10 categories. 12 categories for industry and 10 categories for occupation are used.

² "Primary" denotes 0 to 9 years of schooling, "high school" denotes 12 years of schooling, "junior college" denotes 14 years of schooling, and "college or above" denotes 16 or more years of schooling.

D2. Imputation of Hours of Work

As discussed in Appendix C, some workers' hours of work are missing. I impute the hours by using the normal linear regression imputation method. To ensure that normality is more closely approximated, I model the log of hours of work. Regression models are estimated separately by year, gender, and class of work. Each regression model uses the same set of explanatory variables as in the log earnings regression models described above.

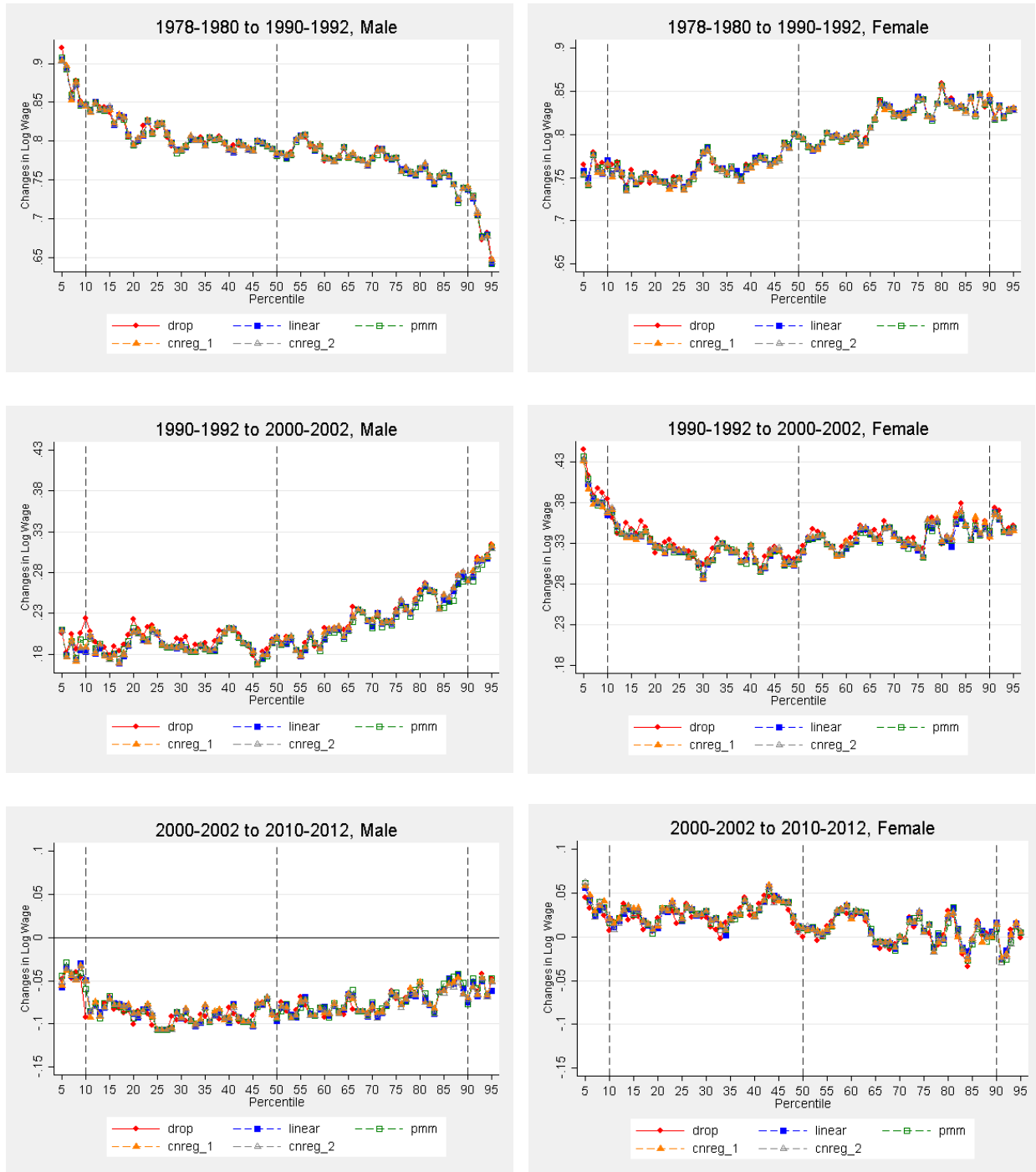
D3. Comparing Wage Inequality for Different Imputation Methods

After imputing the log monthly earnings and log hours of work, I construct log real hourly wage using the similar procedure described in Appendix C. In addition to the log real hourly wages calculated based on the imputed earnings and hours, I also construct another hourly wage measure using the raw data without imputed earnings and hours of work. This unadjusted log real hourly wage is labeled "drop."

This section compares changes in wage inequality for the different imputation methods. These changes are calculated using the selected sample.³ Figure 1.3 illustrates the changes in the wage distribution. It shows the change at each percentile of the log real hourly wage distribution for the three periods by gender. As shown in Figure 1.3, the change in the wage distribution is very similar (or almost identical) in terms of its trends and levels across alternative imputation methods. The results are not surprising, as the top-coding and missing data problems are not severe in the MS/MUS data.

³ The sample selection criteria can be found in Appendix C.

Figure 1.3 Changes in Log Wage by Percentile

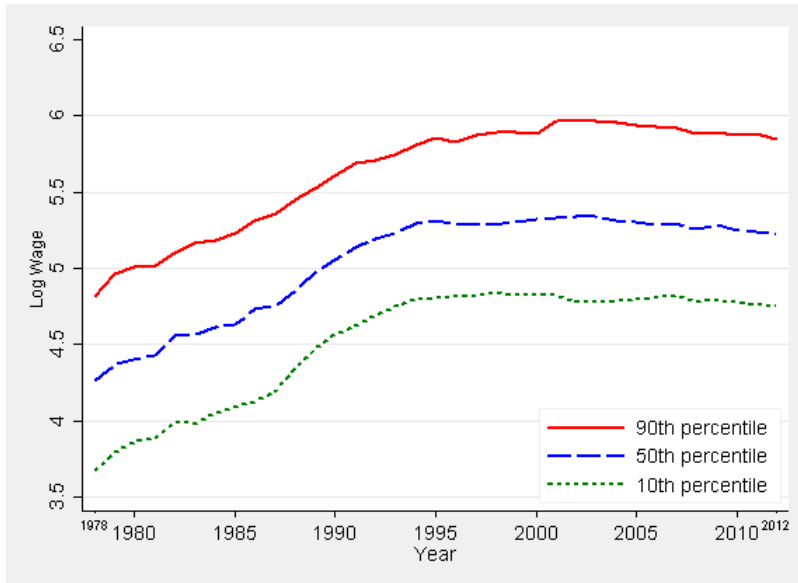


Note: The changes are between 3-year averages.

APPENDIX E - ADDITIONAL FIGURES

Figure 1.4 Evolution of Log Wage

A. Men



B. Women

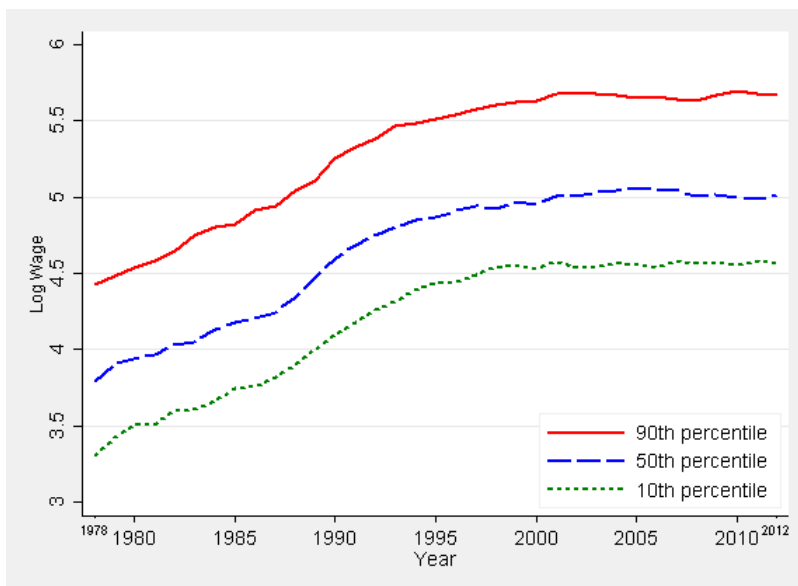
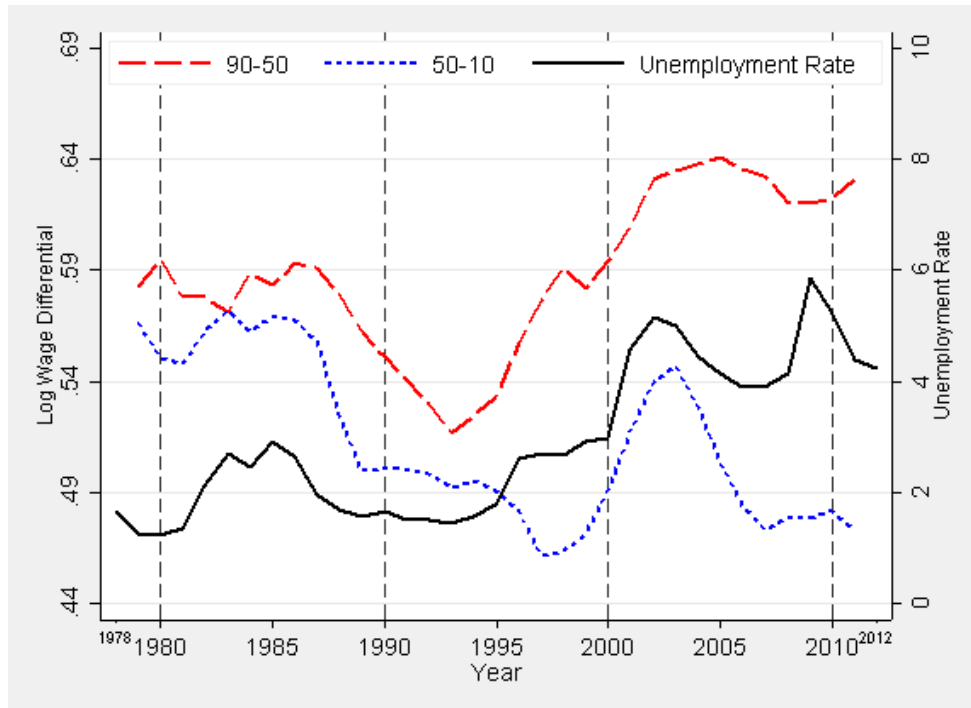
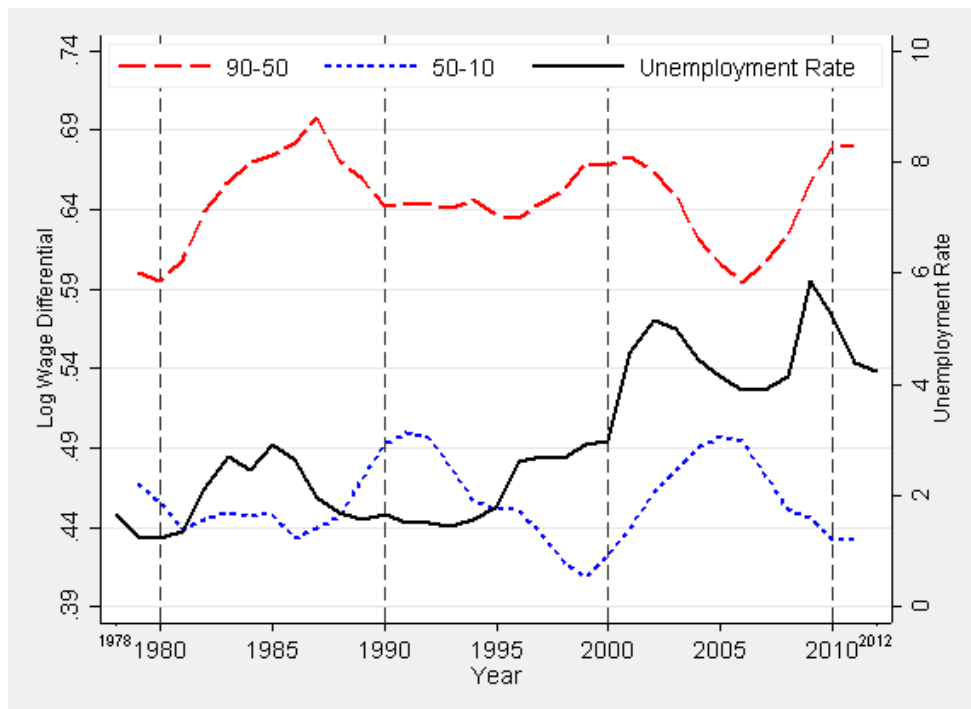


Figure 1.5 Cyclicality in Measures of Wage Dispersion: 1978-2012

A. Men



B. Women



APPENDIX F - ADDITIONAL TABLES

Table 1.3 Descriptive Statistics, Men

	1978/80		1990/92		Difference in	2000/02		Difference in	2010/12		Difference in
	Means	Standard Deviation	Means	Standard Deviation	Means (90/92 - 78/80)	Means	Standard Deviation	Means (00/02 - 90/92)	Means	Standard Deviation	Means (10/12 - 00/02)
Log Hourly Real Wages	4.354	0.527	5.142	0.456	0.788	5.361	0.472	0.220	5.289	0.464	-0.072
Education											
Primary	0.648	0.477	0.473	0.499	-0.175	0.318	0.466	-0.155	0.203	0.402	-0.115
High School	0.208	0.406	0.313	0.464	0.105	0.356	0.479	0.043	0.341	0.474	-0.015
Junior College	0.067	0.250	0.116	0.320	0.049	0.177	0.382	0.061	0.179	0.383	0.002
College or Above	0.076	0.265	0.098	0.297	0.021	0.149	0.356	0.052	0.277	0.448	0.128
Potential Experience											
<10	0.266	0.442	0.224	0.417	-0.042	0.218	0.413	-0.006	0.197	0.398	-0.020
10-14	0.152	0.359	0.184	0.388	0.032	0.158	0.365	-0.026	0.147	0.354	-0.011
14-19	0.124	0.329	0.160	0.367	0.037	0.155	0.362	-0.006	0.142	0.349	-0.013
20-24	0.093	0.291	0.118	0.323	0.025	0.145	0.352	0.027	0.133	0.340	-0.012
25-29	0.084	0.278	0.100	0.300	0.016	0.124	0.330	0.024	0.123	0.328	-0.001
30+	0.280	0.449	0.214	0.410	-0.067	0.200	0.400	-0.013	0.257	0.437	0.056
Age	35.145	12.306	36.169	10.795	1.024	37.399	10.111	1.230	39.860	10.486	2.460
Years of Education	8.826	3.889	10.382	3.506	1.556	11.703	3.148	1.321	12.860	3.049	1.156
Years of Potential Experience	20.319	13.411	19.787	12.186	-0.532	19.696	11.245	-0.090	21.000	11.749	1.304
No. of Observations	34919		40917			43859			40874		

Note: Statistics are weighted by sample weights.

Table 1.4 Descriptive Statistics, Women

	1978/80		1990/92		Difference in Means (90/92 - 78/80)	2000/02		Difference in Means (00/02 - 90/92)	2010/12		Difference in Means (10/12 - 00/02)
	Means	Standard Deviation	Means	Standard Deviation		Means	Standard Deviation		Means	Standard Deviation	
Log Hourly Real Wages	3.913	0.466	4.699	0.485	0.786	5.043	0.470	0.344	5.065	0.444	0.022
Education											
Primary	0.636	0.481	0.426	0.495	-0.210	0.245	0.430	-0.181	0.129	0.335	-0.116
High School	0.247	0.431	0.372	0.483	0.125	0.397	0.489	0.025	0.336	0.473	-0.060
Junior College	0.064	0.245	0.120	0.324	0.056	0.206	0.405	0.087	0.200	0.400	-0.006
College or Above	0.053	0.224	0.082	0.275	0.029	0.152	0.359	0.070	0.335	0.472	0.183
Potential Experience											
<10	0.577	0.494	0.406	0.491	-0.171	0.343	0.475	-0.064	0.278	0.448	-0.065
10-14	0.119	0.324	0.155	0.362	0.036	0.155	0.362	0.000	0.161	0.367	0.006
14-19	0.068	0.251	0.122	0.328	0.055	0.135	0.341	0.012	0.143	0.350	0.008
20-24	0.053	0.223	0.099	0.299	0.047	0.118	0.323	0.019	0.127	0.333	0.009
25-29	0.050	0.218	0.082	0.274	0.032	0.102	0.302	0.020	0.107	0.309	0.006
30+	0.134	0.340	0.135	0.342	0.001	0.148	0.355	0.013	0.184	0.388	0.036
Age	27.312	10.267	31.809	9.839	4.497	34.441	9.782	2.632	37.479	10.055	3.038
Years of Education	8.553	4.098	10.312	3.713	1.759	11.904	3.175	1.592	13.311	2.875	1.407
Years of Potential Experience	12.760	12.157	15.497	11.949	2.737	16.537	11.425	1.040	18.168	11.442	1.631
No. of Observations	17448		24659			28760			30544		

Note: Statistics are weighted by sample weights.

