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Essays on Wage Inequality and Economic Growth

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Essays on Wage Inequality and Economic Growth

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Abstract

This thesis is about the relationship between wage inequality and minimum wage, and then about parental choice and the impact of this on economic growth. First, it empirically examines the relation between wage inequality and the federal minimum wage. Then it develops a theory of how a parent of children with heterogeneous abilities makes choices on (a) investments in education for her children and (b) on the number of children she will have. Parental choices on these margins are shown to affect the rate of economic growth.

Chapter 1 briefly introduces my studies for the dissertation. In Chapter 2, I use a time-series analysis to examine whether real federal minimum wage is an important factor of wage inequality. Revisionists claim that non-market factors — falling real minimum wage and unionization in the United States labor market — rather than market factors — shifts in labor supply and demand — are responsible for increasing wage inequality, especially in the 1980s. Traditional economists, while disagreeing with the revisionist view, have yet to show explicitly that the falling real minimum wage is unrelated to wage inequality. The chapter demonstrates, using a time-series analysis, that non-market factors (minimum wage) may have a spurious relationship with wage inequality, and that market factors (shifts in labor supply and demand) are still important in determining wage inequality.

In Chapter 3, I show that when children's ability is heterogeneous, a parent's

choices about educational expenditures and fertility may be a pooling equilibrium or a separating equilibrium. Which of the two equilibria will prevail depends on the probability of getting a child with high ability to accumulate human capital. The outcome of the pooling choice in the pooling regime and the outcome of the separating choice in the separating regime make the growth rate of human capital higher than otherwise. However, as the probability of producing a child with high ability increases, the growth rate of human capital in the separating equilibrium exceeds that in the pooling equilibrium. Finally, I summarize and conclude in Chapter 4.

Dedication

I would like to dedicate this dissertation to my fiancée Sung-min Kim, family, and friends who have trusted and encouraged me to complete the journey to an economist.

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Chapter 1

Introduction

The relationship between wage inequality and economic growth is an important theme in economics. The wage inequality between different education and experience groups, which held stable in the 1960s and declined somewhat in the 1970s, rose sharply in the 1980s. At the same time, there was a rise in the within-group wage inequality (Juhn, Murphy, and Pierce 1993) [41]. Many studies have been carried out in an attempt to identify the reason for the rapid rise. Among them, traditional economists have argued that the labor market factors (i.e., labor demand and supply) are an important determinant of the earnings inequality, and that the phenomenon of rising inequality is 'secular'. In addition, they studied why shifts in the demand and supply took place.

According to previous literature on the shifts in labor demand and supply, rising inequality can be explained primarily by two theories. One is skill-biased technical change (SBTC) theory, which posits that development in technology toward high-skilled workers led to an increase in the labor demand of high-skilled workers in the 1980s (Krueger 1993 [46]; and Juhn, Murphy, and Pierce 1993 [41]). The other theory is that the large international trade deficit in the 1980s caused a decrease in labor demand for the manufacturing sector but an increase for high-skilled and female workers (Murphy and Welch 1992) [54].

In contrast, recent literature (DiNardo, Fortin, and Lemieux 1996 [28]; Lee 1999 [48]; Card and DiNardo 2002 [20]; and Lemieux 2006 [49]) on inequality argues that the sharp increase in wage inequality in the 1980s is an 'episodic' event due to government policies such as the constant federal nominal minimum wage (leading to the fall in the real minimum wage) and declining unionization rather than labor market factors. In fact, the Reagan administration raised no nominal federal minimum wage during his presidency.

However, building on Autor, Katz, and Kearney's (2005) [7] study, I try to demonstrate in Chapter 2 that there may be a spurious relationship between non-market factors such as minimum wage and the earnings inequality (in particular, between-group wage inequality). I use both static and time-series models. For the analyses, I use the March Current Population Survey (CPS) data extracted from the IPUMS-CPS database.[1] In addition, I use quantile regressions as well as ordinary least squares to calculate the inequalities for both educational groups and quantiles prior to the time-series analysis. Through these empirical methods, my findings support the traditional economists' view.

Chapter 3 addresses how a parent chooses educational expenditures for her children and then fertility when her children's abilities are heterogeneous. To analyze these, I introduce human capital, which is regarded as an engine of economic growth, into the model. The human capital theory, first introduced by Adam Smith, was pioneered and contributed considerably to by Mincer (1958) [52], Schultz (1961) [58], Becker (1962, 1964, 1993) [10] [11] [12], and Ben-Porath (1967) [14]. Additionally, it was examined by Lucas (1988) [50], Becker, Murphy, and Tamura (1990) [13], and

[1] King, Ruggles, Alexander, Leicach, and Sobek. Integrated Public Use Microdata Series, Current Population Survey: Version 2.0. [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor], 2004. www.ipums.org/cps.

Tamura (1991) [59].

This chapter is motivated by Acemoglu's (1999) [3] notion. Assuming that there are workers in the labor market whose skills are heterogeneous, his model shows that there may be two equilibria — a pooling equilibrium and a separating equilibrium. Relying on his model, I use the overlapping generations model for a theoretical framework with the assumption that a person lives only for two periods and the fraction of children with high ability is exogenously given. Then, as in Acemoglu (1999) [3], I derive two different equilibria when children's abilities are heterogeneous.

One is the pooling equilibrium where a parent invests in education for her children regardless of their ability. The other is the separating equilibrium where, after observing the children's ability, the parent makes a discriminatory decision on whether she will spend her resources educating her children. This decision depends on whether the children's abilities are high or low. It should be noted that the pooling choice may mean a more equal chance to be educated, compared to the separating choice. That is, since the pooling choice has a parent choosing without consideration of how her child's ability, it may provide her child only with public or compulsory education. In contrast, the separating choice utilizes her discriminatory decision on education, and thus may lead her child to go to a private school if he is smart. The less intelligent child, she would provide with public education or no formal education at all. This notion might be similar to Glomm and Ravikumar's (1992) [34] conclusion. In addition, with the model with fertility, I show how her fertility choices are different in each equilibrium. Furthermore, based on the two equilibria, I explore how the economy grows by using the discrete dynamics of human capital. In Chapter 4, I summarize and conclude for these two chapters.

Chapter 2

Wage Inequality and Minimum Wage: Some Evidence from Time-Series Analysis

2.1 Introduction

The literature on wage inequality is not new in labor economics, but it is a persistent issue among labor economists. In particular, the growth in wage inequality between high school and college graduates has been rising (Bound and Johnson 1992) [16] during the 1980s. This phenomenon is shown in Figure 2.1.[1] The rise in between-group wage inequality[2] continues until the early 1990s and then weakens. Together with the rising between-group earnings inequality, the within-group (or residual) wage inequality rose rapidly during the 1980s. Juhn, Murphy, and Pierce (1993) [41] suggest that between 1963 and 1989 an increase in wage inequality for males is apparently observed, and that much of the increase is explained by the increased returns to skill components other than years of education and experience.

[1]Figures are provided in Appendix 2.6. Using the Current Population Survey (CPS) datasets from 1962 to 2005, the log wage inequality in this study is the log ratio of predicted values over years. I will explain in details later on.

[2]Between-group wage inequality refers to the ones caused by differences between demographic characteristics, such as education, gender, age, experience, etc.

According to conventional or 'traditional' economists, wage inequality is caused primarily by the structure of the labor market, such as labor supply and demand (Katz and Murphy 1992) [42]. Their claim is that the earnings inequality during the last two decades is structural and 'secular' due to differential shifts in labor supply and demand in different skill groups. Specifically, the rise in inequality in the 1980s is caused largely by increases in the relative demand for skilled workers and females. Krueger (1993) [46] argues that the computer revolution in the 1980s has an explanatory power of 33 to 50 percent for the increase in the rate of return to education, implying an increase in the relative demand for skilled workers. His argument supports the skill-biased technical change (SBTC) story. Advocates for the SBTC believe that it explains changes in 1980's earnings inequality, along with the rise in residual wage inequality (Juhn, Murphy, and Pierce 1993) [41]. Another argument for the relative demand increase is that the United States' large deficits in international trade in the 1980s shifted up the relative demand for skilled workers and female. Deficits led to a decrease in employment for manufacture and an increase in employment for industries which require highly educated workers and females (Murphy and Welch 1992) [54].