BIBLIOGRAPHY

BIBLIOGRAPHY

- Acemoglu, Daron. 2002. "Technical Change, Inequality and the Labor Market." *Journal of Economic Literature*, 40(1): 7–72.
- Acemoglu, Daron, and David H. Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, vol.4B, Orley Ashenfelter and David Card, eds. (Amsterdam: Elsevier-North Holland).
- Autor, David H., Lawrence F. Katz, and Alan B. Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics*, 113(4): 1169–1213.
- Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in U.S. Wage Inequality: Reassessing the Revisionists." *Review of Economics and Statistics*, 90(2): 300–323.
- Boudarbat, Brahim, Thomas Lemieux, and Craig W. Riddell. 2006. "Recent Trends in Wage Inequality and the Wage Structure in Canada." In *Dimensions of Inequality in Canada*, David A. Green and Jonathan R. Kesselman, eds. (Vancouver, BC: UBC Press).
- Bound, John, and George Johnson. 1992. "Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations." *American Economic Review*, 82(3): 371–392.
- Card, David, and John E. DiNardo. 2002. "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles." *Journal of Labor Economics*, 20(4): 733–783.
- Card, David, and Thomas Lemieux. 2001. "Can Falling Supply Explain the Rising Return to College for Young Men?" *Quarterly Journal of Economics*, 116(2): 705–746.
- Chen, Lii-Tarn. 2002. "The Impact of Minimum Wages on the Change in Wage Structure - Evidence from Taiwan's Data." *Taiwan Economic Review*, 30(3): 383–420. (In Chinese) doi:10.6277/ter.2002.303.5
- Chen, Uniko. 2013. "The Impact of the Expansion in Post-Secondary Education on the University Wage Premium in Taiwan." Unpublished manuscript, Department of Economics, University of Michigan, Ann Arbor.
- DiNardo, John E., Nicole Fortin, and Thomas Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." *Econometrica*, 64(5): 1001–1004.
- Dustmann, Christian, Johannes Ludsteck, and Uta Schonberg. 2009. "Revisiting the German Wage Structure." *Quarterly Journal of Economics*, 124(2): 843–881.
- Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux. 2007. "Decomposing Wage Distribution using Recentered Influence Functions Regressions." Mimeo, University of British Columbia.
- Fortin, Nicole, Thomas Lemieux, and Sergio Firpo. 2011. "Decomposition Methods in

- Economics." *Handbook of Labor Economics*, vol.4A: 1–102.
- Gindling, Thomas H., and Way Sun. 2002. "Higher Education Planning and the Wages of Workers with Higher Education in Taiwan." *Economics of Education Review*, 21(2): 153–169.
- Goldin, Claudia, and Lawrence F. Katz. 2007. "Long-Run Changes in the Wage Structure: Narrowing, Widening, Polarizing." *Brookings Papers on Economic Activity*, 2007(2): 135–165.
- Gosling, Amanda, Stephen Machin, and Costas Meghir. 2000. "The Changing Distribution of Male Wages, 1966-1992." *Review of Economic Studies*, 67(4): 635–666.
- Huang, Fung-Mey. 2011. "Human Capital and Wage Dynamics: Evidence from Taiwan." *Taiwan Economic Forecast and Policy*, 42(1): 1–37. (In Chinese) <http://econ.sinica.edu.tw>
- Juhn, Chinhui, Kevin M. Murphy, and Brooks Pierce. 1993. "Wage Inequality and the Rise in Returns to Skill." *Journal of Political Economy*, 101(3): 410–441.
- Katz, Lawrence F., and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." *Quarterly Journal of Economics*, 107(1): 35–78.
- Lee, David S. 1999. "Wage Inequality in the United States in the 1980s: Rising Dispersion or Falling Minimum Wage?" *Quarterly Journal of Economics*, 114(3): 977–1023.
- Lemieux, Thomas. 2002. "Decomposing Changes in Wage Distributions: A Unified Approach." *The Canadian Journal of Economics*, 35(4): 646–688.
- Lemieux, Thomas. 2006. "Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill?" *American Economic Review*, 96(3): 461–498.
- Lemieux, Thomas. 2008. "The Changing Nature of Wage Inequality." *Journal of Population Economics*, 21(1): 21–48.
- Levy, Frank, and Richard J. Murnane. 1992. "U.S. Earnings Levels and Earnings Inequality: A Review of Recent Trends and Proposed Explanations." *Journal of Economic Literature*, 30(3): 1333–1381.
- Lin, Chun-Hung A., and Peter F. Orazem. 2003. "Wage Inequality and Returns to Skill in Taiwan, 1978-96." *The Journal of Development Studies*, 39(5): 89–108.
- Murphy, Kevin M., and Finis Welch. 1992. "The Structure of Wages." *Quarterly Journal of Economics*, 107(1): 285–326.
- Solon, Gary, Robert Barsky, and Jonathan A. Parker. 1994. "Measuring the Cyclicity of Real Wages: How Important Is Composition Bias?" *Quarterly Journal of Economics*, 109(1): 1–25.
- Vere, James P. 2005. "Education, Development, and Wage Inequality: The Case of Taiwan." *Economic Development and Cultural Change*, 53(3): 711–735.

CHAPTER 2

BIRTH ORDER AND EDUCATIONAL ATTAINMENT: EVIDENCE FROM TAIWAN

2.1 Introduction

The ways in which the family environment affects child outcomes have long fascinated researchers. A number of arguments suggest that siblings are likely to receive unequal shares of educational resources allocated by their parents, and birth order is one important dimension of sibling composition that could play a critical role in determining within-family resource allocation.¹

Various hypotheses in the literature outline potential reasons for why children's educational attainment varies by birth order; however, the relationship predicted by these hypotheses between the two variables is ambiguous. Those predicting that educational attainment decreases as birth order increases are based on the assumptions of: fixed parental time endowment and a greater share of time endowment received by children of a lower birth order, mothers are older when they give birth to children of a higher birth order, and older mothers are more likely to have children with a lower birth weight.² Meanwhile, the hypotheses predicting that educational attainment increases with birth order are based on the assumptions of: younger siblings benefit from the increase in family income over the life cycle, and the earlier entry of older siblings into the labor

¹ Another focus has been on understanding differences between families, and family size is one of the factors believed to determine inter-family differences. The economics of the family suggests that there is a negative correlation between family size and children's education (Becker and Lewis 1973; Becker and Tomes 1976), and extensive empirical literature has attempted to identify the causal effect of family size and examine whether a quantity–quality trade-off exists (Angrist et al. 2010; Black et al. 2005; Lee 2008; Li et al. 2008; Maralani 2008; Rosenzweig and Wolpin 1980; Rosenzweig and Zhang 2009).

² If differences in parental time endowment and birth weight lead to differences in ability and thereby the return to education, parents will invest differentially in their children's education.

market increases the resources available for the younger ones. The empirical findings on the relationship in the literature are mixed: studies using data from high-income countries find that later-born children fare worse, whereas those using data from middle- and low-income countries find that they fare better.³

This discrepancy found between developed and developing countries suggests that birth order patterns may vary by place and/or stages of development. However, it might also result from the difference in empirical methodologies employed. One of the most influential recent birth order studies by Black et al. (2005) aims to explore the relationship between birth order and educational attainment by estimating a family fixed effects model, with dummy variables for birth order, using administrative data for the entire Norwegian population. Similarly, this study employs the fixed effects approach to explore how children's educational attainment varies by birth order in Taiwan, a middle-income country.^{4,5} As discussed in the literature, controlling for family fixed effects rules out that estimated birth order patterns are driven by differences in observed family characteristics (e.g., family size and parental education) and unobserved family characteristics that are shared by siblings. Furthermore, because of Taiwan's rapid economic development and social change, family budgets and norms and values may have varied over time. Exploring this changing pattern across cohorts therefore provides a unique opportunity to examine how intra-family educational resource allocation changes as a society develops.

Contrary to the opposing findings in developed and developing countries presented

³ See de Haan et al. (2014) for a detailed summary of birth order studies in developed and developing countries.

⁴ Black et al. (2005) used the fixed effects method (within estimator) to control for family heterogeneity, and used dummy variables to capture potential nonlinear patterns of birth order. To overcome the challenge that birth order relates to family size, they also estimated this pattern by family size.

⁵ As discussed later, studies using data from Taiwan, which find later-born children fare better, did not take into account the *unobserved* family heterogeneity.

in the literature, this study finds that high-income countries' and Taiwanese birth order patterns share some similarities: in smaller Taiwanese families, later-born boys and girls have an educational disadvantage compared with their older siblings, a pattern typically found in high-income countries. This finding in smaller families also contradicts the finding of Yu and Su (2006), who show that later-born children receive more education in Taiwan.⁶ In addition, while later-born children have been shown to fare better in the developing country studies, I find no evidence that later-born children have an educational advantage, even in larger families. Moreover, taking advantage of a sample that contains a wide range of birth cohorts, ranging from 1921 to 1978, I found that the disadvantage of being born later in smaller families is more evident in recent cohorts.

The remainder of the paper is organized as follows: Section 2.2 provides the theoretical and empirical background to birth order patterns and briefly describes the Taiwanese context; Section 2.3 discusses the data and introduces the fixed effects approach; Section 2.4 presents the results; Section 2.5 tests the sensitivity of the main results using interval regression; and Section 2.6 provides conclusions.

2.2 Background

2.2.1 Theoretical and Empirical Background

There are a number of hypotheses suggesting that birth order might affect educational investment. As outlined in Strauss and Thomas (1995), the factors that could bring about differences between siblings due to birth order are time and financial constraints, as well as biological factors.

First, given that parents have a fixed time endowment, the firstborn will receive a greater parental time input than later-born children, who have to compete for parental

⁶ The household survey data used by Yu and Su (2006) are the same as those in this study.

attention. To the extent that greater parental time input translates into higher educational achievement, firstborns may fare better than later-born children. However, this argument also serves to emphasize the role of gaps between children; if the age difference between siblings (spacing) is large, then the youngest child might benefit more as either older siblings leave the family nest or through the increase in time input, since both parents and older siblings spend time with the youngest child (Behrman and Taubman 1986; Birdsall 1991; Hanushek 1992).

Life cycle effects can also be important. The younger parents are at their first birth, the more financially constrained they may be compared with later in their life cycle; hence, available resources might be lower for the firstborns of young—and possibly immature—parents. In contrast, later-born children might benefit through the increase in family income over the life cycle (Parish and Willis 1993).

In addition, biological factors may be important. By definition, mothers giving birth to children of a higher birth order are older than when they had those of a lower birth order. To the extent that older mothers tend to have children with lower birth weight, and who may be less healthy, later-born children may thus fare worse. On the other hand, parents may learn with practice and experience, and hence, later-born children might have an advantage over their older siblings.

Furthermore, other factors can work in both directions. Older children may be encouraged to leave school early to contribute to the family income, giving an advantage to their younger siblings with regard to educational attainment. On the other hand, if older children are expected to assume more responsibility in caring for their younger siblings, this training may lead them to perform more responsibly at school and become higher achievers.

Finally, cultural and legal factors may play a part as well. If there is land or an estate to be passed on, and inheritance customs favor the firstborns, parents may choose to invest more in the formal education of their younger children to compensate. Cultural

factors can also work in the opposite direction where firstborns will assume the responsibility of caring for elderly parents and inherit paternal authority, and thus receive higher educational investment. The next subsection will discuss further how cultural factors influence intra-family educational resource allocation in the Taiwanese context.

In summary, educational achievement might be positively or negatively associated with birth order, depending on the degree to which the above-mentioned factors affect children who are otherwise similar. Ultimately, it is an empirical question as to which dominates.

The empirical findings in the literature are mixed. The bulk of the studies on the birth order patterns in the developed countries found that later-born children have educational disadvantage compared with their older siblings. For instance, Behrman and Taubman (1986) find that children of a higher birth order in the U.S. have lower educational attainment. A recent study by Kantarevic and Mechoulam (2006) finds that firstborns in the U.S. have higher education and earnings. Black et al. (2005) use a data set of the entire population of Norway, finding strong evidence for a negative association between birth order and children's educational attainment and adult earnings. Using the British Household Panel Survey, Booth and Kee (2009) find that children's education decreases with birth order.

Whereas there is evidence in high-income countries that children of a higher birth order tend to do worse in many dimensions, studies using data from middle- or low-income countries usually find a reversed pattern, showing that later-born children have an educational advantage over their older siblings. See Parish and Willis (1993) and Yu and Su (2006) for evidence in Taiwan, Li et al. (2008) for China, Ejrnaes and Portner (2004) for the Philippines, Edmonds (2006) for Nepal, Dammert (2010) for Nicaragua and Guatemala, Tenikue and Verheyden (2010) for 12 African countries, and de Haan et

al. (2014) for Ecuador.⁷

2.2.2 The Taiwanese Context

To briefly introduce the context for this study, Taiwan industrialization began just before World War II, and the country experienced rapid economic development in the postwar decades. In 1955, 61% of the workforce was in the agricultural sector, which declined to 20% by 1980, and nearly 10% in the 1990s. The changing industrial structure not only increased the demand for more educated workers and returns to education for both men and women but also affected the government's educational policies. Primary school education became mandatory for children born after 1945, while children born in 1956 and after further benefited from the extension of mandatory education for an additional three years.

The Taiwanese literature on educational attainment suggests the importance of family background, including characteristics such as socioeconomic status and both parents' education (Parish and Willis 1993; Tsai et al. 1994). The association between sibship characteristics and education might differ for sons and daughters if parental investment strategies depend on a child's gender: parents under financial constraints allocate educational funds according to their conscious assessment of sons' and daughters' relative market opportunities and returns (Brinton 1993; Parish and Willis 1993). The lower return to education for women hence leads to daughters having fewer educational opportunities compared with sons in East Asia (Brinton 1993). In addition, son preference and Taiwanese family norms with regard to seniority have been considered critical factors in determining intra-family resource allocation in Taiwanese society. Yu and Su (2006) found evidence that parental investment strategies are

⁷ One exception is that Yu and Su (2006) find first-born sons have an educational advantage. The privilege for firstborns, however, does not extend to daughters.

conditioned not only by family budgets but also by culturally defined family norms. They showed that male firstborns, who are the ultimate inheritors of paternal authority in Taiwanese families, have additional leverage in the sibling competition for family resources. Conversely, this firstborn privilege does not extend to daughters; rather, they have a general educational disadvantage associated with being older children.

Due to Taiwan's rapid economic development and social change, family budgets and norms and values may have changed over time. We therefore might expect intra-family educational resource allocation to vary across cohorts depending on the stages of economic and social development; hence, exploring cohort differences provides a unique opportunity to examine how intra-family educational resource allocation changes as society develops.

2.3 Data and Methods

2.3.1 Data

I use the 1999, 2000, and 2003 waves of the Taiwan Panel Study of Family Dynamics (PSFD), in which respondents provided information on themselves, their parents and spouse's parents, their siblings, and their children. The information about siblings and children includes year of birth, gender, birth order, and educational attainment; respondents were also asked how many brothers and sisters and how many sons and daughters they have (including those deceased), from which family sizes were calculated.⁸

The PSFD reports each individual's highest educational qualification, but not years of schooling; nor were respondents asked whether their siblings or offspring graduated. Thus, the typical number of years required to complete each educational qualification

⁸ In the sample, the respondent, their siblings, and parents form one family unit, while they and their children form another family.

was used: a master's degree was coded as requiring 18 years and a doctorate as 21 years of schooling.⁹ One potential problem with this method is that the presumed number of years may not reflect the actual years of schooling an individual completed.¹⁰ For example, it is possible that an individual giving high school as their highest qualification did not actually graduate from high school; therefore, this individual's actual years of schooling may be between 9 and 12 years. To check whether the coding for years of schooling affected the estimation results, the sensitivity of the results was tested using interval regression (see Section 2.5).