In contrast, recent literature suggests that rising wage inequality is not a 'secular' phenomenon from the structure of labor market. Rather, it was an episode only in the 1980s deriving from government policies, such as falling real minimum wage, declining unionization, etc. (DiNardo, Fortin, and Lemieux 1996 [28]; Lee 1999 [48]; Card and DiNardo 2002 [20]) — these economists are called 'revisionists' by Autor, Katz, and Kearney (2005) [7]. Specifically, using the kernel density methods, DiNardo et al. (1996) [28] suggest that the fall in the real minimum wage is an important factor of the U.S. wage distribution in the 1980s. In addition, Lee (1999) [48] examines the differential impact of the falling real value of federal minimum wage across regions within the United States to capture the contribution of the minimum wage to the earnings dispersion increase in the lower tail of wage distribution during the 1980s. Lee concludes that the falling minimum wage greatly affects the increased earnings inequality in the lower half of wage distribution over the same period. Card and DiNardo (2002) [20] point out that earnings inequality slowed down in the 1990s and that Krueger (1993)'s [46] SBTC is hard to reconcile with the slowdown because computer use continued in the 1990s, but inequality decreased over the same period. They find that the SBTC story is inadequate to explain various shifts in wage structure in the United States labor market. They also argue that the falling real minimum wage in the United States gave rise to a rapid increase in wage inequality in the 1980s. Lemieux (2006) [49] argues that the rising residual wage inequality during the 1980s is not due to price effects from the increase in relative demand for skilled workers, but rather it is due to composition effects from an increase in the fraction of high skilled and experienced workers in the United States labor market. He suggests that the real minimum wage is closely connected with the residual wage inequality in perspective of the time series pattern. The falling log real minimum wage[3] is presented in Figure 2.4, where we can confirm that the real minimum wage is decreasing during most of the periods, especially in the 1980s.

In contrast to the revisionists' arguments, Autor et al. (2005) [7] point out that while the fall in the real value of the federal minimum wage in the 1980s might be seen as an important factor in the rising lower-tail inequality of wage distribution, it does not explain the increase in upper-tail wage inequality over the same period. A decline in the federal minimum wage is unlikely to raise the upper-tail earnings inequality.[4] Then, they conclude that "a single factor (i.e., the naive SBTC hypoth-

[3]Minimum wage is deflated by personal consumption expenditures: chain-type price index (PCEPI) in terms of 2000. Figure 2.4 is similar to Autor et al. (2005) [7].

[4]We can see in Figure 2.7 that the upper-tail wage inequality is increasing during the 1980s.

esis, the minimum wage, declining unionization, immigration, international trade, or shifts in labor force composition) cannot explain changes in the whole wage structure in the United States over the past decades." They do not, however, show explicitly that the minimum wage is unrelated to wage inequality. Thus, in this research I try to examine the relationship between wage inequality (in particular, between-group wage inequality) and the real minimum wage (along with corresponding relative labor supply). Section 2.2 shows basic theoretical and empirical models. Section 2.3 describes data to be used and the wage equation I use to get predicted log weekly wages for college and high school graduates and for percentiles (or quantiles). Using static and time-series analyses, I present and interpret empirical results in Section 2.4, and Section 2.5 concludes.

2.2 Theoretical and Empirical Models

The theoretical framework associated with wage inequality starts with the CES production function that Autor et al. (2005) [7] use as follows:

$$Y_t = \left[\lambda_t \left(\alpha_t L_{st}\right)^{\rho} + \left(1 - \lambda_t\right)\left(\beta_t L_{ut}\right)^{\rho}\right]^{1/\rho}, \tag{2.1}$$

where t is time period (i.e., year), s, skilled workers, u, unskilled workers, L, the work hours of labor employed, and λ_t, a time-varying technology factor of how important skilled workers are relative to unskilled workers in production. In addition, α_t and β_t are time-varying technological changes augmented to skilled and unskilled workers, respectively, which stand for specific technology levels of each worker, and ρ is a time-invariant production factor, which makes the elasticity of substitution $\sigma = 1/(1-\rho)$.

Using the CES production function and the assumption that the wage rate of each skill group is their marginal product times shadow value under cost minimization, it is straightforward to get the wage ratio of each group in the ratio of marginal product below:

$$\frac{w_{st}}{w_{ut}} = \frac{\lambda_t}{1-\lambda_t}\left(\frac{\alpha_t}{\beta_t}\right)^{\rho}\left(\frac{L_{st}}{L_{ut}}\right)^{\rho-1}. \tag{2.2}$$

Taking logs in both sides, the log wage ratio (or log wage inequality) is given by

$$\ln\left(\frac{w_{st}}{w_{ut}}\right) = \ln\left(\frac{\lambda_t}{1-\lambda_t}\right) + \frac{\sigma-1}{\sigma}\ln\left(\frac{\alpha_t}{\beta_t}\right) - \frac{1}{\sigma}\ln\left(\frac{L_{st}}{L_{ut}}\right). \tag{2.3}$$

Not surprisingly, this equation is well known and classical, but the prediction of this model is interesting, i.e., since σ is positive, it shows wage inequality has an inverse relationship with relative labor demand. Additionally, the first two terms in the right hand side represent relative demand shifts between skilled and unskilled workers, which mean skill-biased demand shifts.[5] Then I assume that there exists a relative labor supply. Using this relative labor demand equation and assumed relative labor supply, we can get the equilibrium wage inequality and the equilibrium relative quantity of labor employed in the labor market. As labor supply and/or demand shift over time, the locus of the equilibrium points in the space of relative wage and quantity of labor employed may decrease, increase, or remain constant. Focusing on the two forces of the price effect and the market size effect in terms of skill-biased technical change (SBTC), Acemoglu (2002) [4] shows that if the elasticity of substitution is sufficiently large, the (long-run) endogenous technology demand curve for a factor may be upward sloping.

[5]Although I control for the shifters in the empirical model (i.e., real minimum wage, unemployment rate, time trend, and so on) as in Autor et al. (2005) [7], I do not think that the model is fully specified.

Based on the theoretical model and Autor et al. (2005) [7], I specify the basic regression model as follows:

$$\ln\left(\frac{w^*_{st}}{w^*_{ut}}\right) = \phi_0 + \phi_1 \ln\left(\frac{L^*_{st}}{L^*_{ut}}\right) + \phi_2 \ln(mWage_t) + \phi_3 Unrate_t + \epsilon_t, \qquad (2.4)$$

where $mWage_t$ is a time-varying real minimum wage, $Unrate_t$, a time-varying annual unemployment rate. The asterisks in Equation (2.4) indicate that the associated variables are in equilibrium where labor markets clear. As mentioned earlier, the long-run equilibrium in a labor market may decrease, increase, or remain constant over time, which implies the sign of ϕ_1 in the specification can be negative, positive, or zero. In the standard case, if relative labor supply increases, wage inequality will decrease, i.e., the sign of ϕ_1 will be negative. However, the wage inequality would rather increase only if labor demand shifts out much relative to labor supply for any reason. As a matter of fact, relative supply of college workers in the United States rose suddenly in the 1970s and 1980s (Autor et al. 2005) [7] as shown in Figure 2.2, and wage inequality also increased (Bound and Johnson 1992) [16]. Using search and matching models, Acemoglu (1999) [3] presents a theoretical model resolving this puzzle. He suggests that an increase in supply of skilled workers changes the composition of jobs in the labor market, and, in turn, makes profit-maximizing firms increase demand for skilled workers. Specifically, he shows that if skilled workers in a labor market with friction got relatively abundant, then firms would find it profitable to design jobs for skilled workers rather than for both types of workers. Consequently, his view is that without any possibilities of skill-biased technical change, the labor demand for skilled workers could increase due to an increase in the labor supply of skilled workers in the 1970s and 1980s.

2.3 Data and Estimation

2.3.1 Data

In this research I use primarily the 'harmonized' March Current Population Survey (CPS) data, which are extracted from the IPUMS-CPS database.[6] The U.S. household survey of the CPS is carried out monthly by the U.S. Census Bureau and the Bureau of Labor Statistics together. The CPS contains labor statistics as well as basic demographic files of household, family, and individuals, such as age, sex, race, marital status, educational attainment, annual income, hours per week and weeks worked last year, etc. In fact, the CPS data are not longitudinal data, but "each household is surveyed once a month for four consecutive months per year, and again for the corresponding time period a year later." (For more information, see the CPS data codebook.)

The sample period in this study is 1962 and from 1964 to 2005 because the 1963 CPS dataset does not include any variable measuring educational attainment (i.e., years of schooling). I consider only full-time workers[7] who had positive annual earnings last year with positive person weights. I exclude observations for workers who did not work previous week in datasets before 1976 since their hourly wages lead to missing values even though I do not focus on hourly wage. It should be noted that in the CPS datasets prior to 1976, the usual work hours a week last year are not reported, but only the hours worked previous week. In addition, they have no variable for weeks worked last year, but they report intervals of weeks worked, such as 1-13 weeks, 14-26 weeks, etc. Thus, I assign to a respondent's weeks worked an arithmetic

[6] King, Ruggles, Alexander, Leicach, and Sobek. Integrated Public Use Microdata Series, Current Population Survey: Version 2.0. [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor], 2004. www.ipums.org/cps.

[7] A full-time worker refers to one who worked 35 hours a week or more during the previous year.

Table 2.1: Descriptive statistics of sampled CPS data

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Year	2168537	1986.86	11.84	1962.00	2005.00
Age	2168537	39.09	12.43	14.00	98.00
Wage and salary income	2168537	22671.39	27257.01	1.00	748263.00
Weekly wage	2168537	458.89	538.21	0.02	30791.06
Years of schooling	2167927	12.77	2.93	0.00	20.00
Experience[a]	2168537	20.32	12.93	0.00	88.00
Total hours worked last year	2168537	2083.54	551.31	7.00	5148.00
Male[b]	2168537	0.60	0.49	0.00	1.00
Female	2168537	0.40	0.49	0.00	1.00
Northeast	2168537	0.23	0.42	0.00	1.00
Midwest[b]	2168537	0.25	0.43	0.00	1.00
South[b]	2168537	0.30	0.46	0.00	1.00
West	2168537	0.23	0.42	0.00	1.00
White[b]	2168537	0.87	0.34	0.00	1.00
Black[b]	2168537	0.09	0.29	0.00	1.00
Other	2168537	0.04	0.19	0.00	1.00

[a]Experience = age - years of schooling - 6. The negative experience with this process is coded zero.
[b]Dummy variables to be used in the regression below.

average of each interval. From 1976 on, the CPS datasets have variables indicating usual hours worked per week and weeks worked last year. I use years of schooling as a variable measuring educational attainment, which is coded based on highest grade completed (HIGRADE) in 1962 and 1964 to 1991 datasets and on highest level of educational attainment (EDUC99) in 1992 to 2005. Recall that there is no variable for educational attainment in 1963. Table 2.1 shows descriptive statistics of sample data from the CPS.

As macro data, I collect nominal minimum wage and unemployment rate data from the U.S. Department of Labor (Bureau of Labor Statistics), and the real U.S. GDP chained 2000 dollars and the personal consumption expenditures: chain-type price index (PCEPI) from the U.S. Department of Commerce (the Bureau of Economic Analysis). Using the PCEPI, I calculate the nominal minimum wage into real minimum wage in terms of 2000.[8] I also calculate real GDP per capita using the mean U.S. population in the year.

2.3.2 History of Minimum Wage

This subsection is a brief historic sketch of U.S. federal minimum wage, depending heavily upon Waltman (2000) [61].[9] Massachusetts passed the first U.S. minimum wage in 1912, although it covered only women and minors in some industries. Since then, many other states have established statutes associated with the minimum wage. In 1923 the Supreme Court struck down the minimum wage law of the District of Columbia because it was unconstitutional based on "liberty of contracts" by employers and employees. For this reason, in the 1920s the minimum wage statutes were virtually useless.

During the Great Depression, Franklin D. Roosevelt's administration tried to restore purchasing power by making the National Industrial Recovery Act of 1933 contain the minimum wage provision of $0.30 per hour at the federal level. However, it was again struck down by the Supreme Court in 1935. Through several political debates and procedures, the Fair Labor Standards Act of 1938 (FLSA), the first U.S. federal minimum wage law, was finally passed. Initially it set a minimum wage of $0.25, with increases by $0.05 per year up to $0.40. However, the minimum wage was not increased to $0.40 until 1945. The act covers all workers in manufacturing, mining, transportation, and public utilities associated with interstate commerce. Interestingly, the agricultural and retail sectors are excluded. I conjecture that the exclusion might stem from fear of the possibility of a downfall in small business.

In 1949, the Truman administration succeeded in passing a bill to increase

[8] See Figure 2.3.

[9] For details, see Waltman (2000) [61] pp. 28-47.

minimum wage to $0.75, but with a compromise accepting the reduction of coverage in that it applies only to workers whose jobs are indispensable to interstate commerce. The reduction, attributable to political frictions with Congressional Republicans associated with the Taft-Hartley Act in 1948, led to keeping about one million workers away from the protection of the minimum wage law.

In 1956, the minimum wage increased to $1.00 in the Eisenhower administration, but new coverage was not considered. In 1961, although a bill to cover retail workers and to increase to $1.25 was suggested by Senator John F. Kennedy, in the end the minimum wage increased to $1.15 by a compromise. After Kennedy was elected President of the United States, he submitted a bill increasing minimum wage to $1.25 and covering all retail workers engaged by firms with more than $1 million in sales. However, it was not easy to pass the bill, and so coverage was reduced, compared to the original bill, although it was successful in increasing the minimum wage to $1.25.

Under the Johnson administration, minimum wage increased to $1.40 in 1967, and then to $1.60 in 1968. Coverage expanded, but agricultural workers were still excluded. Under the Nixon administration, minimum wage rose to $2.00 in 1974, $2.10 in 1975, and $2.30 in 1976. During this period, the practice of paying 85 percent (subminimum) of the minimum wage to youth holding part-time jobs was first introduced. During the Carter administration, the minimum wage increased to $2.65 in 1978, $2.90 in 1979, $3.10 in 1980, and $3.35 in 1981, along with defeating the youth subminimum. In the Carter administration, the minimum wage increased annually and labor unions were powerful. According to some studies, this continual increase in minimum wage led to a stagflation in the early 1980s.

The Reagan administration thought that the minimum wage caused high unemployment and recession, and so there was no increase in minimum wage during his period. George Bush increased the minimum wage to $4.25 in 1991, along with an attempt to restore a youth subminimum "training wage". Finally, the Clinton administration increased the minimum wage twice, to $4.75 in 1996 and then $5.15 in 1997.