Due to the design of the survey, respondents only provided information on their living siblings and children,¹¹ which raises a potential problem that the birth order of the reported siblings and children may not be representative of their actual position in the family.¹² For example, in a four-child family where one child had died, if the deceased child was the third-born, then the fourth-born child will be treated as the third-born when their parents allocate educational resources between the surviving children.¹³ The robustness check presented in the Appendix C confirms that the estimation results, which follow, were not affected by this limitation.

In this study, the sample of children provides information on three broad cohorts: those born in 1921–1955 (Cohort 1), 1956–1969 (Cohort 2), and 1970–1978 (Cohort 3). Table 2.1 presents descriptive statistics for the full sample and each birth cohort: children in the full sample, around half of whom were female, received 10.89 years of schooling

⁹ Eighteen years of schooling include: six years of elementary, three years of junior high, three years of high school, four years of college, and two years of graduate school. Twenty-one years of schooling includes an additional three years of graduate school.

¹⁰ As the survey did not ask whether respondents graduated, using either educational qualification or years of schooling encounters the problem of measurement error.

¹¹ Respondents only provided demographic information for their five oldest siblings and children who were alive at the time of the interview.

¹² I thank Steven Haider for pointing out this issue.

¹³ On the other hand, if the third-born child died after all the children had grown up and completed their education, their death is not likely to be an issue.

on average; in 2003, these children were approximately 43 years old; on average, families had 4.4 children, with approximately 90% of those surveyed having three or more; and the educational attainment of respondents' parents was much lower than that of their children, with mothers having completed 4.41 and fathers 6.47 years.

The average years of schooling and family size have changed across cohorts. The former, for both children and their parents, has increased steadily: children's average schooling was about eight years in the first cohort, increasing to almost 13 years in the third cohort. Meanwhile, the average family size of 5.76 in the first cohort has declined to 3.67 in the third cohort.

Table 2.2 cross-tabulates the average years of schooling by family size and birth order. The top panel shows that educational attainment decreases with birth order for smaller families, but the difference is not substantial. Larger families exhibit a different pattern: educational attainment increases with birth order, and the educational gap between earlier-born and later-born children is larger. For example, the firstborn child in families with six children completes 8.61 years of schooling on average, but the sixth child completes 11.20 years. This positive relationship between educational attainment and birth order for larger families may be due to birth cohort effects. As shown in Figure 2.1, which presents the average years of schooling by birth year, there is an upward trend in years of schooling. For a given family, younger children (with a higher birth order) are more likely to benefit from the rapid growth in education, particularly children in larger families.¹⁴ Therefore, it is important to control for the trend in years of schooling when investigating birth order patterns.

¹⁴ Later-born children may receive more education due to changes in education policy, such as the extension of compulsory schooling. Compulsory schooling in Taiwan was extended from six to nine years in 1968, so children born in 1956 and later further benefited from the extension of mandatory education for an additional three years.

2.3.2 Method

Consider the following model in which the educational attainment of each child in a family can be written as

$$ED_{ij} = \beta_0 + \mathbf{D}(\text{birthorder})_{ij}\beta_1 + \beta_2 \text{birthyear}_{ij} + c_i + u_{ij} \quad (2.1)$$

where ED_{ij} is the educational attainment of the child j in family i as measured by years of schooling. $\mathbf{D}(\text{birthorder})_{ij}$ is a $1 \times k$ vector of dummy variables for the second, third, fourth, fifth, sixth and higher order of birth, leaving the firstborn child as the omitted category. The advantage of birth order dummies is that they allow us to capture potential nonlinear patterns of birth order compared to an absolute birth order variable that takes the value 1 for the first born, 2 for the second born and so on. birthyear_{ij} is the value obtained by subtracting the mean of year of birth, 1960, from year of birth, and is used to control for the rapid growth in educational attainment across birth cohorts observed in Figure 2.1.^{15,16} c_i is the family-specific effect that may be correlated with the covariates, and absorbs both *observed* and *unobserved* family characteristics that are constant within a family, such as family size, both parents' education and birth cohort, and mother's age at first birth, which are important factors that affect the estimation of birth order patterns, as described in Blake (1989) and related literature. To examine the pattern of birth order net of family characteristics, I employ the

¹⁵ Another way of controlling for the rapid growth in educational attainment is to include year of birth dummies, which capture cohort effects and education policy changes. However, as depicted in Figure 2.1, the assumption of a linear birth year trend, captured by birthyear_{ij} , seems consistent with the data. Although not reported in this paper, regressions using year of birth dummies instead of birthyear_{ij} were run and yielded very similar results.

¹⁶ Since birth order is mechanically positively correlated with the year of birth and the year of birth is used to control for the upward trend of educational attainment, excluding the year of birth from regressions would result in a misleading (positive) birth order-education relationship.

fixed effects (FE) approach (within estimators) to difference out any family-specific characteristics (i.e., c_i).¹⁷

As discussed in Section 2.2.2, the relationship between birth order and educational attainment is likely to be different between girls and boys; hence, the full sample was divided into two subsamples, a girl sample and a boy sample, throughout the estimation. Because data on multiple children within a family are used in estimations, I use standard errors (clustered at family level) that are robust to heteroscedasticity and arbitrary within-family correlation.

2.4 Results

2.4.1 Overall Birth Order Patterns

Tables 2.3–2.5 provide the fixed effects (FE) estimates for the full sample, girl sample, and boy sample, respectively. Point estimates in Column 1 of Table 2.3 show that there is a pattern of falling then rising educational attainment with respect to birth order in the full sample. The estimates for the second, third, fourth, and fifth children, ranging from -0.222 to -0.391, are negative, with precise estimates being given for the second and third child. The estimates for the sixth and seventh or later children (0.092 and 0.376, respectively) are positive but statistically insignificant.

Columns 2–7 in Table 2.3 present separate regressions for particular family sizes, and indicate that birth order patterns vary somewhat with family size. For smaller families, the estimates are all negative and monotonically decreasing with birth order, while for larger families, the point estimates imply that later-born children receive more education; however, they are typically not statistically significant, even jointly. To

¹⁷ The FE method described in this section denotes the within estimator. In other words, the (observed and unobserved) family heterogeneity is removed by family demeaning. Applying least squares with dummy variables for family units (i.e., the so-called family fixed effects) yields estimates that are numerically identical to within estimates.

improve the precision, certain classes of family size were pooled to form two groups: families with four or less children, and families with five or more children.

Columns 8 and 9 present the results for these two groups. In Column 8, all values for birth order dummies, ranging from -0.256 to -0.774, are precisely estimated, and suggest that average educational attainment monotonically decreases with birth order in smaller families: in other words, later-born children receive less education. Pooling the observations for families with five or more children improves the precision as well, but the estimates in Column 9 are still generally not significantly different from zero.¹⁸ Estimates of birth order dummy variables for the sixth child and seventh and later child in Column 9 are positive, but are not statistically significant, even jointly. Furthermore, the estimates on birth year are all positive and precisely estimated, accurately capturing the upward trend of educational attainment depicted in Figure 2.1.¹⁹

Table 2.4 provides the results for girls, and shows that the estimation results are similar to those for the full sample in Table 2.3.²⁰ Column 8 of Table 2.4 shows that for girls in smaller families, there is an educational disadvantage associated with being later-born: birth order dummies, ranging from -0.015 to -1.124, are precisely estimated, except for the second child, indicating that later-born girls in smaller families fare worse. For later-born girls in larger families, the estimates are positive but not statistically significant, even jointly.

The estimation results for boys are shown in Table 2.5. Similar to the girls in smaller families (see Column 8 in Table 2.4), Column 8 in Table 2.5 shows a monotonic decline

¹⁸ The exception is the estimate for the second child.

¹⁹ The exception is the estimate for birth year in 2-child families, which is positive but statistically insignificant.

²⁰ The observations in Table 2.4 represent the number of girls in each family. For example, observations in Column 2 are the total number of girls in 2-child families, including those from families with one girl and one boy. Girls who have a brother in 2-child families do not contribute to estimation due to the FE method (those observations drop out). In other words, if there is only one girl observation in each family, this observation drops out from the FE estimation. The same applies to Table 2.5.

in average education as birth order increases for boys in smaller families, indicating that later-born boys in smaller families fare worse. Column 9 presents the estimation results for boys from larger families, showing that the point estimates for birth order dummies are all negative but not significantly different from zero, except for the second child.

In summary, although the relationship between educational attainment and birth order has been found to be opposite for developed and less developed countries in the empirical literature, I find that their birth order patterns share some similarities: later-born children in smaller families have an educational disadvantage, regardless of their gender. In addition, while later-born children have been shown to fare better in the developing country studies, I find no evidence that later-born children have an educational advantage, even in larger families. The disadvantage associated with being later-born in smaller families also contradicts the finding of Yu and Su (2006), who show that later-born children receive more education in Taiwan.²¹ This discrepancy in the findings probably results from the difference in model specifications, estimation methods, and statistical inference. Yu and Su (2006) use an absolute birth order variable to capture birth order patterns, and include dummy variables for firstborn sons and daughters in some specifications to capture the privilege for firstborns. By contrast, I follow Black et al. (2005) and use a set of birth order dummies to capture potential nonlinear patterns of birth order. In addition, I utilize the fixed effects approach (i.e., within estimators) to remove potential biases resulting from *unobserved* family heterogeneity, an issue not taken into account in Yu and Su (2006). Moreover, their statistical inference relies on the homoscedasticity assumption, which tends to be too strong and usually does not hold in practice. In contrast, I use standard errors that are robust to both heteroscedasticity and within-family correlation.

²¹ The household survey data used in Yu and Su (2006) are the same as those in this study.

2.4.2 Changing Patterns across Cohorts

Because of Taiwan's rapid economic development and social change, family budgets and norms and values may have varied over time. Therefore, we might expect intra-family educational resource allocation to vary across cohorts, depending on the stages of economic and social development. Taking advantage of the sample that contains a wide range of birth cohorts, ranging from 1921 to 1978, I explore how birth order patterns in smaller families have changed across cohorts.

To obtain the birth order pattern for different cohorts, the interaction between birth order dummies and three birth cohort dummies were examined: Cohort 1 (1 if born 1921–1955 and 0 otherwise), Cohort 2 (1 if born 1956–1969 and 0 otherwise), and Cohort 3 (1 if born 1970–1978 and 0 otherwise). I then applied the fixed effects method (within estimators) to a regression of a child's years of schooling on *second child*cohort1*, *second child*cohort2*, *second child*cohort3*, *third child*cohort1*, *third child*cohort2*, *third child*cohort3*, *fourth child*cohort1*, *fourth child*cohort2*, *fourth child*cohort3*, and year of birth.^{22,23} Table 2.6 presents the results for girls and boys.²⁴

The first three columns of Table 2.6 present the results for children from families with four or less children, with the results for girls in the middle three columns and boys in the last three columns. The estimates for birth order dummies are generally negative (significant for most cases) and the magnitude of the estimates become larger for younger cohorts, implying that being later-born children in a family is more of a disadvantage in

²² The omitted category is firstborns. Using the firstborns in the oldest cohort (Cohort 1, born 1921–1955) as the base group (i.e., included in the model *first child*cohort2* and *first child*cohort3*) yielded similar results, but the resulting estimates are less precise. In addition, the estimates for *first child*cohort2* and *first child*cohort3* are not significant at any traditional levels, even jointly.

²³ Although not reported in this paper, regressions using year of birth dummies instead of a linear birth year trend were run and yielded similar but less precisely estimated birth order patterns across cohorts.

²⁴ The estimate, 0.307, in the first cell of Table 2.6 is the coefficient estimate of *second child*cohort1* (born 1921–1955).

younger than older cohorts.²⁵ This pattern might reflect emerging educational inequality within a family. Furthermore, the changing birth order pattern across cohorts in smaller families also implies that the behavior of Taiwanese families increasingly resembles that of families in developed or high-income countries such as the U.S.

2.5 Sensitivity Analysis

The PSFD reports each individual's highest educational qualification, but not years of schooling; nor were respondents asked whether their siblings or offspring graduated. Thus, the typical years of schooling required to complete each educational qualification were used. As discussed in Section 2.3, one potential problem of the presumed years of schooling is that the presumed years may not reflect the actual years of schooling an individual completed. In this section, to check whether the coding of years of schooling affects the estimated birth order patterns already shown in Section 2.4, I conduct a robustness check using interval regression.

Following Wooldridge (2010, Chapter 19), the Chamberlain-Mundlak device was employed to control for the family heterogeneity, c_i , in equation (2.1):

$$c_i = \gamma + \overline{\mathbf{D}(\text{birthorder})}_i \delta + \lambda \overline{\text{birthyear}}_i + \omega_i \quad (2.2)$$

where $\overline{\mathbf{D}(\text{birthorder})}_i$ is a vector of family means of birth order dummies and $\overline{\text{birthyear}}_i$ is the family mean of birthyear_{ij} . By construction, ω_i is uncorrelated with the explanatory variables. Substituting equation (2.2) into equation (2.1),

²⁵ The joint F test for (*second child*cohort1 = second child*cohort2*), (*third child*cohort1 = third child*cohort2*), (*fourth child*cohort1 = fourth child*cohort2*) indicates that the difference in birth order dummy variables between cohorts 1 and 2 is jointly significant for the full sample but not for the girl and boy samples. Similar joint tests for the difference in birth order dummy variables between cohorts 1 and 3 suggest the difference is jointly significant for the full and boy samples but not for the girl sample.

$$ED_{ij} = \alpha_0 + \mathbf{D}(\text{birthorder})_{ij}\boldsymbol{\beta} + \beta_2 \text{birthyear}_{ij} + \overline{\mathbf{D}(\text{birthorder})_i}\boldsymbol{\delta} + \lambda \overline{\text{birthyear}_i} + \eta_{ij}, \quad (2.3)$$

where $\eta_{ij} = \omega_i + u_{ij}$. Interval regression is applied to equation (2.3), and the parameters on birth order dummies contain the partial effects of interest, which permit a direct comparison with the FE estimates presented in Section 2.4.²⁷

As discussed in Section 2.3.1, due to the survey design, the actual years of schooling completed by an individual were not available, and so the "usual" number of years of schooling were used in the estimations. To run interval regression, two variables, $upper_{ij}$ and $lower_{ij}$, were specified for each individual, which represent the interval endpoints and thereby determine the interval into which an individual's actual years of schooling fall.

For an individual whose reported highest educational qualification was elementary school, $lower_{ij}$ and $upper_{ij}$ were set to 0 and 6, respectively; for an individual whose reported highest educational qualification was junior high school, $lower_{ij}$ and $upper_{ij}$ were set to 6 and 9, respectively, and so on. For an individual who received zero schooling, $lower_{ij}$ was set to missing and $upper_{ij}$ was set to 0. In other words, the intervals were $ED \leq 0$, $0 < ED \leq 6$, $6 < ED \leq 9$, $9 < ED \leq 12$, $12 < ED \leq 16$, and $16 < ED$.

The results in Table 2.7 show that the magnitude and statistical significance of interval regression estimates are close to those of the FE estimates reported in Tables 2.3–2.5. The robustness check of the results to alternative interval regression showed that the birth order patterns were not affected by the presumed number of years of schooling and the estimator chosen.

²⁷ Note that we are still interested in the regression of years of schooling on birth order dummies. The structure of interval regression (i.e., the log likelihood) looks a lot like that of the ordered probit model, but there is an important difference: in ordered probit, the cut points are parameters to estimate and the coefficient estimators do not measure interesting partial effects. With interval regression, the interval endpoints are given and coefficient estimators contains the partial effects of interest.

2.6 Conclusion

This study uses data from the Taiwan Panel Study of Family Dynamics to explore how children's educational attainment varies by birth order. The relationship between educational attainment and birth order predicted by several hypotheses is ambiguous, and the empirical findings in the literature are mixed. While empirical studies using data from high-income countries find that later-born children fare worse, studies using data from middle- and low-income countries find the opposite is true.

Despite the divergent findings in developed and developing countries, I find that birth order–education patterns in high-income countries and Taiwan share some similarities. For instance, in smaller Taiwanese families, once a linear birth year trend is accounted for, later-born boys and girls have an educational disadvantage compared with their older siblings, a pattern typically found in high-income countries.²⁸ Furthermore, the birth order pattern found in smaller families contradicts the findings of Yu and Su (2006), and other researchers, that later-born children fare better in Taiwan. In addition, while later-born children have been shown to fare better in the developing country studies, I find no evidence that later-born children have an educational advantage, even in larger families.

Moreover, taking advantage of a sample that contains a wide range of birth cohorts, ranging from 1921 to 1978, I found that the disadvantage of being later-born children in smaller families is more evident in recent cohorts, a changing pattern which might reflect emerging educational inequality within a family. Furthermore, the changing birth order pattern across cohorts implies that the behavior of Taiwanese families might increasingly resemble that of families in high-income countries.

As discussed in Section 2.2, educational achievement might be positively or

²⁸ The birth order pattern shown in Black et al. (2005) was estimated by controlling for indicators for age in 2000. Therefore, the pattern they found is the one net of birth year trend as well.

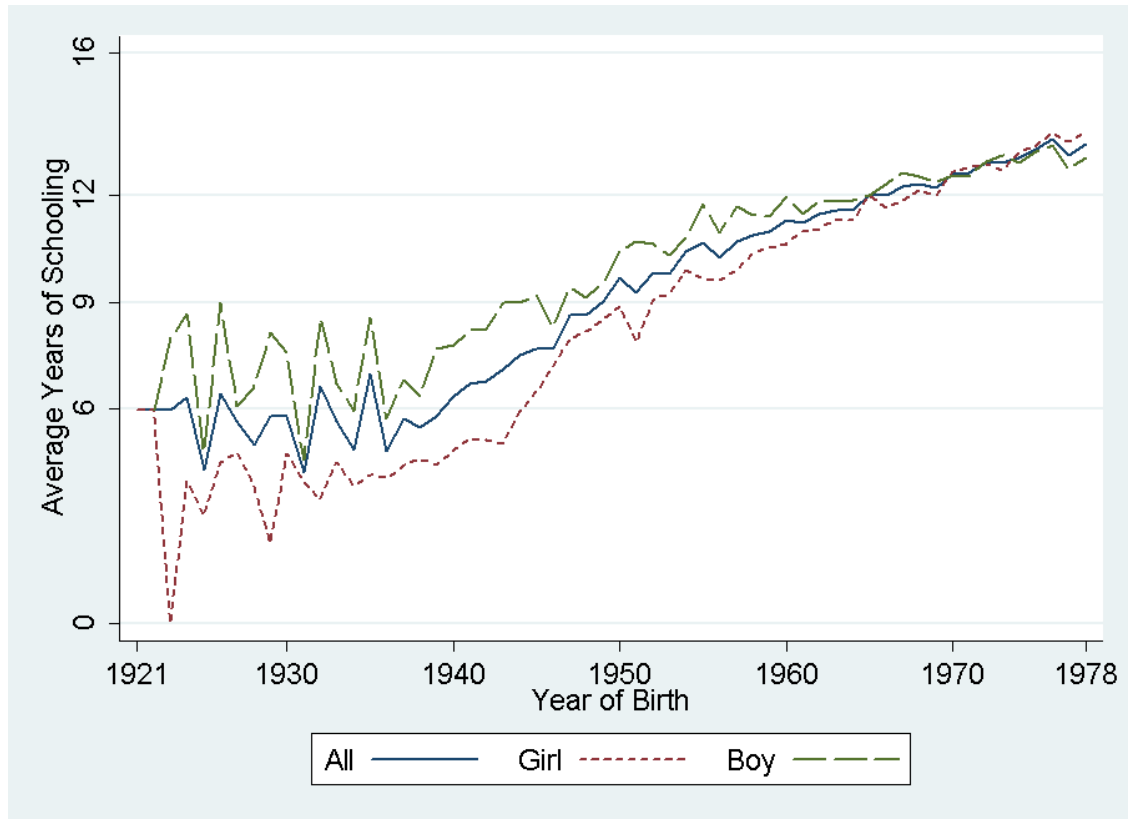
negatively associated with birth order, depending on the degree to which the various factors affect children who are otherwise similar; ultimately, it is an empirical question as to which dominates. For smaller families, the data used in the current study suggest that the hypotheses predicting the negative relationship between birth order and educational attainment takes precedence. With limited information, however, we remain less clear on precisely which factor was driving the birth order pattern observed in smaller families.

Clearly, more research is needed. By providing a description of the different birth order patterns in smaller and larger families and across cohorts, this study will guide further research into the underlying factors driving these patterns, particularly in smaller families, which may be more representative of contemporary household behavior and consequently merit further attention.

APPENDICES

APPENDIX A - FIGURE

Figure 2.1 Average Years of Schooling by Year of Birth



Note: Author's calculation based on the sample.

APPENDIX B - TABLES

Table 2.1 Descriptive Statistics: Means and Proportions

	Full Sample	Cohort 1 1921–1955	Cohort 2 1956–1969	Cohort 3 1970–1978
Years of schooling	10.89	8.36	11.60	12.97
Birth order	2.68	2.77	2.69	2.55
Female	0.50	0.50	0.50	0.48
Year of birth	1960	1947	1963	1973
Age in 2003	42.79	56.39	39.82	30.13
Number of children	13,549	4,340	5,932	3,277
Family size (number of children)	4.41	5.76	4.34	3.67
Family with 2 children	0.28	0.08	0.27	0.39
Family with 3 children	0.24	0.15	0.28	0.29
Family with 4 children	0.16	0.22	0.19	0.13
Family with 5 children	0.11	0.22	0.13	0.05
Family with 6 children	0.05	0.11	0.04	0.01
Family with 7 or more children	0.12	0.30	0.08	0.02
Father's age in 2003	70.47	83.48	69.97	61.35
Mother's age in 2003	66.38	80.39	65.78	56.56
Father's years of schooling	6.47	4.51	6.49	7.75
Mother's years of schooling	4.41	2.75	4.80	6.90
Number of families	3,672	1,277	2,300	1,654

Table 2.2 Average Years of Schooling by Family Size and Birth Order

		Family size						
		All families	2	3	4	5	6	7 or more
Birth order	All children							
	Mean	10.89	12.98	12.59	11.94	10.85	9.70	7.97
	1	10.92	13.02	12.63	11.57	10.25	8.61	6.87
	2	11.10	12.92	12.60	11.97	10.32	8.86	7.31
	3	11.07		12.51	12.12	10.95	9.31	7.72
	4	10.87			12.17	11.44	10.25	8.22
	5	10.28				11.62	10.55	8.50
	6	10.17					11.20	9.06
	7 or more	9.51						9.51
	N	13,549	580	2,757	3,228	2,594	2,138	2,252
	Girls							
	Mean	10.40	12.54	12.52	11.80	10.58	9.29	7.23
	1	10.36	12.36	12.39	11.41	10.12	8.41	5.89
	2	10.65	12.79	12.70	11.94	10.03	8.77	6.44
	3	10.64		12.47	12.01	10.68	8.87	7.21
	4	10.33			11.97	11.31	9.97	7.38
	5	9.64				11.31	9.94	7.96
	6	9.73					10.89	8.77
	7 or more	8.82						8.82
	N	6,704	221	1,067	1,578	1,435	1,153	1,250
	Boys							
	Mean	11.38	13.25	12.63	12.07	11.18	10.17	8.88
	1	11.47	13.44	12.77	11.76	10.45	8.88	8.03
	2	11.53	13.00	12.55	12.00	10.73	8.99	8.56
	3	11.52		12.54	12.22	11.33	9.97	8.41
	4	11.36			12.30	11.57	10.58	9.30
	5	10.94				11.88	11.15	9.29
	6	10.53					11.39	9.37
	7 or more	9.99						9.99
	N	6,845	359	1,690	1,650	1,159	985	1,002

Note: N represents the number of children observations.

Table 2.3 Fixed Effects Estimates by Family Size (Full Sample)

Dependent variable: years of schooling	All families	2-child families	3-child families	4-child families	5-child families	6-child families	7+ children families	Families with 4 or less children	Families with 5 or more children
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Second child	-0.271*** (0.067)	-0.094 (0.274)	-0.436*** (0.132)	-0.066 (0.123)	-0.404** (0.162)	-0.307 (0.222)	-0.233 (0.216)	-0.256*** (0.084)	-0.324*** (0.113)
Third child	-0.391*** (0.102)		-0.782*** (0.241)	-0.363* (0.191)	-0.207 (0.223)	-0.308 (0.286)	-0.169 (0.277)	-0.568*** (0.143)	-0.216 (0.149)
Fourth child	-0.280* (0.143)			-0.707** (0.275)	-0.159 (0.299)	0.178 (0.371)	0.041 (0.333)	-0.774*** (0.217)	0.012 (0.192)
Fifth child	-0.222 (0.195)				-0.371 (0.398)	0.115 (0.478)	0.056 (0.421)		-0.07 (0.250)
Sixth child	0.092 (0.252)					0.377 (0.597)	0.289 (0.505)		0.263 (0.316)
Seventh or later child	0.376 (0.411)						0.749 (0.695)		0.567 (0.476)
Birth year	0.175*** (0.018)	0.132 (0.089)	0.178*** (0.048)	0.199*** (0.036)	0.176*** (0.037)	0.174*** (0.042)	0.155*** (0.039)	0.186*** (0.027)	0.167*** (0.023)
Constant	11.054*** (0.075)	12.152*** (0.499)	11.718*** (0.247)	11.286*** (0.087)	11.107*** (0.191)	10.480*** (0.455)	9.640*** (0.672)	11.526*** (0.100)	10.481*** (0.245)
F (joint test of birth order dummies)	8.96***		6.05***	2.97**	2.45**	2.42**	1.06	5.30***	4.30***
R-squared	0.086	0.023	0.013	0.039	0.085	0.153	0.124	0.025	0.121
Observations	13,549	580	2,757	3,228	2,594	2,138	2,252	6,565	6,984
Number of families	3,672	325	1,026	890	594	405	432	2,241	1,431

Notes: Firstborns are the omitted category. Robust standard errors (in parentheses) clustered in family. *** p<0.01. ** p<0.05. * p<0.1.

Table 2.4 Fixed Effects Estimates by Family Size (Girls)

Dependent variable: years of schooling	All families	2-child families	3-child families	4-child families	5-child families	6-child families	7+ children families	Families with 4 or less children	Families with 5 or more children
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Second child	-0.045 (0.105)	-0.549 (0.751)	-0.094 (0.298)	0.047 (0.172)	-0.396* (0.208)	0.045 (0.284)	-0.010 (0.289)	-0.015 (0.148)	-0.148 (0.147)
Third child	-0.222 (0.151)		-0.466 (0.514)	-0.549* (0.289)	-0.104 (0.291)	-0.101 (0.320)	-0.200 (0.384)	-0.619** (0.254)	-0.114 (0.190)
Fourth child	-0.049 (0.214)			-1.058** (0.444)	0.057 (0.393)	0.474 (0.446)	0.158 (0.477)	-1.124*** (0.410)	0.231 (0.252)
Fifth child	-0.056 (0.287)				-0.317 (0.545)	0.473 (0.566)	0.262 (0.607)		0.159 (0.330)
Sixth child	0.425 (0.379)					1.038 (0.742)	0.719 (0.733)		0.696 (0.429)
Seventh or later child	0.286 (0.586)						0.621 (0.974)		0.625 (0.636)
Birth year	0.210*** (0.026)	0.577** (0.241)	0.234** (0.106)	0.288*** (0.055)	0.213*** (0.050)	0.164*** (0.048)	0.190*** (0.055)	0.292*** (0.050)	0.188*** (0.029)
Constant	10.433*** (0.114)	9.335*** (1.187)	11.049*** (0.551)	10.633*** (0.158)	10.569*** (0.195)	9.666*** (0.473)	9.090*** (0.931)	10.669*** (0.194)	9.843*** (0.290)
F (joint test of birth order dummies)	2.55**		0.54	4.29***	2.12*	1.54	1.280	4.96***	2.64**
R-squared	0.166	0.481	0.071	0.096	0.160	0.202	0.209	0.100	0.190
Observations	6,704	221	1,067	1,578	1,435	1,153	1,250	2,866	3,838
Number of families	3,157	195	798	813	558	390	403	1,806	1,351

Notes: Firstborns are the omitted category. Robust standard errors (in parentheses) clustered in family. *** p<0.01. ** p<0.05. * p<0.1.

Table 2.5 Fixed Effects Estimates by Family Size (Boys)

Dependent variable: years of schooling	All families	2-child families	3-child families	4-child families	5-child families	6-child families	7+ children families	Families with 4 or less children	Families with 5 or more children
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Second child	-0.451*** (0.112)	0.136 (0.435)	-0.593*** (0.194)	-0.237 (0.203)	-0.538* (0.283)	-0.48 (0.375)	-0.248 (0.388)	-0.453*** (0.130)	-0.426** (0.198)
Third child	-0.488*** (0.169)		-0.832** (0.331)	-0.376 (0.287)	-0.061 (0.414)	-0.559 (0.565)	-0.307 (0.438)	-0.593*** (0.208)	-0.265 (0.272)
Fourth child	-0.609** (0.237)			-0.807** (0.381)	-0.513 (0.537)	-0.503 (0.717)	0.035 (0.539)	-0.905*** (0.316)	-0.323 (0.344)
Fifth child	-0.421 (0.324)				-0.291 (0.693)	-0.818 (0.952)	0.164 (0.691)		-0.289 (0.450)
Sixth child	-0.629 (0.390)					-1.167 (1.124)	-0.254 (0.805)		-0.500 (0.535)
Seventh or later child	-0.446 (0.642)						0.223 (1.130)		-0.337 (0.804)
Birth year	0.151*** (0.029)	-0.18 (0.118)	0.157** (0.065)	0.153*** (0.045)	0.122** (0.061)	0.230*** (0.085)	0.116* (0.064)	0.143*** (0.037)	0.151*** (0.041)
Constant	11.692*** (0.121)	14.437*** (0.674)	11.972*** (0.341)	11.806*** (0.118)	11.638*** (0.430)	11.967*** (1.015)	10.315*** (1.161)	12.014*** (0.131)	11.308*** (0.492)
F (joint test of birth order dummies)	3.99***		4.77***	1.69	1.85	0.56	0.55	4.30***	0.99
R-squared	0.049	0.032	0.015	0.017	0.056	0.110	0.079	0.012	0.078
Observations	6,845	359	1,690	1,650	1,159	985	1,002	3,699	3,146
Number of families	3,328	266	951	815	536	371	389	2,032	1,296

Notes: Firstborns are the omitted category. Robust standard errors (in parentheses) clustered in family. *** p<0.01. ** p<0.05. * p<0.1.

Table 2.6 Fixed Effects Estimates by Birth Cohort (Families with Four or Less Children)

Dependent variable: years of schooling	Full sample			Girls			Boys		
	Cohort 1	Cohort 2	Cohort 3	Cohort 1	Cohort 2	Cohort 3	Cohort 1	Cohort 2	Cohort 3
	1921–1955	1956–1969	1970–1978	1921–1955	1956–1969	1970–1978	1921–1955	1956–1969	1970–1978
Second child	0.307 (0.220)	-0.292*** (0.102)	-0.319*** (0.111)	0.345 (0.363)	-0.110 (0.188)	0.072 (0.197)	0.169 (0.309)	-0.457*** (0.162)	-0.626*** (0.181)
Third child	0.268 (0.315)	-0.482*** (0.154)	-0.705*** (0.164)	0.456 (0.551)	-0.721*** (0.278)	-0.535* (0.297)	-0.001 (0.390)	-0.402* (0.237)	-0.836*** (0.243)
Fourth child	-0.105 (0.670)	-0.568 ** (0.246)	-0.847*** (0.223)	0.038 (0.689)	-0.828* (0.479)	-1.303*** (0.409)	-0.423 (1.014)	-0.764** (0.352)	-0.890*** (0.325)
Birth year		0.177*** (0.027)			0.276*** (0.050)			0.136*** (0.037)	
Constant		11.551*** (0.099)			10.724*** (0.193)			12.028*** (0.131)	
R-squared		0.029			0.108			0.018	
Observations		6,565			2,866			3,699	
Number of families		2,241			1,806			2,032	

Notes: Firstborns are the omitted category. The estimates are obtained by applying the fixed effects method (within estimators) to a regression of child's years of schooling on *second child*cohort1*, *second child*cohort2*, *second child*cohort3*, *third child*cohort1*, *third child*cohort2*, *third child*cohort3*, *fourth child*cohort1*, *fourth child*cohort2*, *fourth child*cohort3*, and year of birth for girls and boys, respectively. For instance, the estimate, 0.307 (SE=0.220), is the coefficient estimate of *second child*cohort 1(1921–1955)*. Robust standard errors (in parentheses) clustered in family. *** p<0.01. ** p<0.05. * p<0.1.