2.3.3 Wage Equation and Estimation

I adopt the methods used by Autor et al. (2005) [7] to calculate earnings inequality. Based on actual weekly wage calculated, I estimate the following wage equation and get the predicted values of the dependent variable by year. It should be noted that, as a dependent variable, I focus on weekly wages made by dividing annual earnings by weeks worked.

$$\ln w_i = x_i'\gamma + \epsilon_i, \tag{2.5}$$

where w_i is a weekly wage of individual i in a given year, x_i is a vector of time invariant characteristics of individual i in a given year, and ϵ_i is a random error in a given year. The specific wage equations to be estimated in a given year are presented as follows:[10]

Model 1

$$\begin{aligned} \ln w_i = \gamma_0 + \gamma_1 Exp_i + \gamma_2 Expsq_i + \gamma_3 Yrsed_i + \gamma_4 Male_i + \gamma_5 White_i \\ + \gamma_6 Black_i + \gamma_7 Northeast_i + \gamma_8 Midwest_i + \gamma_9 South_i + \epsilon_i \end{aligned} \tag{2.6}$$

[10]The empirical specifications are based on the Mincer-type wage equation (1974) [53]. To get the predicted log weekly wages for high school and college graduates, the empirical models are evaluated at the sample means of the independent variables in the whole dataset. In contrast, for each quantile, they are evaluated at the sample means of independent variables in high school dropouts and graduates with experience less than or equal to 9 years.

Model 2

$$\ln w_i = \gamma_{0\theta} + \gamma_{1\theta} Exp_i + \gamma_{2\theta} Expsq_i + \gamma_{3\theta} Yrsed_i + \gamma_{4\theta} Male_i + \gamma_{5\theta} White_i \qquad (2.7)$$
$$+\gamma_{6\theta} Black_i + \gamma_{7\theta} Northeast_i + \gamma_{8\theta} Midwest_i + \gamma_{9\theta} South_i + \epsilon_{\theta i}$$

where Exp is experience, $Expsq$, experience squared, and $Yrsed$, years of schooling. Using Model 1 and the ordinary least square (OLS) estimation, I obtain the predicted log weekly wages of high school and college graduates. In Model 2, $\gamma_{j\theta}$ indicates the jth coefficient of θth quantile for $j = 1 \ldots 9$. With Model 2, I use quantile regressions to get the predicted log weekly wages for the 1st, 3rd, 5th, 10th, 50th, and 90th quantiles, which are all evaluated at the sample mean of workers with low education and experience, i.e., high school dropouts and graduates with experience less than or equal to 9 years.

In this chapter, I briefly explain the quantile regression model introduced by Koenker and Basset (1978) [44]. The main advantages of the quantile regression are as follows: (a) we can estimate the responses of a dependent variable at any quantile to changes in regressors, (b) it is efficient relative to OLS estimators when the error terms are not normal or asymmetric, and (c) the estimates of coefficients are not sensitive to outliers because the quantile regressions give the outliers low weights relative to the OLS estimation.

The quantile regression model as in Model 2 can be expressed as

$$y_i = x_i'\beta_\theta + \epsilon_{\theta i} \quad \text{with} \quad Q_\theta(y_i|x_i) = x_i'\beta_\theta, \qquad (2.8)$$

where $Q_\theta(y|x)$ $(0 < \theta < 1)$ indicates the θth conditional quantile of dependent variable, y, given x, and β is $K \times 1$. If the conditional density function, $f(\epsilon|x)$, of the

Table 2.2: Selected regressions in Model 1

Variable	Dependent variable: Log weekly wage				
	1965	1975	1985	1995	2005
Experience	0.036***	0.042***	0.044***	0.043***	0.040***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience squared	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of schooling	0.072***	0.072***	0.091***	0.104***	0.117***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Male	0.498***	0.507***	0.408***	0.312***	0.330***
	(0.011)	(0.007)	(0.007)	(0.006)	(0.005)
White	0.079	0.052*	0.045***	0.053***	0.057***
	(0.053)	(0.028)	(0.017)	(0.011)	(0.009)
Black	-0.214***	-0.084***	-0.060***	-0.060***	-0.064***
	(0.055)	(0.030)	(0.020)	(0.014)	(0.011)
Northeast	-0.025	0.054***	-0.004	0.081***	0.034***
	(0.016)	(0.010)	(0.009)	(0.008)	(0.007)
Midwest	-0.089***	0.031***	-0.067***	-0.020**	-0.040***
	(0.016)	(0.010)	(0.009)	(0.008)	(0.007)
South	-0.241***	-0.066***	-0.067***	-0.036***	-0.027***
	(0.016)	(0.010)	(0.008)	(0.007)	(0.006)
Intercept	2.951***	3.436***	3.872***	4.057***	4.217***
	(0.058)	(0.033)	(0.024)	(0.018)	(0.016)
R-square	0.243	0.285	0.219	0.276	0.281
Observations	19841	35332	56420	54874	78313

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

error term ϵ is symmetric, the conditional median ($\theta = 0.5$) of y is the same as the conditional expectation of dependent variable, $E[y|x]$. According to Koenker and Bassett (1978) [44], the θth quantile regression estimator $\hat{\beta}_\theta$ for β_θ is a solution to the following minimization problem:

$$\min_{\hat{\beta}_\theta \in \mathbb{R}^K} \frac{1}{n} \left[\sum_{t \in \{t: y_t \geq x_t' \hat{\beta}_\theta\}} \theta \left| y_t - x_t' \hat{\beta}_\theta \right| + \sum_{t \in \{t: y_t < x_t' \hat{\beta}_\theta\}} (1-\theta) \left| y_t - x_t' \hat{\beta}_\theta \right| \right]. \quad (2.9)$$

Table 2.3: Quantile regressions (Year 1965)

Variable	Dependent variable: Log weekly wage (estimates and standard errors)					
	q.1	...	q.3	...	q.5	...
Experience	0.068***	0.020	0.083***	0.008	0.078***	0.006
Experience squared	-0.001***	0.000	-0.002***	0.000	-0.001***	0.000
Years of schooling	0.106***	0.024	0.086***	0.015	0.086***	0.007
Male	-0.170	0.144	0.252***	0.097	0.436***	0.039
White	-0.017	0.713	-0.156	0.313	0.282	0.204
Black	-0.143	0.792	-0.384	0.376	-0.125	0.213
Northeast	0.172	0.180	0.094	0.113	0.085	0.087
Midwest	-0.494*	0.264	-0.223**	0.107	-0.214**	0.092
South	-0.534**	0.248	-0.562***	0.125	-0.414***	0.093
Intercept	0.315	0.788	1.338***	0.324	1.237***	0.179
R-square	0.056	...	0.068	...	0.098	...
	q.10	...	q.50	...	q.90	...
Experience	0.062***	0.003	0.030***	0.001	0.025***	0.001
Experience squared	-0.001***	0.000	-0.000***	0.000	-0.000***	0.000
Years of schooling	0.079***	0.003	0.069***	0.001	0.068***	0.001
Male	0.593***	0.020	0.507***	0.008	0.505***	0.009
White	0.139	0.152	0.069	0.064	0.015	0.081
Black	-0.321**	0.155	-0.217***	0.062	-0.160**	0.081
Northeast	0.046	0.035	-0.048***	0.011	-0.072***	0.017
Midwest	-0.102***	0.037	-0.051***	0.012	-0.071***	0.018
South	-0.329***	0.033	-0.208***	0.014	-0.159***	0.021
Intercept	1.926***	0.138	3.145***	0.070	3.707***	0.085
R-square	0.146	...	0.200	...	0.182	...
Observations	19841					

* significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

In Equation (2.9), we can see that the quantile regression model is a solution to the minimization problem of the weighted sum of residuals in absolute value. However, this problem is not solvable by differentiating the objective function like Equation (2.9) with respect to parameters. Instead, since the quantile regression model is represented as a linear programming (LP) model, using the LP method allows us to solve the minimization problem, although generalized method of moments (GMM) is available to use as well. Moreover, using the bootstrap method enables us to obtain