Table 2.7 Interval Regression Estimates (Pooled Maximum Likelihood Estimates with Family Means)

Dependent variable: years of schooling	Full sample			Families with 4 or less children			Families with 5 or more children		
	All	Girls	Boys	All	Girls	Boys	All	Girls	Boys
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Second child	-0.335*** (0.076)	-0.094 (0.119)	-0.524*** (0.126)	-0.310*** (0.094)	-0.038 (0.165)	-0.544*** (0.146)	-0.392*** (0.131)	-0.204 (0.169)	-0.465** (0.229)
Third child	-0.469*** (0.115)	-0.283 (0.173)	-0.602*** (0.189)	-0.646*** (0.159)	-0.634** (0.283)	-0.762*** (0.232)	-0.263 (0.172)	-0.167 (0.222)	-0.282 (0.307)
Fourth child	-0.345** (0.161)	-0.115 (0.243)	-0.761*** (0.264)	-0.864*** (0.241)	-1.125** (0.451)	-1.154*** (0.353)	-0.013 (0.220)	0.172 (0.292)	-0.363 (0.386)
Fifth child	-0.274 (0.221)	-0.112 (0.329)	-0.524 (0.362)				-0.108 (0.288)	0.082 (0.386)	-0.296 (0.508)
Sixth child	0.069 (0.286)	0.485 (0.436)	-0.797* (0.437)				0.258 (0.364)	0.731 (0.502)	-0.565 (0.604)
Seventh or later child	0.364 (0.467)	0.127 (0.678)	-0.628 (0.718)				0.57 (0.548)	0.435 (0.746)	-0.407 (0.903)
Birth year	0.208*** (0.020)	0.248*** (0.030)	0.184*** (0.032)	0.214*** (0.031)	0.310*** (0.056)	0.180*** (0.041)	0.204*** (0.026)	0.233*** (0.035)	0.183*** (0.046)
Constant	9.156*** (0.270)	9.305*** (0.157)	10.059*** (0.156)	9.940*** (0.291)	9.803*** (0.174)	10.573*** (0.190)	6.441*** (0.706)	8.649*** (0.410)	8.758*** (0.375)
Total observations	13,549	6,704	6,845	6,565	2,866	3,699	6,984	3,838	3,146
Left-censored observations	588	413	175	85	47	38	503	366	137
Uncensored observations	0	0	0	0	0	0	0	0	0
Right-censored observations	468	143	325	347	100	247	121	43	78
Interval observations	12,493	6,148	6,345	6,133	2,719	3,414	6,360	3,429	2,931

Notes: Firstborns are the omitted category. Robust standard errors (in parentheses) clustered in family. Interval values are 0, 6, 9, 12, and 16. Each model includes family means of birth order dummies and birth year.*** p<0.01. ** p<0.05. * p<0.1.

APPENDIX C - UNREPRESENTATIVE BIRTH ORDER

To check the sensitivity of estimates in respect of unrepresentative birth order, the sample is divided into two subsamples: one including deceased siblings and the other without deceased siblings. This sample stratification is conducted for smaller families (families with four or less children).¹

The estimation results are presented in Table 2.8, in which Column 1 replicates the results in column 8 in Table 2.3, while Columns 2 and 3 present the results for smaller families with and without deceased siblings, respectively. The estimates in Column 3 (families without deceased siblings) are very similar to those in Column 1. Furthermore, the sign of the estimates on birth order dummies are the same for both Columns 2 and 3. The magnitude of these estimates is smaller in families with deceased siblings (Column 2), but this difference is not statistically significant. Columns 4 through 6 and 7 through 9 present the results for the girl and boy samples, respectively, and are similar to that for the full sample. Overall, the robustness check shows that the birth order patterns in smaller families were not affected by the data limitations.

¹ Since the survey only asks respondents to report on up to five living siblings or offspring, it is impossible to define a subsample for larger families that includes all children in a given family.

Table 2.8 Fixed Effects Estimates (Families with Four or Less Children)

Dependent variable: years of schooling	Full sample			Girls			Boys		
	All	With deceased sibling	Without deceased sibling	All	With deceased sibling	Without deceased sibling	All	With deceased sibling	Without deceased sibling
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Second child	-0.256*** (0.084)	-0.144 (0.220)	-0.275*** (0.091)	-0.015 (0.148)	0.232 (0.496)	-0.039 (0.159)	-0.453*** (0.130)	-0.526 (0.331)	-0.440*** (0.141)
Third child	-0.568*** (0.143)	-0.449 (0.416)	-0.587*** (0.153)	-0.619** (0.254)	0.064 (1.085)	-0.681*** (0.263)	-0.593*** (0.208)	-0.375 (0.518)	-0.592*** (0.223)
Fourth child	-0.774*** (0.217)	-0.335 (1.129)	-0.807*** (0.229)	-1.124*** (0.410)	-0.620 (1.341)	-1.189*** (0.423)	-0.905*** (0.316)	-2.649 (2.234)	-0.860*** (0.331)
Birth year	0.186*** (0.027)	0.164** (0.082)	0.189*** (0.029)	0.292*** (0.050)	0.190 (0.236)	0.300*** (0.052)	0.143*** (0.037)	0.146* (0.084)	0.141*** (0.040)
Constant	11.526*** (0.100)	11.175*** (0.726)	11.619*** (0.082)	10.669*** (0.194)	10.570*** (2.145)	10.852*** (0.152)	12.014*** (0.131)	11.652*** (0.716)	12.073*** (0.113)
Observations	6,565	992	5,573	2,866	469	2,397	3,699	523	3,176

Notes: Firstborn children is the omitted category. Robust standard errors (in parentheses) clustered in family. ***
p<0.01. ** p<0.05. * p<0.1.

BIBLIOGRAPHY

BIBLIOGRAPHY

- Angrist, Joshua, Victor Lavy, and Analia Schlosser. 2010. "Multiple Experiments for the Causal Link between the Quantity and Quality of Children." *Journal of Labor Economics* 28 (October): 773–824.
- Becker, Gary and Gregg Lewis. 1973. "On the Interaction between the Quantity and Quality of Children." *Journal of Political Economy* 81 (March-April): S279–88.
- Becker, Gary and Nigel Tomes. 1976. "Child Endowments and the Quantity and Quality of Children." *Journal of Political Economy* 84 (August): S143–62.
- Behrman, Jere R., and Paul Taubman. 1986. "Birth Order, Schooling, and Earnings." *Journal of Labor Economics* 4 (July): S121–45.
- Birdsall, Nancy. 1991. "Birth Order Effects and Time Allocation." In T. P. Schultz (Ed.), *Research in population economics: A research annual* (pp. 191–123). Greenwich: JAI Press.
- Black, Sandra, Paul Devereux, and Kjell Salvanes. 2005. "The More the Merrier? The Effect of Family Size and Birth Order on Children's Education." *The Quarterly Journal of Economics* 120 (May): 669–700.
- Blake, Judith. 1989. *Family size and Achievement*. University of California Press, Berkeley and Los Angeles, CA.
- Booth, Alison and Hiau Joo Kee. 2009. "Birth Order Matters: the Effect of Family Size and Birth Order on Educational Attainment." *Journal of Population Economics* 22: 367–97.
- Brinton, Mary. C. 1993. *Women and the Economic Miracle: Gender and Work in Postwar Japan*. Berkeley: University of California Press.
- Darmmert, Ana C. 2010. "Siblings, Child Labor, and Schooling in Nicaragua and Guatemala." *Journal of Population Economics* 23(1): 199–224.
- De Haan, Monique, Erik Plug, and Jose Rosero. 2014. "Birth Order and Human Capital Development: Evidence from Ecuador." *Journal of Human Resources* 49(2): 359–92.
- Edmonds, Eric V. 2006. "Understanding Sibling Differences in Child Labor." *Journal of Population Economics* 19(4): 795–821.
- Ejrnæs, Mette and Claus C. Pörtner. 2004. "Birth-Order and the Intrahousehold Allocation of Time and Education." *Review of Economics and Statistics* 86: 1008–1019.
- Hanushek, Eric A. 1992. "The Trade-Off Between Child Quantity and Quality." *Journal of Political Economics* 100(1): 84–117.
- Kantarevic, Jasmin and Stephane Mechoulan. 2006. "Birth Order, Educational Attainment, and Earnings An Investigation Using the PSID." *Journal of Human Resources* 41(4): 755–77.

- Lee, Jungmin. 2008. "Sibling Size and Investment in Children's Education: An Asian Instrument." *Journal of Population Economics* 21: 855–75.
- Li, Hongbin, Junsen Zhang and Yi Zhu. 2008. "The Quantity–Quality Trade–Off of Children in a Developing Country: Identification Using Chinese Twins." *Demography* 45 (1): 223–43.
- Maralani, Vida. 2008. "The Changing Relationship between Family Size and Educational Attainment over the Course of Socioeconomic Development: Evidence from Indonesia." *Demography* 45(3): 693–717.
- Parish, William and Robert Willis. 1993. "Daughters, Education, and Family Budgets Taiwan Experiences." *Journal of Human Resources* 28 (4): 863–98.
- Rosenzweig, Mark and Kenneth Wolpin. 1980. "Testing the Quantity–Quality Fertility Model: The Use of Twins as a Natural Experiment." *Econometrica* 48 (January): 227–40.
- Rosenzweig, Mark and Junsen Zhang. 2009. "Do Population Control Policies Induce More Human Capital Investment? Twins, Birth Weight, and China's 'One Child' Policy." *Review of Economic Studies* 76: 1149–74.
- Strauss, John and Duncan Thomas. 1995. "Human Resources: Empirical Modeling of Household and Family Decision." In J. Behrman, & T. N. Srinivasan (Eds), *Handbook of development economics*, Vol. III (pp. 1883–2023). Amsterdam: Elsevier Science.
- Tenikue, Michel, and Bertrand Verheyden. 2010. "Birth Order and Schooling: Theory and Evidence from Twelve Sub-Saharan Countries." *Journal of African Economics* 19(4): 459–95.
- Tsai, Shu-Ling, Hill Gates and Hei-Yuan Chiu. 1994. "Schooling Taiwan's Women: Women's Educational Attainment in the Mid-Twentieth Century." *Sociology of Education* 67: 243–63.
- Wooldridge, Jeffrey M. 2010. *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, MA: MIT Press.
- Yu, Wei-Hsin and Kuo-Hsien Su. 2006. "Gender, Sibship Structure, and Educational Inequality in Taiwan: Son Preference Revisited." *Journal of Marriage and Family* 68 (November): 1057–68.

CHAPTER 3

WAGE ADJUSTMENT OVER THE BUSINESS CYCLE: EVIDENCE FROM TAIWAN

3.1 Introduction

Because aggregate time series on real wages display little cyclical, macroeconomists long believed that real wages are nearly unresponsive to the business cycle. The stylized fact of weak wage cyclical spawned numerous theories of real wage stickiness. The theories included efficiency wage models, implicit contract models in which employers provide real wage insurance to workers, and inside-outsider models.¹

More recently, a series of studies based on longitudinal microdata have demonstrated that real wages are actually quite procyclical. The true procyclical of real wages is obscured in aggregate time series on real wages because of a composition bias: the aggregate statistics have the tendency to put more weight on low-skill workers during expansions than recessions. By contrast, studies based on longitudinal microdata have been able to avoid the composition bias by tracking the same workers over time and thereby controlling for cyclically changing composition of the workforce.

For example, using the U.S. Panel Study of Income Dynamics data from 1967-68 to 1986-87, Solon, Barsky, and Parker (1994) find when the unemployment rate increases by an additional percentage point, men's real wage growth tends to decline by 1.4 percentage point. Numerous U.S. studies based on longitudinal data, which are summarized in Solon, Barsky, and Parker (1992), Abraham and Haltiwanger (1995), and many follow-up studies, are generally consistent with Solon et al. (1994) in the extent of

¹ See Solon and Barsky (1989) and Solon, Barsky, and Parker (1994) for a detailed summary of the time series evidence and a discussion of how such evidence has influenced macroeconomic theory.

estimated cyclicalities of real wages.²³

Turning to other countries, Hart (2006) and Devereux and Hart (2006) address the issue for the United Kingdom, and Anger (2007) for the German labor market. Peng and Siebert (2007) address the issue for Germany and the United Kingdom and Peng and Siebert (2008) for Italy. Martins (2007), Martins, Solon, and Thomas (2012), and Carneiro, Guimaraes, and Portugal (2012) deal with the Portuguese labor market.⁴ While these studies deal with the European labor market, Shin (2012) provides the first longitudinal evidence on real wage cyclicalities from an Asian economy, South Korea. All these non-U.S. studies support the U.S. evidence, finding that real wages are procyclical.

The U.S. and non-U.S. microdata-based literature mentioned above, however, is based on data extending no later than the mid-2000s and did not explore what the cyclical wage patterns have been during the Great Recession. Recent studies by Elsby, Shin, and Solon (2013, 2014) update the analysis of real wage cyclicalities to 2012 for the U.S. and U.K. labor markets; Blundell, Crawford, and Jin (2014) and Gregg, Machin, and Fernandez-Salgado (2014) update the analysis to 2012 for the United Kingdom. To this date, however, no microdata-based evidence on the cyclical wage patterns during the Great Recession exists for countries other than the United States and United Kingdom. This paper provides the first microdata-based evidence on real wage cyclicalities that involves the cyclical wage pattern during the Great Recession from an Asian economy, Taiwan.

The analysis of real wage cyclicalities in Taiwan is based on the Manpower Survey (MS) and its May supplement, the Manpower Utilization Survey (MUS). I use the

² Examples from the U.S. literature include Stockman (1983), Bils (1985), Bowlus, Liu, and Robinson (2002), and Shin and Solon (2007).

³ Substantial procyclicalities of real wages is a feature of several macroeconomic theories, including those of Lucas and Rapping (1969) and Mortensen and Pissarides (1994).

⁴ See Shin (2012) for a detailed summary of the microdata-based evidence from the non-U.S. studies.

microdata to study cyclical wage patterns over the period 1978 to 2012, with emphasis on the two recessions of the 2000s. The mean real wage series from repeated cross-sections show a secular time trend over the sample period, and exhibit no cyclical variation in the 2000s. However, the longitudinal analyses, which allow us to remove a time trend contaminating cyclical patterns and account for observed and unobserved heterogeneity (i.e., worker fixed effects) that leads to a composition bias, do reveal some cyclical wage patterns. The results show that real wages during the Great Recession are procyclical. On the contrary, real wages in the recession of the early 2000s, which also had a large impact on the unemployment rate, are somewhat acyclical. The finding that real wages are more procyclical in the Great Recession than in the recession of the early 2000s is consistent with that in the United Kingdom. Furthermore, while some literature finds that real wages tend to be more responsive to the cycle for men than for women (Blank, 1989; Tremblay, 1990; Solon et al., 1994; Park and Shin, 2005; Shin, 2012), I find no heterogeneous responses of real wages to cyclical fluctuations between gender groups. This finding is consistent with a U.K. study by Hart (2006) who finds that real wages are equally procyclical between genders. I also find no group heterogeneity among education and age groups and among workers in the public and private sectors.

This paper is organized as follows. Sections 3.2 and 3.3 describe the data and empirical methodology, respectively. Section 3.4 presents evidence on cyclical wage patterns from both repeated cross-sections and longitudinally matched microdata. Section 3.5 concludes.

3.2 Data

The analyses are based on the Manpower Survey (MS) and its May supplement, the Manpower Utilization Survey (MUS). The MS is a monthly survey of labor market activities. The MS is given to approximately 20,000 registered households and there are

nearly 60,000 civilians aged 15 and older in the sampled households. The MS asks detailed questions on hours worked during the previous week (i.e., the reference week) and jobs held, in addition to demographic information such as gender, educational attainment, and age. Every MUS asks sample members about their monthly earnings at their main job, which are a "point-in-time" measure of earnings.

As in most existing studies, my analyses are based on real hourly wages. To construct hourly wage measures, I first convert the monthly earnings to an estimated weekly earnings by dividing by 4.29 ($\approx 30/7$) and then convert the weekly earnings to an estimated hourly wage by dividing by hours worked last week.⁵ Since both hours and earnings used are for main jobs, the estimated hourly wage is the wage for a main job. Hourly wages are deflated by the consumer price index (CPI) and expressed as real wages in 2011 NT dollars. Wage measures used for all analyses are log real hourly wages.

To focus on worker groups with substantial attachment to the labor force, I follow Elsby, Shin and Solon (2013, 2014) and restrict my samples to workers between the ages of 25 and 59. I also exclude workers with non-positive earnings and potential experience (age minus years of education minus 6), and require at least 35 hours of work a week. I only include in the samples workers from non-agricultural sectors. I then trim the remaining sample for each year by excluding the cases with the top and bottom 1% of hourly wages.⁶ The resulting sample of men is typically more than 12,000 per year. The women's sample starts at more than 2,000 in 1978 and exceeds 8,000 in the later years of the sample period. For the sake of national representativeness, I use the provided MS sampling weights.⁷

⁵ The reported monthly earnings are for April, so 30 days are used to calculate the number of weeks.

⁶ I have verified, however, that the cyclical patterns remain much the same if I use a 15-64 age range, if I do not trim the outliers, and also if I do not require at least 35 hours of work a week. Requiring at least 35 hours of work a week results in smaller sample sizes, but the difference is moderate.

⁷ Unweighted estimates turn out to be similar.

To provide context for my analysis, the top panel of Figure 3.1 and Table 3.1 present the 1978-2012 Taiwanese series for the unemployment rate and mean log real hourly wages. Wages shown in the table are scaled by the CPI and express real wages in 2011 NT dollars. The annual unemployment rate is used to emphasize which years are recession years and which are expansion years.⁸ The bottom panel of Figure 3.1 displays the logarithm of the CPI and mean log nominal hourly wages.

As the unemployment rate shows, Taiwan experienced two very severe recessions in the 2000s. The unemployment rate, which was 2.99% in 2000, was brought to 5.17% in the recession of the early 2000s, and was again brought to a record high rate, 5.85%, in the Great Recession. Like the United Kingdom, Taiwan entered the 1980s with high inflation, reaching nearly 20% on an annual basis. Subsequently, inflation fell rapidly in the 1980s. Except for an aberration between the late 1980s and mid 1990s (associated with the boom at that time), inflation remained below 2%.⁹ Inflation did rise somewhat in 2008, though, exceeding 3%.

As displayed in Table 3.1 and the top panel of Figure 3.1, in the first half of the sample period, the upward trends in men's and women's real wages are dramatic. However, after experiencing remarkable wage growth, men's and women's real hourly wages stagnated or even declined in the later years of the sample period. For example, men's mean log real wage declined from 5.360 in 2000 to 5.264 in 2012, a reduction of 0.096, while women's mean wage experienced a relatively moderate growth of 0.023.

The bottom panel of Figure 3.1 decomposes men's and women's log real wage series

⁸ The recessions of the 2000s are similarly classified if real GDP growth rates are used as an alternative indicator. For example, in the recession of the early 2000s, the unemployment rate increased from 2.99% in 2000 to 4.57% in 2001, while the real GDP growth rate declined from 5.80% in 2000 to -1.65% in 2001. In the Great Recession, the unemployment rate rose from 3.91% in 2007 to 5.85% in 2009, while the real GDP growth rate dropped from 5.98% in 2007 to -1.81% in 2009.

⁹ The average inflation rate was nearly 4% on an annual basis between 1989 and 1996. It was below 1% between 2000 and 2005, and nearly 1.5% between 2007 and 2012.

already shown in the top panel into the difference between the mean log nominal wage and the logarithm of the price level. The first thing to notice is that men's nominal wages grew very little in the 2000s (increased from 5.246 in 2000 to 5.274 in 2012, an increase of 0.028), and much more slowly than the log price level (increased from -0.110 in 2000 to 0.010 in 2012, an increase of 0.120). The smaller growth in nominal wages meant that men's real wages underwent a nontrivial decline in the 2000s already shown in Table 3.1 and the top panel of Figure 3.1. On the contrary, women's nominal wage experienced a larger increase (rose from 4.954 in 2000 to 5.100 in 2012, an increase of 0.146) than men's, but the growth in women's nominal wage was largely offset by inflation, resulting in a modest increase in women's real wage.

As depicted in Figure 3.1, men's and women's real wages show no perceptible cyclical variation in the 2000s, even though Taiwan experienced two severe recessions in the 2000s (classified by the unemployment rate). All of this, however, is based on wage measures from repeated cross-sections without correcting for a composition bias potentially resulting from my sample selection criteria and data limitations.¹⁰ The U.S. evidence indicates that such measures could be subject to a substantial countercyclical composition bias. Furthermore, the upward secular trends in men's and women's wages make it trickier to distill the cyclical patterns. In the next section, I will utilize several approaches to achieve a partial correction of the composition bias and a time trend contaminating cyclical patterns.

3.3 Empirical Methodology

Access to the microdata goes a considerable way towards reducing the composition-bias issues associated with aggregate data. As discussed by Solon, Barsky, and Parker (1994) and others, low-skill workers' employment is especially responsive to macroeconomic

¹⁰ I will discuss this issue in the next section.

shocks, so aggregate wage data are substantially countercyclically biased by their tendency to put more weight on low-skill workers during expansions than recessions. This generates a countercyclical composition bias in aggregate wage statistics, making workers' real wages appear less procyclical than they really are.

Using the MUS microdata, I can reduce the composition bias. Unfortunately, I cannot avoid the composition bias entirely by using the MUS microdata. I am unable to measure the wage opportunities of individuals with no work and unpaid family workers, which are excluded from the sample. In addition, because the MUS measures wages only for those working in the reference week in May, it seems potentially subject to a more severe composition bias than the U.S. March Current Population Survey (CPS).

I will achieve a partial correction of the resulting composition bias in three ways. First, following the U.S. and U.K. analyses of real wages in Elsby et al. (2013, 2014), I regression-adjust wage measures for some observable characteristics (education and potential experience) of the worker samples. The regression adjustments are conducted by estimating "regression-adjusted" year effects by applying least squares (weighting by the provided MS weights) to a regression of individual workers' log real wages on year dummies and controls for years of education and an unrestricted set of potential experience dummies.¹¹ Second, I reweight workers' observable characteristics to be the same as those in pre-recession years by the reweighting approach proposed by DiNardo, Fortin, and Lemieux (1996, DFL thereafter), so the observed workforce composition remains unchanged over the business cycle.¹² Finally, I utilize the rotating panel design of the MS and conduct longitudinal analyses that not only hold composition constant by following a portion of workers from one May to the next but also remove a time trend contaminating cyclical patterns.

¹¹ Using a quartic in potential experience yields similar results.

¹² The regression adjustments and DFL reweighting approach are conducted using repeated cross-sections.

3.4 Empirical Results

3.4.1 Overall Wage Adjustment over the Business Cycle

Repeated Cross-sections. I begin by following Elsby et al. (2013, 2014) in regression-adjusting wage measures, which can partly correct for the composition bias by controlling for year-to-year changes in the demographic composition of the samples. For example, as shown in Tables 3.2 and 3.3 and Figure 3.2, in addition to showing mean log wage for each year in the 2000-2005 period, I also estimate "regression-adjusted" year effects by applying least squares (again weighting by the provided MS weights) to a regression of individual workers' log real wages on year dummies for 2001, 2002, 2003, 2004, and 2005 (with 2000 as the omitted reference category) and control for years of education and an unrestricted set of potential experience dummies.

As expected and consistent with U.S. evidence in Elsby et al. (2013, 2014), the regression-adjusted year effects show that mean wage patterns in Table 3.1 are affected by the countercyclical composition bias. Whereas the unadjusted means indicate that men's mean log real wages were 0.004 (s.e.=0.006) less (but not significantly) in 2003 than in 2000, the adjusted 2003 year effect is 0.034 (s.e.=0.005) less than the 2000 effect.^{13,14} Women's unadjusted mean log real wages were 0.037 (s.e.=0.008) higher in 2003 than in 2000, but the adjusted means suggest there is no significant change in mean wages between 2000 and 2003.

I perform the same exercise for the 2007-2012 period. Whereas the unadjusted means indicate that, for men, log real wages were 0.025 (s.e.=0.006) lower in 2009 than in 2007, the adjusted 2009 year effect is 0.056 (s.e.=0.005) less than the 2007 effect.¹⁵ Similar countercyclical composition bias is observed in women's wage patterns between

¹³ The unadjusted and regression-adjusted 2003 year effects are significantly different from each other.

¹⁴ The unemployment rate is 2.99% in 2000 (the pre-recession year) and 4.99% in 2003.

¹⁵ The unemployment is 3.91% in 2007 (the pre-recession year) and 5.85% in 2009.

2007 and 2009. Compared with the recession of the early 2000s, the (regression-adjusted) wage drop in the Great Recession is significantly greater when there is a run-up in the unemployment rate.

However, as shown in Figure 3.2, both men's and women's mean log wages kept declining even in the recovery from the two recessions of the 2000s (classified by the unemployment rate). This suggests that the cyclical patterns based on these mean wage series from repeated cross-sections may be contaminated by the downward trend in mean log real wages. I will return to this issue when I use longitudinally matched data to correct for the composition bias resulting from workers' observable and unobservable characteristics and for the time trend.

In addition to the regression-adjusting, I also employ the DFL reweighting approach to reweight workers' observed characteristics (education and potential experience) in recession years to be the same as in pre-recession years.¹⁶ This also allows us to hold worker composition constant and hence accounts for observed heterogeneity. For example, I construct a reweighting factor, which reweights the composition of the workforce in 2001, 2002, 2003, 2004, and 2005 to be the same as that in 2000 (the pre-recession year). After constructing the reweight factor, I estimate the "DFL reweighted" year effect by applying least squares (weighting by the reweighted factor) to a regression of individual workers' log real wages on year dummies for 2001, 2002, 2003, 2004, and 2005 (with 2000 as the omitted reference category). I perform a similar exercise for the 2007-2012 period. As displayed in Tables 3.2 and 3.3, the results are quite similar to those of regression adjustments.

Longitudinally Matched Microdata. As discussed in the previous subsection, the cyclical patterns based on the mean wage series from repeated cross-sections may be

¹⁶ I estimate a logit model for the group membership. The covariates include an unrestricted set of education and potential experience dummies and the interaction between education dummies and years of potential experience.

contaminated by the downward trend in mean log real wages in addition to the composition bias. As displayed in Figure 3.2, regression-adjusted mean log wages continued to decline even in the recovery from the recessions, suggesting that the year effects seem to not only capture the cyclical fluctuations but also a time trend. Presumably, the time trend is linear.¹⁷ The traditional approach to accounting for a linear time trend is to first-difference wage series and use year-to-year change in wages. Using the first-differenced wage series can not only remove a linear time trend but also account for *unobserved* heterogeneity (i.e., worker fixed effects) that leads to a composition bias.

Fortunately, the rotating panel design of the MS makes it possible to follow a portion of one May's sample to the next May. However, like the CPS, the longitudinally matched MS sample is far from ideal panel data. The sample sizes for May-to-May matches are almost always less than half of the sample sizes for the cross-sections. Another source of the sample loss is that the MS does not follow residential movers, resulting in an endogenous sample selection in a study of wage changes. Nevertheless, I perform year-to-year matches from the samples of workers between adjacent MUS's (the MS's May supplement). I follow the guidance of Madrian and Lefgren (2000) in verifying that longitudinal matches on identification numbers are true matches by requiring that gender also matches, that year-to-year change in reported age is one, and that years of education is greater than or equal to that in previous years ($t-1$). Following Elsby et al. (2013), I weight individuals by the simple average of their weights across the two years.¹⁸

Table 3.4 shows mean year-to-year change in log real wages by gender for each pair of years from 1978-79 to 2011-12. Figure 3.3 adds a visual display for each gender. The

¹⁷ As depicted in Figure 1, there seems to be a trend break around 1995, so the assumption of a linear time seems implausible for the whole sample period. However, since the focus of this paper is on the recessions of the 2000s, the assumption of a linear time trend seems consistent with wage series in the 2000s.

¹⁸ Unweighted estimates turned out to be similar.

first thing to notice is that, because of normal life-cycle wage growth, the mean changes are almost always positive except for 2007-2008, and real wage growth in the 2000s was much slower than in early years of the sample period. In stark contrast to Figure 3.1 displaying no cyclical variation, Figure 3.3 depicts some cyclical patterns in the 2000s, suggesting that using the first-differenced wages does control for the downward trend observed in mean wage series displayed in Figure 3.2. Furthermore, the cyclical patterns in the recession of the early 2000s and the Great Recession differ. In the Great Recession, both men's and women's wages followed a procyclical pattern. The year-to-year change in log wages turned negative as the unemployment rate increased, and then rebounded as the unemployment rate improved. By contrast, men's and women's wage adjustment seemed to be disconnected with the cyclical fluctuations in the recession of the early 2000s.

To have a better picture of how year-to-year change in log real wages evolves over the business cycle, I estimate "regression-adjusted" year effects by applying least squares (again weighting by the simple average of their MS weights across the two years) to a regression of individual workers' year-to-year change in log real wages on year dummies for 2000-2001, 2001-2002, 2002-2003, 2003-2004, and 2004-2005 (with 1999-2000 as the omitted reference category) and controls for years of education and an unrestricted set of potential experience dummies. A similar exercise was also performed for the 2007-2012 period.

Along with the regression-adjusted year effects, Table 3.5 also displays the unadjusted year effects. As shown in Table 3.5, the variation over time in the estimated regression-adjusted year effects is virtually identical to that for the unadjusted year effects. Figure 3.4 provides a visual display by plotting the estimated regression-adjusted year effects and their 95% confidence interval for the two recessions of the 2000s for each gender. As shown in Table 3.5 and Figure 3.4, in the Great Recession, men's year-to-year change in log wages was 0.033 (s.e.=0.005) lower in 2007-2008 than in 2006-2007 (prerecession years), while women's change in log wages was 0.025

(s.e.=0.006) lower. Subsequently, both men's and women's change in log wages rebounded as the unemployment rate improved. In contrast to the procyclical pattern in the Great Recession, men's and women's wage adjustment seemed to be disconnected with the cyclical fluctuations in the recession of the early 2000s.

3.4.2 Group Heterogeneity

In this section, I explore between-group heterogeneity. Figure 3.5 displays the estimated regression-adjusted year effects and their 95% confidence interval for the two recessions of the 2000s for men, and Figure 3.6 for women. The year effects are estimated using the year-to-year change in log real wages. I compare two education groups, a high-education group (defined as some college and above) and a low-education group (defined as high school and less), and two age groups, a younger group (defined as $\text{age} \leq 40$) and an older group (defined as $\text{age} > 40$).¹⁹ I also compare workers in the public sector with those in the private sector. The inspection of these figures suggests that there is no group heterogeneity in the response of wages to cyclical fluctuations for both genders in the recessions of the 2000s.

3.5 Conclusion

Using the microdata from the Manpower Survey (MS) and its May supplement, the Manpower Utilization Survey (MUS), I study cyclical wage patterns over the period 1978 to 2012, with emphasis on the two recessions of the 2000s. The results of longitudinal analyses show that real wages during the Great Recession are procyclical, whereas real wages in the recession of the early 2000s are somewhat acyclical. The finding that real wages are more procyclical in the Great Recession than in the recession of the early

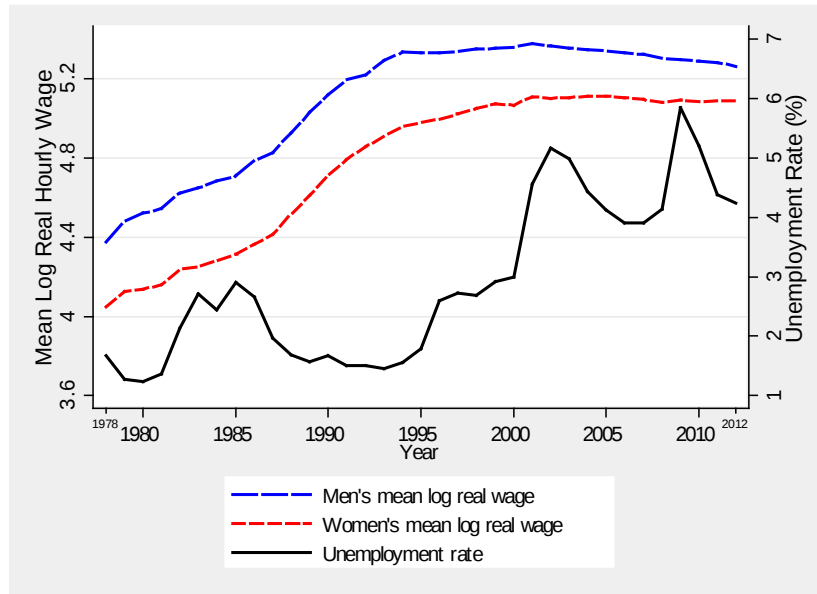
¹⁹ I also tried different age cutoffs, such as 35 and 45, and obtained quite similar results.

2000s is consistent with that in the United Kingdom. In addition, while most literature finds that men's real wages tend to be more procyclical than women's, the results suggest that the response of real wages to cyclical fluctuations among gender groups is quite similar in the recessions of the 2000s, a finding similar to that in the British labor market.