Table 2.4: Quantile regressions (Year 1975)

Variable	Dependent variable: Log weekly wage (estimates and standard errors)					
	q.1	...	q.3	...	q.5	...
Experience	0.086***	0.011	0.091***	0.007	0.073***	0.004
Experience squared	-0.002***	0.000	-0.002***	0.000	-0.001***	0.000
Years of schooling	0.106***	0.017	0.074***	0.007	0.070***	0.004
Male	0.296***	0.085	0.546***	0.041	0.555***	0.024
White	0.125	0.153	0.348	0.217	0.219*	0.113
Black	-0.033	0.304	0.060	0.260	-0.087	0.129
Northeast	0.395*	0.214	0.162**	0.072	0.142***	0.041
Midwest	0.125	0.205	0.096	0.085	0.110**	0.049
South	0.117	0.197	0.028	0.102	0.000	0.047
Intercept	0.491	0.329	1.432***	0.263	2.076***	0.154
R-square	0.056	...	0.086	...	0.103	...
	q.10	...	q.50	...	q.90	...
Experience	0.057***	0.002	0.037***	0.001	0.034***	0.001
Experience squared	-0.001***	0.000	-0.001***	0.000	-0.001***	0.000
Years of schooling	0.071***	0.003	0.073***	0.001	0.073***	0.001
Male	0.546***	0.009	0.506***	0.007	0.519***	0.009
White	0.161***	0.034	0.039*	0.021	-0.017	0.016
Black	-0.057	0.049	-0.085***	0.023	-0.107***	0.018
Northeast	0.101***	0.023	0.024***	0.007	0.009	0.011
Midwest	0.080***	0.023	0.019**	0.010	-0.001	0.011
South	-0.041*	0.021	-0.090***	0.010	-0.065***	0.011
Intercept	2.615***	0.064	3.582***	0.026	4.108***	0.022
R-square	0.135	...	0.231	...	0.231	...
Observations	35332					

* significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

the covariance matrix of estimators from the LP method.[11]

2.3.4 Estimation Results

The selected regression results over ten-year intervals with Models 1 and 2 are shown from Table 2.2 to Table 2.7. Using Model 1 with the OLS estimation, Table 2.2 shows that the selected regression results are similar to those of conventional studies

[11]For details, see Buchinsky (1994, 1998) [18] [19].

Table 2.5: Quantile regressions (Year 1985)

Variable	Dependent variable: Log weekly wage (estimates and standard errors)					
	q.1	...	q.3	...	q.5	...
Experience	0.061***	0.012	0.062***	0.003	0.060**	0.002
Experience squared	-0.001***	0.000	-0.001***	0.000	-0.001***	0.000
Years of schooling	0.098***	0.018	0.098***	0.007	0.092***	0.006
Male	0.300***	0.089	0.256***	0.025	0.301***	0.017
White	-0.265	0.212	0.007	0.066	0.005	0.032
Black	0.018	0.322	0.001	0.075	-0.062*	0.033
Northeast	0.202	0.128	0.177***	0.053	0.124***	0.028
Midwest	-0.497***	0.174	-0.112***	0.041	-0.065**	0.028
South	0.128	0.082	0.056*	0.031	0.003	0.023
Intercept	1.946***	0.328	2.497***	0.145	2.856***	0.109
R-square	0.025	...	0.053	...	0.070	...
	q.10	...	q.50	...	q.90	...
Experience	0.053***	0.001	0.044***	0.001	0.038***	0.001
Experience squared	-0.001***	0.000	-0.001***	0.000	-0.001***	0.000
Years of schooling	0.098***	0.002	0.093***	0.001	0.090***	0.001
Male	0.340***	0.012	0.415***	0.006	0.426***	0.005
White	0.053**	0.024	0.057***	0.019	0.016	0.021
Black	-0.054**	0.025	-0.071***	0.020	-0.096***	0.020
Northeast	0.065***	0.016	-0.008	0.008	-0.067***	0.009
Midwest	-0.050***	0.015	-0.039***	0.009	-0.084***	0.010
South	-0.031**	0.015	-0.075***	0.008	-0.088***	0.009
Intercept	3.076***	0.050	3.903***	0.027	4.579***	0.028
R-square	0.101	...	0.203	...	0.218	...
Observations	56420					

* significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

for estimations of wage equation. In particular, it is noticeable in Figure 2.9 that, while the rates of return to schooling are stable in the 1960s and 1970s[12], they increase rapidly by about 2.3 percentage points in the 1980s. However, the rise in returns to schooling weakens in the 1990s and 2000s. Table 2.2 shows that the rate of return to experience is increasing at a decreasing rate across years. Using $\gamma_1 + 2\gamma_2\overline{Exp}$, where $\overline{Exp}$ is the sample mean of experience each year, I calculate the rates of return to

[12]Note that the rates of return to schooling in the 1970s are somewhat low relative to in the 1960s due to a rapid increase in college graduates in the 1970s (Murphy and Welch 1992) [54].

Table 2.6: Quantile regressions (Year 1995)

Variable	Dependent variable: Log weekly wage (estimates and standard errors)					
	q.1	...	q.3	...	q.5	...
Experience	0.046***	0.007	0.056***	0.003	0.052***	0.001
Experience squared	-0.001***	0.000	-0.001***	0.000	-0.001***	0.000
Years of schooling	0.071***	0.012	0.085***	0.005	0.093***	0.004
Male	0.192***	0.070	0.230***	0.028	0.231***	0.018
White	-0.012	0.115	0.093	0.076	0.083**	0.041
Black	-0.246	0.171	-0.063	0.087	-0.054	0.046
Northeast	0.058	0.131	0.141***	0.041	0.121***	0.028
Midwest	-0.288**	0.132	0.019	0.039	0.010	0.018
South	0.159*	0.085	0.055**	0.027	0.011	0.018
Intercept	2.892***	0.231	3.071***	0.119	3.230***	0.050
R-square	0.028	...	0.058	...	0.079	...
	q.10	...	q.50	...	q.90	...
Experience	0.049***	0.002	0.044***	0.001	0.037***	0.001
Experience squared	-0.001***	0.000	-0.001***	0.000	0.000***	0.000
Years of schooling	0.104***	0.002	0.112***	0.001	0.105***	0.001
Male	0.267***	0.013	0.330***	0.005	0.344***	0.008
White	0.100***	0.025	0.058***	0.016	0.013	0.017
Black	-0.026	0.030	-0.061***	0.017	-0.085***	0.023
Northeast	0.107***	0.019	0.082***	0.007	0.053***	0.008
Midwest	0.004	0.015	-0.015***	0.005	-0.038***	0.010
South	-0.021**	0.010	-0.048***	0.006	-0.052***	0.011
Intercept	3.338***	0.047	3.966***	0.022	4.756***	0.027
R-square	0.110	...	0.200	...	0.209	...
Observations	54874					

* significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

experience by year. The rates of return to experience are presented in Figure 2.10. The returns to experience increase rapidly in the 1970s, and the rise weakens in the 1980s. Then, they begin to decrease in the late 1980s. According to Murphy and Welch (1992) [54], when the baby boom cohorts, regardless of whether they are college or high school graduates, entered the labor market, that is, in the 1970s, the returns to experience rose rapidly. Then when they became experienced workers in the late 1980s, the returns began to decrease. This phenomenon is due to their

Table 2.7: Quantile regressions (Year 2005)