APPENDICES

APPENDIX A - FIGURES

Figure 3.1 Men's and Women's Mean Log Real Wages over the Business Cycle
A. Real Wages



B. Nominal Wages

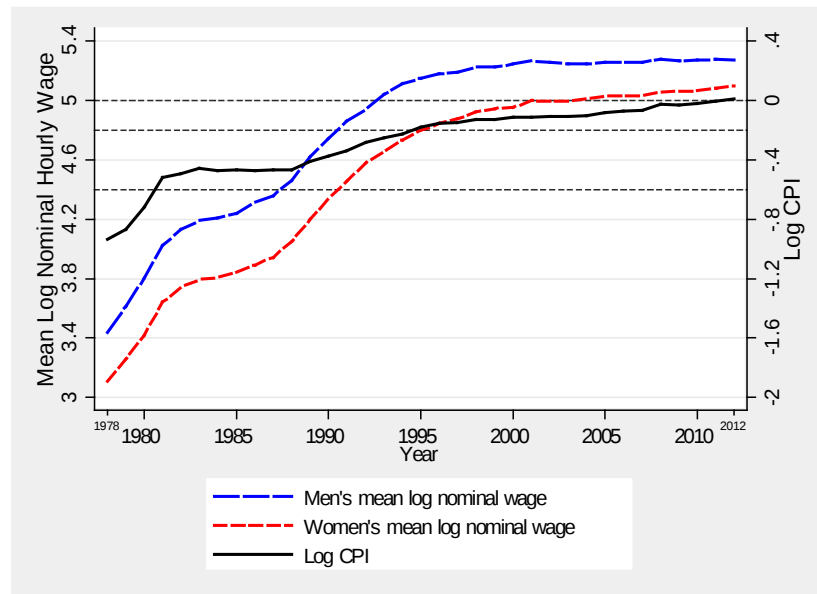
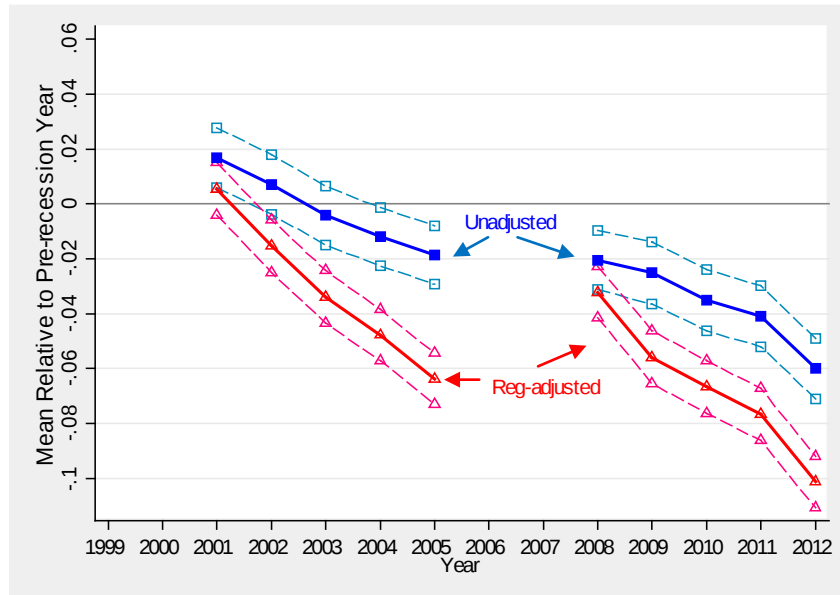
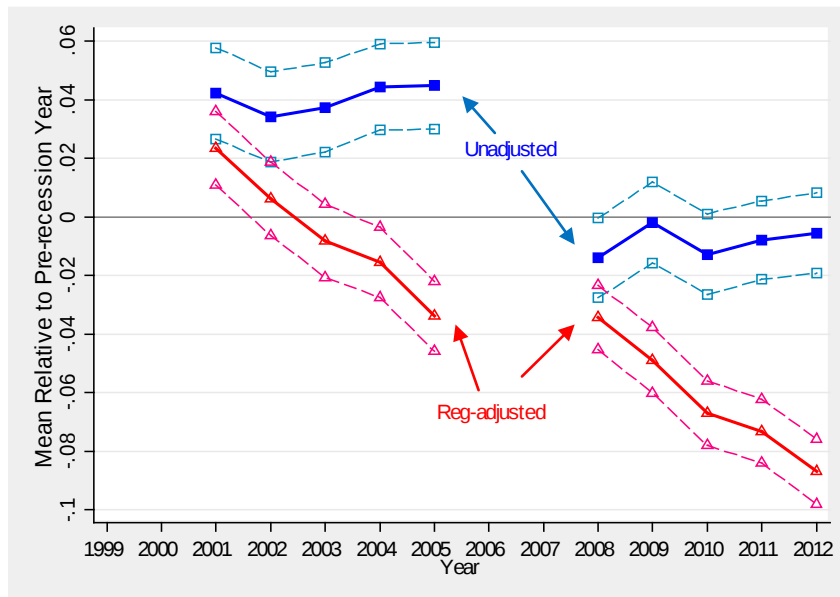


Figure 3.2 Log Real Wages in the Recessions in the 2000s

A. Men



B. Women



Notes: The figures plot the estimation results presented in Tables 3.2 and 3.3. Since the results from the regression adjustment and DFL reweighting are quite similar, only the regression adjustment results are plotted here for simplicity. Each point represents the estimate of mean relative to pre-recession year with its 95% confidence interval. Pre-recession years are 2000 and 2007, respectively. Means in 2000 and 2007 are normalized to zero.

Figure 3.3 Mean Year-to-Year Changes in Log Real Wage by Gender from Longitudinally Matched MS/MUS Data

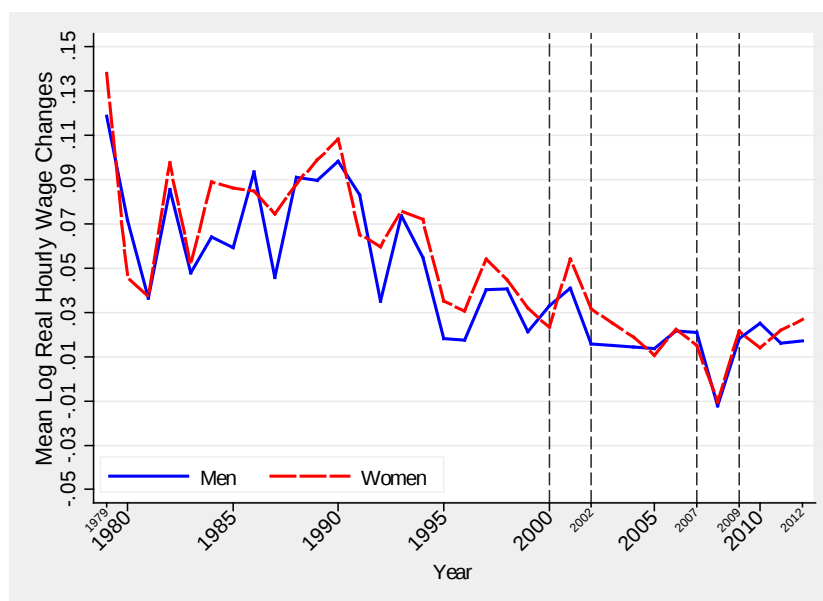
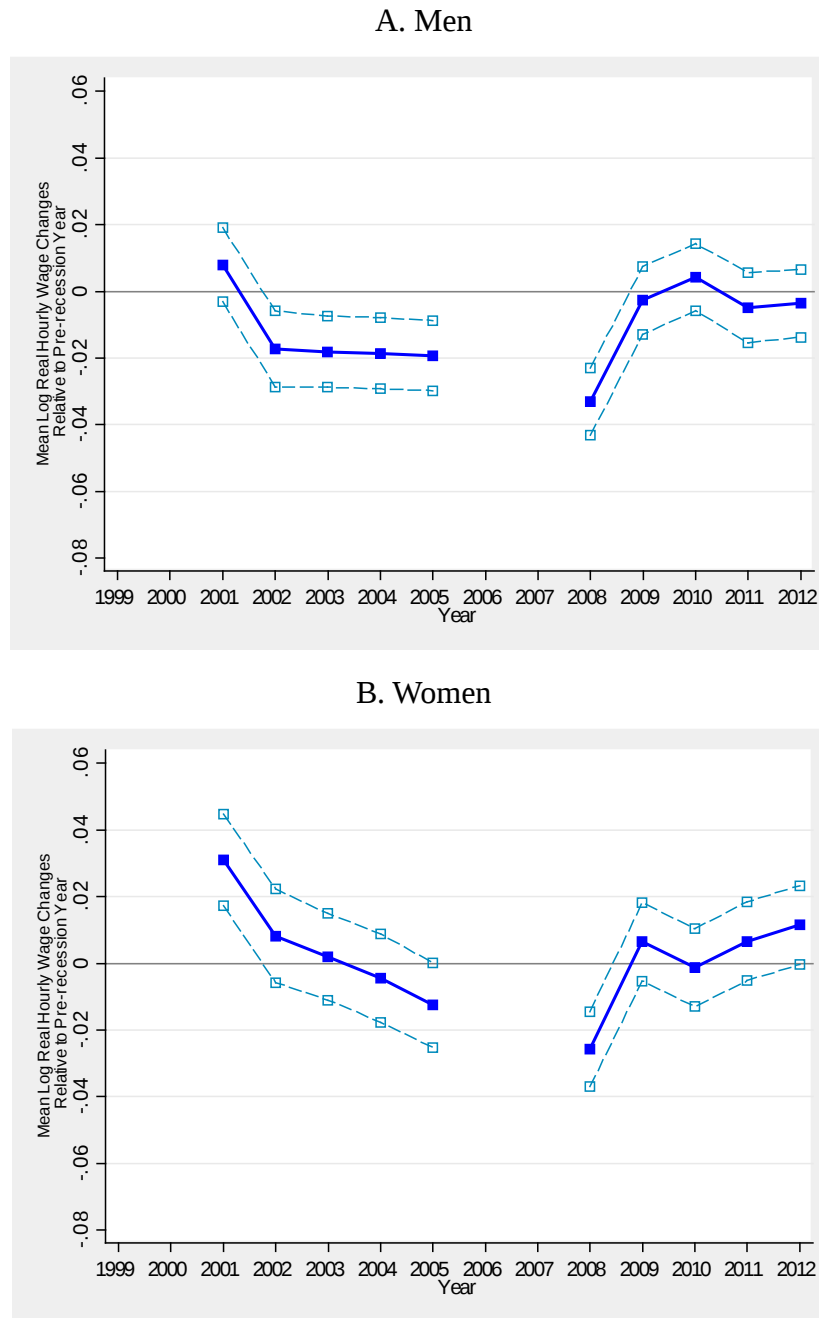
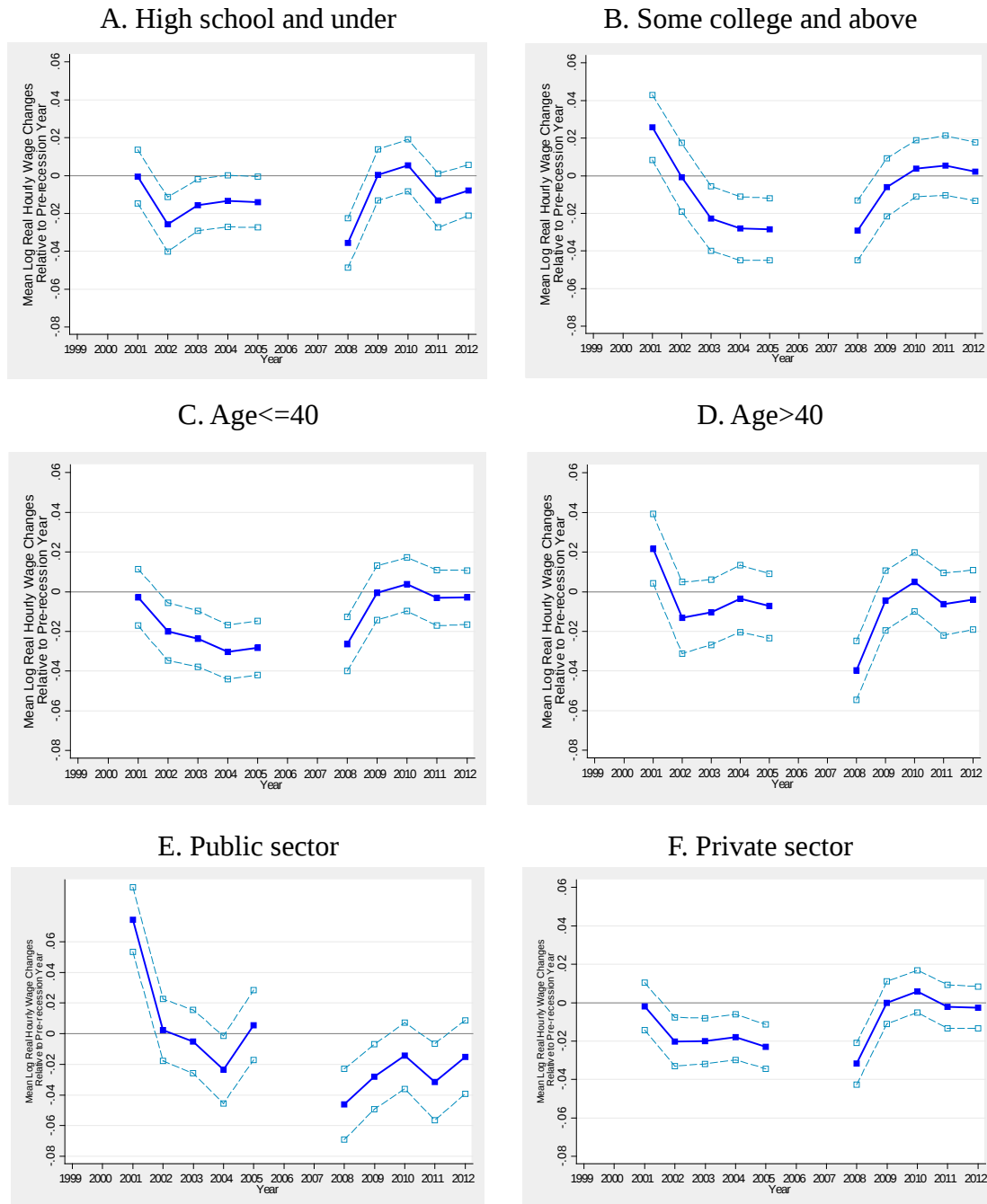


Figure 3.4 Log Real Wage Changes in the Recessions in the 2000s



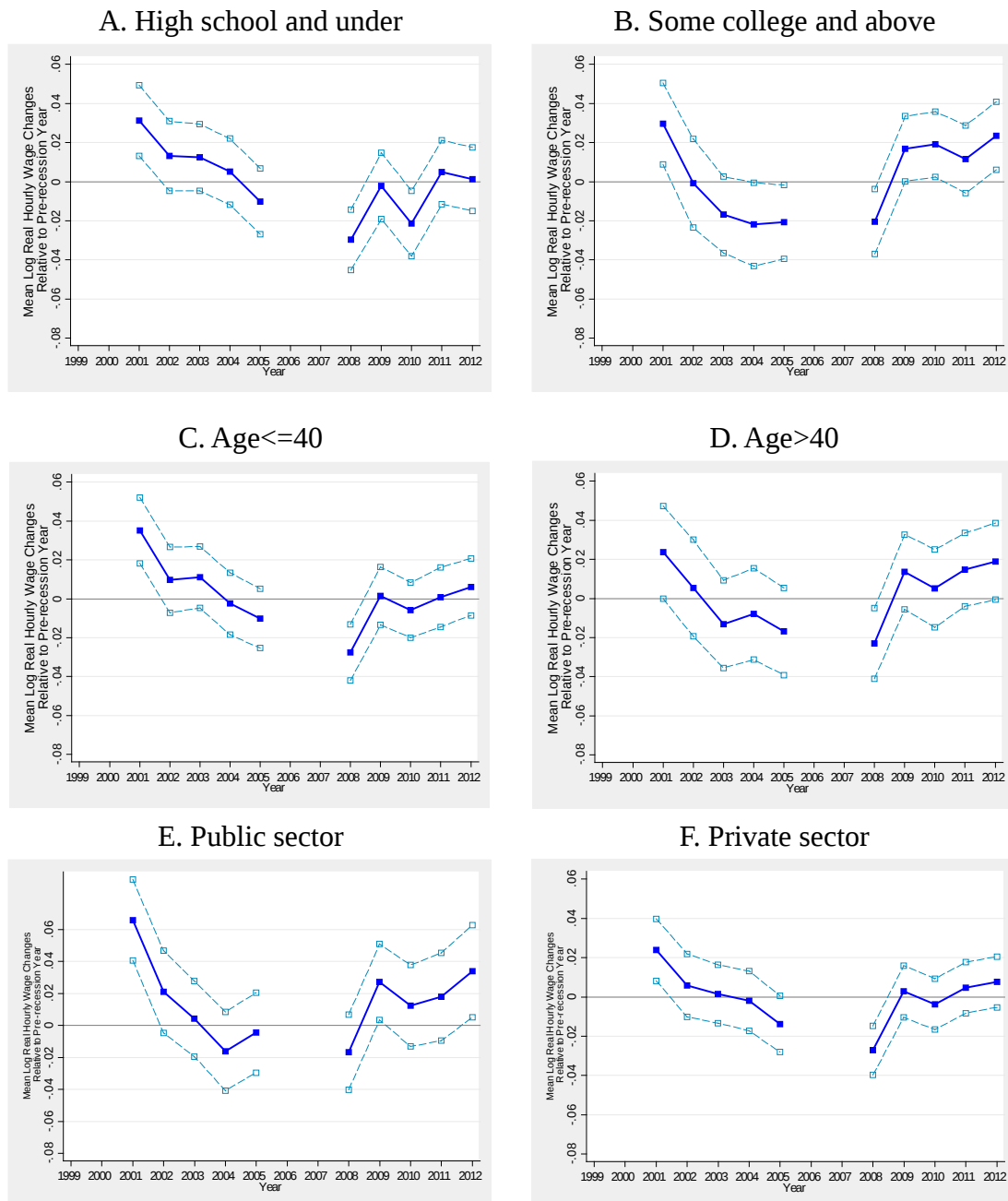
Notes: The figures plot the estimation results presented in Tables 3.4. Since the unadjusted and regression-adjusted results are quite similar, only the regression adjustment results are plotted here for simplicity. Each point represents the estimate of mean changes relative to pre-recession year with its 95% confidence interval. Pre-recession years are 1999-2000 and 2006-2007, respectively. Mean changes in 1999-2000 and 2006-2007 are normalized to zero.

Figure 3.5 Log Real Wage Changes in the Recessions in the 2000s
by Education, Age, and Sector, Men



Notes: Each point represents the estimate of mean changes relative to pre-recession year with its 95% confidence interval. Pre-recession years are 1999–2000 and 2006–2007, respectively. Mean changes in 1999–2000 and 2006–2007 are normalized to zero.

Figure 3.6 Log Real Wage Changes in the Recessions in the 2000s
by Education, Age, and Sector, Women



Notes: Each point represents the estimate of mean changes relative to pre-recession year with its 95% confidence interval. Pre-recession years are 1999–2000 and 2006–2007, respectively. Mean changes in 1999–2000 and 2006–2007 are normalized to zero.

APPENDIX B - TABLES

Table 3.1 Mean Log Real Hourly Wages by Gender and Year

Year	Annual Unemployment Rate	Men's Log Real Wages		Women's Log Real Wages	
		Mean	S.E.	Mean	S.E.
1978	1.67	4.375	0.005	4.047	0.011
1979	1.27	4.479	0.005	4.124	0.010
1980	1.23	4.522	0.005	4.137	0.010
1981	1.36	4.544	0.004	4.160	0.009
1982	2.14	4.624	0.004	4.236	0.009
1983	2.71	4.650	0.004	4.252	0.009
1984	2.45	4.685	0.004	4.283	0.008
1985	2.91	4.710	0.004	4.314	0.007
1986	2.66	4.786	0.004	4.363	0.007
1987	1.97	4.828	0.004	4.414	0.007
1988	1.69	4.926	0.004	4.518	0.007
1989	1.57	5.030	0.003	4.610	0.006
1990	1.67	5.119	0.004	4.714	0.006
1991	1.51	5.198	0.003	4.794	0.006
1992	1.51	5.221	0.003	4.857	0.006
1993	1.45	5.293	0.003	4.910	0.006
1994	1.56	5.336	0.003	4.959	0.006
1995	1.79	5.331	0.003	4.978	0.005
1996	2.60	5.331	0.003	4.996	0.005
1997	2.72	5.337	0.003	5.024	0.005
1998	2.69	5.351	0.003	5.050	0.005
1999	2.92	5.354	0.004	5.073	0.005
2000	2.99	5.360	0.004	5.068	0.005
2001	4.57	5.377	0.004	5.110	0.006
2002	5.17	5.367	0.004	5.102	0.006
2003	4.99	5.356	0.004	5.106	0.006
2004	4.44	5.348	0.004	5.113	0.005
2005	4.13	5.341	0.004	5.113	0.005
2006	3.91	5.331	0.004	5.106	0.005
2007	3.91	5.324	0.004	5.096	0.005
2008	4.14	5.304	0.004	5.082	0.005
2009	5.85	5.299	0.004	5.094	0.005
2010	5.21	5.289	0.004	5.083	0.005
2011	4.39	5.283	0.004	5.088	0.005
2012	4.24	5.264	0.004	5.091	0.005

Notes: The standard errors (S.E.) are robust to heteroskedasticity.

Table 3.2 Men's Log Real Wages in the Recessions in the 2000s

Year	Unadjusted	Regression- Adjusted	DFL Reweighted
2000	0 (normalized)	0 (normalized)	0 (normalized)
2001	0.017 (0.006)	0.006 (0.005)	0.009 (0.006)
2002	0.007 (0.006)	-0.015 (0.005)	-0.010 (0.006)
2003	-0.004 (0.006)	-0.034 (0.005)	-0.032 (0.006)
2004	-0.012 (0.005)	-0.048 (0.005)	-0.046 (0.005)
2005	-0.019 (0.005)	-0.064 (0.005)	-0.062 (0.006)
2007	0 (normalized)	0 (normalized)	0 (normalized)
2008	-0.020 (0.006)	-0.032 (0.005)	-0.033 (0.005)
2009	-0.025 (0.006)	-0.056 (0.005)	-0.056 (0.006)
2010	-0.035 (0.006)	-0.067 (0.005)	-0.069 (0.006)
2011	-0.041 (0.006)	-0.077 (0.005)	-0.079 (0.006)
2012	-0.060 (0.006)	-0.101 (0.005)	-0.105 (0.006)

Note: The standard errors (in parentheses) are robust to heteroskedasticity.

Table 3.3 Women's Log Real Wages in the Recessions in the 2000s

Year	Unadjusted	Regression- Adjusted	DFL Reweighted
2000	0 (normalized)	0 (normalized)	0 (normalized)
2001	0.042 (0.008)	0.024 (0.006)	0.029 (0.008)
2002	0.034 (0.008)	0.006 (0.006)	0.009 (0.008)
2003	0.037 (0.008)	-0.008 (0.006)	0.001 (0.008)
2004	0.044 (0.008)	-0.015 (0.006)	0.000 (0.008)
2005	0.045 (0.008)	-0.034 (0.006)	-0.012 (0.008)
2007	0 (normalized)	0 (normalized)	0 (normalized)
2008	-0.014 (0.007)	-0.034 (0.006)	-0.029 (0.007)
2009	-0.002 (0.007)	-0.049 (0.006)	-0.040 (0.007)
2010	-0.013 (0.007)	-0.067 (0.006)	-0.055 (0.007)
2011	-0.008 (0.007)	-0.073 (0.006)	-0.053 (0.007)
2012	-0.006 (0.007)	-0.087 (0.006)	-0.058 (0.007)

Note: The standard errors (in parentheses) are robust to heteroskedasticity.

Table 3.4 Mean Year-to-Year Changes in Log Real Wage by Gender from
Longitudinally Matched MS/MUS Data

Year	Unemployment Rate (End of Period)	Men's Mean Year-to-Year Changes in Log Real Wages		Women's Mean Year-to-Year Changes in Log Real Wages	
		Mean	S.E.	Mean	S.E.
1978-1979	1.27	0.119	0.008	0.138	0.015
1979-1980	1.23	0.072	0.007	0.046	0.012
1980-1981	1.36	0.036	0.007	0.037	0.013
1981-1982	2.14	0.086	0.006	0.098	0.013
1982-1983	2.71	0.048	0.006	0.052	0.011
1983-1984	2.45	0.064	0.006	0.089	0.010
1984-1985	2.91	0.059	0.006	0.086	0.008
1985-1986	2.66	0.094	0.005	0.085	0.008
1986-1987	1.97	0.046	0.005	0.075	0.007
1987-1988	1.69	0.091	0.005	0.088	0.007
1988-1989	1.57	0.090	0.005	0.099	0.007
1989-1990	1.67	0.098	0.004	0.108	0.006
1990-1991	1.51	0.083	0.005	0.065	0.008
1991-1992	1.51	0.035	0.004	0.060	0.006
1992-1993	1.45	0.074	0.004	0.076	0.006
1993-1994	1.56	0.055	0.004	0.072	0.007
1994-1995	1.79	0.018	0.005	0.035	0.006
1995-1996	2.60	0.018	0.004	0.031	0.006
1996-1997	2.72	0.040	0.004	0.054	0.006
1997-1998	2.69	0.041	0.004	0.045	0.005
1998-1999	2.92	0.021	0.004	0.032	0.005
1999-2000	2.99	0.033	0.004	0.023	0.005
2000-2001	4.57	0.041	0.004	0.054	0.005
2001-2002	5.17	0.016	0.004	0.032	0.005
2002-2003	4.99	0.015	0.004	0.025	0.005
2003-2004	4.44	0.015	0.004	0.019	0.005
2004-2005	4.13	0.014	0.004	0.011	0.004
2005-2006	3.91	0.022	0.004	0.022	0.004
2006-2007	3.91	0.021	0.004	0.015	0.004
2007-2008	4.14	-0.012	0.003	-0.010	0.004
2008-2009	5.85	0.018	0.003	0.022	0.004
2009-2010	5.21	0.025	0.003	0.014	0.004
2010-2011	4.39	0.016	0.004	0.022	0.004
2011-2012	4.24	0.017	0.003	0.027	0.004

Note: The standard errors (S.E.) are robust to heteroskedasticity.

Table 3.5 Log Real Wage Changes in the Recessions in the 2000s

Year	Unemployment Rate (End of Period)	Change in Log CPI	Men's Mean Log Real Hourly Wage Changes		Women's Mean Log Real Hourly Wage Changes	
			Unadjusted	Regression- Adjusted	Unadjusted	Regression- Adjusted
1999-2000	2.99	0.012	0 (normalized)	0 (normalized)	0 (normalized)	0 (normalized)
2000-2001	4.57	0.004	0.008 (0.006)	0.008 (0.006)	0.031 (0.007)	0.031 (0.007)
2001-2002	5.17	0.002	-0.017 (0.006)	-0.017 (0.006)	0.008 (0.007)	0.008 (0.007)
2002-2003	4.99	-0.001	-0.018 (0.005)	-0.018 (0.005)	0.002 (0.007)	0.001 (0.007)
2003-2004	4.44	0.009	-0.019 (0.005)	-0.019 (0.005)	-0.004 (0.007)	-0.005 (0.007)
2004-2005	4.13	0.016	-0.019 (0.005)	-0.019 (0.005)	-0.013 (0.006)	-0.014 (0.006)
2006-2007	3.91	0.007	0 (normalized)	0 (normalized)	0 (normalized)	0 (normalized)
2007-2008	4.14	0.038	-0.033 (0.005)	-0.033 (0.005)	-0.026 (0.006)	-0.025 (0.006)
2008-2009	5.85	-0.005	-0.003 (0.005)	-0.002 (0.005)	0.006 (0.006)	0.007 (0.006)
2009-2010	5.21	0.013	0.004 (0.005)	0.005 (0.005)	-0.001 (0.006)	-0.001 (0.006)
2010-2011	4.39	0.013	-0.005 (0.005)	-0.004 (0.005)	0.007 (0.006)	0.007 (0.006)
2011-2012	4.24	0.014	-0.004 (0.005)	-0.003 (0.005)	0.012 (0.006)	0.012 (0.006)

Note: The standard errors (in parentheses) are robust to heteroskedasticity.

BIBLIOGRAPHY

BIBLIOGRAPHY

- Abraham, Katharine G., and John C. Haltiwanger. 1995. "Real Wages and the Business Cycle." *Journal of Economic Literature*, 33(3): 1215–64.
- Anger, Silke. 2007. "The Cyclicalities of Effective Wages within Employer-Employee Matches: Evidence from German Panel Data." ECB/CEPR Labour Market Workshop on Wage and Labour Cost Dynamics, Working Paper Series No. 783.
- Bils, Mark J. 1985. "Real Wages over the Business Cycle: Evidence from Panel Data." *Journal of Political Economy*, 93(4): 666–89.
- Blank, Rebecca M. 1989. "Disaggregating the Effect of the Business Cycle on the Distribution of Income." *Economica*, 56(222): 141–63.
- Blundell, Richard, Claire Crawford, and Wenchao Jin. 2014. "What Can Wages and Employment Tell Us about the UK's Productivity Puzzle." *Economic Journal*, 124(576): 377–407.
- Bowlus, Audra, Haoming Liu, and Chris Robinson. 2002. "Business Cycle Models, Aggregation, and Real Wage Cyclicalities." *Journal of Labor Economics*, 20(2): 308–35.
- Carneiro, Anabela, Paulo Guimarães, and Pedro Portugal. 2012. "Real Wages and the Business Cycle: Accounting for Worker, Firm, and Job Title Heterogeneity." *American Economic Journal: Macroeconomics*, 4(2): 133–52.
- Devereux, Paul J., and Robert A. Hart. 2006. "Real Wage Cyclicalities of Job Stayers, Within- Company Job Movers, and Between-Company Job Movers." *Industrial and Labor Relations Review*, 60(1): 105–19.
- DiNardo, John E., Nicole Fortin, and Thomas Lemieux. 1996. "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach." *Econometrica*, 64(5): 1001–1004.
- Elsby, Michael W., Donggyun Shin, and Gary Solon. 2013. "Wage Adjustment in the Great Recession." NBER Working Paper No. 19478.
- Elsby, Michael W., Donggyun Shin, and Gary Solon. 2014. "Wage Adjustment in the Great Recession and Other Downturns: Evidence from the United States and Great Britain." Forthcoming in *Journal of Labor Economics*.
- Gregg, Paul, Stephen Machin, and Marina Fernandez-Salgado. 2014. "Real Wages and Unemployment in the Big Squeeze." *Economic Journal*, 124(576): 408–32.
- Hart, Robert A. 2006. "Worker-Job Matches, Job Mobility and Real Wage Cyclicalities." *Economica*, 73(290): 287–98.
- Lucas, Robert E., Jr., and Leonard A. Rapping. 1969. "Real Wages, Employment, and Inflation," *Journal of Political Economy*, 77(5): 721–54.
- Madrian, Brigitte C., and Lars John Lefgren. 2000. "An Approach to Longitudinally Matching Current Population Survey (CPS) Respondents." *Journal of Economic and*

- Social Measurement*, 26(2000): 31–62.
- Martins, Pedro. 2007. “Heterogeneity in Real Wage Cyclicalities.” *Scottish Journal of Political Economy*, 54(5): 684–98.
- Martins, Pedro S., Gary Solon, and Jonathan P. Thomas. 2012. “Measuring What Employers Do about Entry Wages over the Business Cycle: A New Approach.” *American Economic Journal: Macroeconomics*, 4(4): 36–55.
- Mortensen, Dale T., and Christopher A. Pissarides. 1994. “Job Creation and Job Destruction in the Theory of Unemployment.” *Review of Economic Studies*, 61(3): 397–415.
- Park, Seonyoung, and Donggyun Shin. 2005. “Explaining Procyclical Male-Female Wage Gaps.” *Economics Letters*, 88(2): 231–55.
- Peng, Fei, and W. Stanley Siebert. 2007. “Real Wage Cyclicalities in Germany and the UK: New Results Using Panel Data.” IZA Discussion Paper No. 2688.
- Peng, Fei, and W. Stanley Siebert. 2008. “Real Wage Cyclicalities in Italy.” *Labour*, 22(4): 569–91.
- Shin, Donggyun. 2012. “Cyclicalities of Real Wages in Korea.” *B.E. Journal of Economic Analysis and Policy (Contributions)*, 12(1): Article 2.
- Shin, Donggyun, and Gary Solon. 2007. “New Evidence on Real Wage Cyclicalities within Employer-Employee Matches.” *Scottish Journal of Political Economy*, 54(5): 648–60.
- Solon, Gary, and Robert Barsky. 1989. “Real Wages over the Business Cycle.” NBER Working Paper No. 2888.
- Solon, Gary, Robert Barsky, and Jonathan A. Parker. 1992. “Measuring the Cyclicalities of Real Wages: How Important Is Composition Bias?” NBER Working Paper No. 4202.
- Solon, Gary, Robert Barsky, and Jonathan A. Parker. 1994. “Measuring the Cyclicalities of Real Wages: How Important Is Composition Bias?” *Quarterly Journal of Economics*, 109(1): 1–26.
- Stockman, Alan C. 1983. “Aggregation Bias and the Cyclical Behavior of Real Wages.” Unpublished manuscript.
- Tremblay, Carol H. 1990. “Wage Patterns of Women over the Business Cycle.” *Quarterly Review of Economics and Business*, 30: 90–101.