Variable	Dependent variable: Log weekly wage (estimates and standard errors)					
	q.1	...	q.3	...	q.5	...
Experience	0.073***	0.008	0.064***	0.003	0.054***	0.002
Experience squared	-0.001***	0.000	-0.001***	0.000	-0.001***	0.000
Years of schooling	0.090***	0.009	0.093***	0.005	0.104***	0.004
Male	0.375***	0.049	0.286***	0.015	0.295***	0.013
White	-0.037	0.074	0.078**	0.033	0.078***	0.013
Black	-0.236**	0.101	-0.095*	0.052	-0.057	0.035
Northeast	0.118*	0.064	0.034*	0.019	0.029*	0.017
Midwest	-0.214**	0.090	0.002	0.028	0.003	0.018
South	0.087	0.064	0.007	0.021	0.001	0.018
Intercept	2.575***	0.184	3.171***	0.093	3.334***	0.071
R-square	0.047	...	0.075	...	0.089	...
	q.10	...	q.50	...	q.90	...
Experience	0.046***	0.001	0.040***	0.001	0.035***	0.001
Experience squared	-0.001***	0.000	-0.001***	0.000	0.000***	0.000
Years of schooling	0.113***	0.002	0.117***	0.001	0.122***	0.001
Male	0.275***	0.012	0.320***	0.005	0.381***	0.006
White	0.074***	0.010	0.051***	0.007	0.049***	0.013
Black	-0.042***	0.014	-0.057***	0.010	-0.075***	0.018
Northeast	0.032***	0.010	0.029***	0.005	0.017	0.012
Midwest	0.004	0.011	-0.033***	0.005	-0.082***	0.010
South	-0.014	0.012	-0.034***	0.004	-0.041***	0.012
Intercept	3.578***	0.034	4.271***	0.014	4.843***	0.026
R-square	0.118	...	0.192	...	0.203	...
Observations	78313					

* significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

relatively high numbers in labor supply. In Figure 2.11, we can see the gender gap in wages declining in the 1970s and 1980s. From the mid 1990s on, the gender wage gaps are stable. The racial wage differentials in Figure 2.12 decline until the 1970s and are stable from the 1980s on. These results are consistent with previous studies (Buchinsky 1994 [18]; Card and DiNardo 2002 [20]; and Autor, Katz and Kearney 2005 [7]). According to Farley (1977) [30], with urbanization and improvement in civil rights for black people, the economic expansion in the 1960s decreased the racial wage gaps, although the gaps weakened due to the recession in the 1970s.

Using Model 1, I get R-squares from 19.89 to 31.58 percent over the sample period. We can see that regressors like education, experience, sex, race, and regions explain less than one third of the wage variations as in Juhn et al. (1993) [41], and so the within-group wage inequality explains the remaining part of the overall wage dispersion. Using the method by Card and DiNardo (2002) [20][13], I try to show overall standard deviation of log weekly wages and the within-group wage inequality in Figure 2.13. The figure shows that the within-group wage inequalities are parallel to overall dispersion of log weekly wages because the R-squares are relatively constant. It also shows that the within-group wage inequalities are stable in the 1970s, rise in the early and mid 1980s, plummet in the late 1980s, and then are stable again in the 1990s.[14]

Using quantile regressions for six percentile (or quantile) groups in wages by year, Tables 2.3 through 2.7 still present the positive rates of return to schooling for all the selected quantiles. Specifically, Figure 2.14 shows the returns to schooling over the sample periods for the 10th, 50th, and 90th percentiles. It should be noted that unlike the quantile regression, the OLS estimation assumes that, given regressors, the same returns to schooling across all the quantiles. As such, it estimates the conditional mean of dependent variable (i.e., log weekly wages) given the regressors. As described earlier, however, the quantile regression allows us to estimate all the conditional quantiles of dependent variable given regressors. Together with the returns to schooling by the OLS estimation in Table 2.2, the rates of return to schooling at the 10th, 50th, and 90th percentiles show us a similar time trend. That is, as in the

[13] I calculate the within-group wage inequality as $\sqrt{\sigma^2(1-R^2)}$, where σ is standard deviation of log weekly wages and R^2 is obtained from the OLS estimation with Model 1.

[14] The time trend of the within-group wage inequalities shown in Figure 2.13 appears to be somewhat different from that of Card and DiNardo (2002) [20] who analyzed it by sex.

Table 2.8: Descriptive statistics of time series data

Variable	Obs.[a]	Mean	Std. Dev.	Min.	Max.
Year	44	1983.5	12.84523	1962	2005
Total work hrs of high school last year[b]	43	5.92×10^{10}	1.48×10^{10}	2.10×10^{10}	7.45×10^{10}
Total work hrs of college last year[b]	43	2.53×10^{10}	1.50×10^{10}	4.99×10^{9}	5.07×10^{10}
Predicted log weekly wage of high school[c]	43	5.50881	0.58886	4.44035	6.33446
Predicted log weekly wage of college[c]	43	5.87278	0.65415	4.73265	6.80395
Predicted log weekly wage of 1st[d]	43	3.12999	0.87297	1.12527	4.20172
Predicted log weekly wage of 3rd[d]	43	3.90215	0.74670	2.34566	4.79182
Predicted log weekly wage of 5th[d]	43	4.19790	0.67683	2.81888	5.04807
Predicted log weekly wage of 10th[d]	43	4.53036	0.60293	3.32640	5.32071
Predicted log weekly wage of 50th[d]	43	5.25964	0.55870	4.20450	6.02670
Predicted log weekly wage of 90th[d]	43	5.80243	0.61934	4.67926	6.65807
Average annual unemployment rate	44	0.05890	0.01458	0.03492	0.09708
Log real minimum wage	44	1.67809	0.10304	1.47069	1.89084
Log real GDP per capita	44	10.09691	0.26566	9.58327	10.52408

[a]The number of observations associated with years of schooling is 43 since the variable is omitted in 1963.
[b]The total work hours are weighted by person weight.
[c]To get the predicted log weekly wages for college and high school graduates, the estimated regressions are evaluated at the sample means of the independent variables.
[d]To get the predicted log weekly wages for each quantile with low education and experience, the estimated regressions are evaluated at the sample means of high school dropouts and graduates with experience less than or equal to 9.

OLS estimations, the returns to schooling at the three percentiles in Figure 2.14 are stable in the 1960s and 1970s, but go up rapidly in the 1980s. Then, the rise weakens in the 1990s and 2000s.

Controlling for a schooling variable (i.e., years of schooling in Model 2), if the returns to schooling at the quantile above the mean are high, *ceteris paribus*, and relative to the OLS estimates, it would indicate that the wage dispersion in high education (or schooling) group (i.e., college graduates) is large relative to that in low education group (i.e., high school dropouts and graduates).[15] In contrast, if

[15]As pointed out by Buchinsky (1998) [19], we should be cautious in interpreting coefficients of quantile regression because it does not guarantee that a person at a certain quantile of a conditional distribution would be at the same quantile after his regressor changes. But depending upon Koenker and Hallock's (2001) [45] interpretation, it might be possible to interpret about the within-group

the returns to schooling at the quantile below the mean are high, *ceteris paribus*, and relative to the OLS estimates, it implies that the wage dispersion in high school dropouts and graduates is large relative to that in college graduates. In Figure 2.15, we can see that the return differentials to schooling for 90/10, 90/50, and 50/10 have a positive relationship with the time, although the regression of the 90/50 return differentials on year is not significant.

Although it requires careful interpretation, we can speculate that the wage dispersions in college graduates are relatively increasing with years, but the wage dispersions in high school dropouts and graduates are relatively decreasing with years. In addition, the increases in return differentials to schooling for the 90/10 and 50/10 from the 1970s on are remarkable relative to the 1960s, which implies that when controlling for schooling, the differentials in high-educated workers have increased relative to those in low-educated workers during the same period. The results may be consistent with the stylized facts that within-group wage inequality of skilled workers increased throughout the 1970s and 1980s (Juhn, Murphy, and Pierce 1993) [41].

The descriptive statistics, including the predicted weekly wage by year based on the results in Models 1 and 2, are shown in Table 2.8. In addition, using person weight in the CPS, total hours worked last year are included by education groups.[16] The 'total' annual work hours capture labor supply better than per capita work hours.[17] For instance, per capita work hours do not represent well a rapid increase in supply of college graduates in the 1970s and 1980s, since a college worker does not

wage inequality as shown in the text.

[16] I use the person weight as in Katz and Murphy (1992) [42] so that the total work hours may be calculated as $\sum_i \omega_{it} L_{it}$, where given year t, ω is the person weight and L is the total annual work hours for individual i.

[17] I do not use the total work hours for each quantile because we cannot get the total work hours with quantile regressions. In addition, note that total work hours for each inter-quantile give us little variations, and so the relative labor supply between the quantiles is not useful as an independent variable.

do more work in those periods. Thus, when calculating relative labor supply, I use the total work hours in the sample by year and educational group. Note that all the variables in Table 2.8 are time-varying, i.e., time series ones.

2.4 Empirical Methodology and Results

2.4.1 Static Regressions

With the time-series data described in Table 2.8, I estimate some regressions by OLS, and the specifications are based on Equation (2.4). All the regressions in Table 2.9 show high R-squared values of more than 90%. Additionally, log relative supply and average unemployment rate are all significant under 1% level in all the four regressions. As mentioned earlier, the positive sign of log COL/HS relative labor supply in Table 2.9 reflects that shifts in relative labor demand make equilibrium relative work hours employed have a positive relationship with equilibrium wage inequality between college and high school workers, even controlling for some shifters such as year, log real minimum wage, and unemployment rates as in Equation (2.4). The significant negative interaction terms of year and post 1992 dummy in Regressions (2) and (4) capture a significant slowdown of the growth of COL/HS wage inequality since 1992, but still show stronger impacts of relative labor supply (Autor et al. 2005) [7]. The coefficients of log real minimum wage are also significant in Regressions (1) and (2), but with the inclusion of the interaction terms, its significance weakens.

With the high R-squared values and the significance of log real minimum wage, however, we cannot rule out the possibility that these results are not reliable, i.e., the OLS regressions in Table 2.9 may be spurious. Accordingly, based on these regressions, I do a time-series analysis in the next subsection focusing on the minimum

Table 2.9: Dependent variable: Log COL/HS wage inequality

Variable	(1)	(2)	(3)	(4)
Log COL/HS relative	0.113***	0.125***	0.176***	0.181***
labor supply	(0.022)	(0.016)	(0.041)	(0.033)
Log real minimum wage	-0.087***	-0.086***	-0.057*	-0.056*
	(0.024)	(0.025)	(0.029)	(0.028)
Average annual unemployment	-0.750***	-0.697***	-0.825***	-0.825***
rate	(0.128)	(0.122)	(0.130)	(0.134)
Year	0.001*	. .	0.000	. .
	(0.001)	. .	(0.001)	. .
Log real GDP per capita	. .	0.040	. .	-0.001
	. .	(0.025)	. .	(0.032)
Interaction term of	. .	. .	-0.000*	-0.000*
year and post 1992 dummy	. .	. .	(0.000)	(0.000)
Intercept	-1.739	0.275	0.494	0.706**
	(1.424)	(0.276)	(1.840)	(0.345)
R-square	0.976	0.976	0.978	0.978
Observations	43	43	43	43

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

wage variable.

In the meantime, Figure 2.5 shows negative log ratios of 10th quantile weekly wage to weekly minimum wage during the whole sample period, meaning that the 10th quantile wages may be affected by the minimum wage. Tables 2.10, 2.11, and 2.12 from Model 2 show the relationship of log wage ratios for quantiles and the log real minimum wage, along with unemployment rates. Unlike Table 2.9, I do not include relative labor supply for each quantile in the model because we cannot get total work hours by using quantile regressions, and the total work hours for each inter-quantile give us little variation. In addition, I include only the 'year' in the model to capture a trend property of log wage inequalities.

In Tables 2.10, 2.11, and 2.12, the OLS estimations in Regressions (1) and (3) show that the estimates of the log real minimum wage are significantly negative, but based on the Durbin-Watson (DW) tests, we can see that the errors are significantly positively autocorrelated, which means that the standard errors by OLS are biased, leading to biases in t-tests. To check robustness, I use the Prais-Winsten method (1954) [57] in Regressions (2) and (4) for the three tables.

The Prais-Winsten method is a feasible generalized least squares (FGLS) estimation used when the errors are autocorrelated. With autocorrelations of error terms, the OLS estimators are not efficient. To remedy such inefficiency, the quasi-differencing method is used, but it makes us lose the first observation. However, the Prais-Winsten method allows us to keep the first observation. The procedures are similar to the Cochrane-Orcutt method (1949) [25] which is a typical example of the FGLS when errors are autocorrelated. The Cochrane-Orcutt method estimates an autocorrelation coefficient (i.e., $\hat{\rho}$) from regressing the residuals on the lagged residuals obtained from the original OLS regression of a dependent variable on regressors. Using the estimated $\hat{\rho}$, the dependent and independent variables are transformed. Using the transformed data, the process is iterated until the $\hat{\rho}$ converges to a certain number. Even though we use the estimated $\hat{\rho}$, the FGLS by the Cochrane-Orcutt method still loses the first observation. In addition to the Cochrane-Orcutt procedures, the Prais-Winsten method transforms the first observation of the dependent and independent variables by multiplying by $\sqrt{1-\hat{\rho}^2}$, and so allows us to keep the first observation.

Going back to Table 2.10, we can see that the coefficients of the real minimum wage by OLS are no longer robust. Further, in Table 2.11 the real minimum wage shows a robust negative relationship with the log 90/50 wage ratios which are, in fact, not related to the minimum wage. As in Table 2.10, we cannot find any special robust negative relationship between the 50/10 wage inequalities and the real minimum wage in Table 2.12.

Table 2.10: Dependent variable: Log 90/10 wage inequality

Variable	(1)	(2)[a]	(3)	(4)[a]
Log real minimum wage	-0.319***	-0.123	-0.310**	-0.132
	(0.089)	(0.116)	(0.127)	(0.121)
Average annual unemployment rate	-1.899***	-0.632	-1.900***	-0.610
	(0.624)	(0.650)	(0.632)	(0.655)
Year	. .	. .	0.000	-0.001
	. .	. .	(0.001)	(0.002)
Intercept	1.919***	1.540***	1.687	3.082
	(0.156)	(0.199)	(2.230)	(4.085)
Durbin-Watson (DW) test	0.462**	1.757	0.460**	1.793
R-square	0.342	0.908	0.342	0.904
Observations	43	43	43	43

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.
[a] The Prais-Winsten method is used in order to implement robust estimations.

Looking at Figures 2.6, 2.7, and 2.8, we can see that 90/10 and 90/50 wage inequalities are increasing in the 1970s and 1980s, while 50/10 wage inequalities are stationary during the same period. Using the figures and the results in Tables 2.10, 2.11, and 2.12, we can conjecture that the rapid increase in wage inequality in the 1970s and 1980s is not due to the fall in the real minimum wage, because the log wage ratios of the 50th quantile to the 10th quantile applicable to the minimum wage worker group were stationary as the real minimum wage fell. Consequently, the revisionists' argument that the increase in wage inequality in the 1970s and 1980s is due to the fall in the real minimum wage may be fragile as in Autor et al. (2005) [7]. To examine more explicitly such a relationship between wage inequality and minimum wage, I do a time-series analysis for wage inequality, focusing only on wage inequality between high school and college graduates. Time-series analyses on wage inequalities for percentiles (or quantiles) will be done in my future research.

Table 2.11: Dependent variable: Log 90/50 wage inequality

Variable	(1)	(2)[a]	(3)	(4)[a]
Log real minimum wage	-0.484***	-0.113**	-0.142***	-0.120**
	(0.063)	(0.053)	(0.045)	(0.051)
Average annual unemployment	0.093	-0.062	0.066	-0.027
rate	(0.439)	(0.288)	(0.222)	(0.272)
Year	. .	. .	0.004***	0.004***
	. .	. .	(0.000)	(0.001)
Intercept	1.349***	0.704***	-7.110***	-6.750***
	(0.110)	(0.133)	(0.785)	(1.142)
Durbin-Watson (DW) test	0.354***	2.345	0.612***	2.093
R-square	0.601	0.291	0.900	0.876
Observations	43	43	43	43

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

[a] The Prais-Winsten method is used in order to implement robust estimations.

Table 2.12: Dependent variable: Log 50/10 wage inequality

Variable	(1)	(2)[a]	(3)	(4)[a]
Log real minimum wage	0.165*	0.024	-0.168*	-0.029
	(0.084)	(0.101)	(0.095)	(0.101)
Average annual unemployment	-1.992***	-0.482	-1.966***	-0.595
rate	(0.593)	(0.554)	(0.469)	(0.545)
Year	. .	. .	-0.004***	-0.004***
	. .	. .	(0.001)	(0.002)
Intercept	0.570***	0.777***	8.797***	9.532***
	(0.148)	(0.178)	(1.655)	(3.109)
Durbin-Watson (DW) test	0.382***	1.888	0.615***	1.898
R-square	0.286	0.780	0.564	0.875
Observations	43	43	43	43

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

[a] The Prais-Winsten method is used in order to implement robust estimations.

2.4.2 Time Series Analysis

2.4.2.1 OLS Regression, Order of Integration, and Cointegration Test

Though they suspect trends in real minimum wage, revisionists argue that a decrease in the real minimum wage is an important factor in rising wage inequality in the 1970s and 1980s (DiNardo, Fortin, and Lemieux 1996 [28]; Lee 1999 [48]; Card and DiNardo 2002 [20]; and Lemieux 2006 [49]). Table 2.9 shows high R-squared values and significantly negative estimates of log real minimum wages in all the regressions. These results might support revisionists, but it should be taken into account a possibility that the OLS regressions are spurious. This spuriousness indicates that there exists no long-run relationship between dependent and independent variables in a regression model. Thus, to consider the likelihood of the spuriousness, I do a time-series analysis in this subsection. To begin with, I consider only specifications without time trend variable. The OLS regressions with the relative labor supply variable presented in Table 2.13 show also high R-squared values similar to Table 2.9, while without it, the R-squares get quite low. The log real minimum wage in all the regressions is still significant at 5% level.

To judge whether or not there is a true long-run relationship between log between-group earnings inequality and log real minimum wage along with other independent variables, I first examine the stationarity of all the variables used in the regressions since if they are stationary, the regressions automatically have a long-run relationship. Otherwise, the cointegration tests for the four regressions should be done. To test the stationarity of all the variables, I use the augmented Dickey-Fuller (ADF) test for unit root. The results for the stationarity of the variables are presented in Table 2.14. All the test statistics except for average annual unemployment with lag 1 fail to reject the null hypothesis of unit root, which means that overall

Table 2.13: Dependent variable: Log COL/HS wage inequality

Variable	(1)	(2)	(3)	(4)
Log COL/HS relative	. .	0.152***	. .	0.148***
labor supply	. .	(0.008)	. .	(0.006)
Log real minimum wage	-0.506***	-0.074**	-0.515***	-0.089***
	(0.070)	(0.033)	(0.068)	(0.025)
Average annual unemployment	. .	. .	-0.946*	-0.676***
rate	. .	. .	(0.477)	(0.123)
Intercept	1.212***	0.640***	1.283***	0.703***
	(0.118)	(0.049)	(0.119)	(0.039)
Durbin-Watson (DW) test	0.362***	0.733***	0.425***	1.238**
R-square	0.559	0.954	0.598	0.974
Observations	43	43	43	43

Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

all the variables seem to have unit root, i.e., they have a random walk process or are integrated of order 1, I(1). Thus, to see if the OLS regressions in Table 2.13 are spurious or not, cointegration tests for each regression are required.

Though there are several ways to test the cointegration, I use the method to test the stationarity of associated OLS residuals, where the ADF test is employed again. Associated with Table 2.13, Table 2.15 shows the test results, and it is likely that there are no long-run relationships between log COL/HS wage inequality and log real minimum wage (along with average unemployment rate) in Regressions (1) and (3) in Table 2.13 since the residuals are not stationary, i.e., fail to reject the null hypothesis of unit root. In contrast, the residuals look stationary in Regression (2) and (4), and so the two regressions can be said to have a long-run relationship, respectively. Accordingly, the long-run relationship is not likely due to the real minimum wage, but rather to log relative labor supply.

Table 2.14: Augmented Dickey-Fuller test for unit root

Variable	lag 0	lag 1	lag 2	lag 3	lag 4	lag 5
Log COL/HS wage inequality	-0.192	0.050	0.273	0.127	-0.006	-0.343
	[0.939]	[0.963]	[0.976]	[0.968]	[0.958]	[0.919]
Log COL/HS relative labor supply	0.334	0.147	0.180	-0.135	-0.050	-0.176
	[0.979]	[0.969]	[0.971]	[0.946]	[0.954]	[0.941]
Log real minimum wage	-1.248	-1.496	-1.376	-0.955	-1.004	-1.143
	[0.652]	[0.536]	[0.594]	[0.769]	[0.752]	[0.698]
Average annual unemployment rate	-2.016	-2.829*	-2.058	-1.956	-1.822	-2.074
	[0.280]	[0.054]	[0.262]	[0.306]	[0.370]	[0.255]

* significant at 10% level, ** significant at 5% level, and *** significant at 1% level. The figures are test-statistics and the ones in brackets are p-value. The number of lag refers to the one of lagged differences.

2.4.2.2 Error Correction Model

Despite the high possibility of spuriousness of log real minimum wage, to speak robustly, suppose that according to revisionists an important factor in the long-run relationship with rising wage inequality is real minimum wage. To get consistent estimates, I here consider the long-run relationship in Regression (4) showing the highest R-square and strong negative effect of log real minimum wage in Table 2.13. The Durbin-Watson (DW) statistics in Table 2.13 imply the residuals in the regressions are significantly positively correlated at 5% level, i.e., the regressions are significantly autocorrelated. To solve the autocorrelation problem, I use quasi-differencing to estimate robustly. Assume the simple empirical specification in Table 2.13 with autocorrelations (AR(1)) is expressed as follows:

$$y_t = \phi_0 + \phi_1 x_t + u_t, \tag{2.10}$$

Table 2.15: Cointegration test using augmented Dickey-Fuller test

Residuals	lag 0	lag 1	lag 2	lag 3	lag 4	lag 5
Residuals in regression (1)	-2.174	-2.086	-2.124	-1.484	-1.018	-0.834
	[0.216]	[0.250]	[0.235]	[0.541]	[0.747]	[0.809]
Residuals in regression (2)	-2.988**	-2.586*	-2.520	-2.838*	-2.663*	-2.519
	[0.036]	[0.096]	[0.111]	[0.053]	[0.081]	[0.111]
Residuals in regression (3)	-2.472	-2.612*	-2.475	-1.665	-1.197	-1.069
	[0.122]	[0.091]	[0.122]	[0.449]	[0.675]	[0.727]
Residuals in regression (4)	-4.357***	-3.938***	-3.441**	-3.116**	-2.309	-1.838
	[0.000]	[0.002]	[0.010]	[0.025]	[0.169]	[0.362]

* significant at 10% level, ** significant at 5% level, and *** significant at 1% level. The figures are test-statistics and the ones in brackets are p-value. The number of lag refers to the one of lagged differences. Associated with Table 2.13, independent variable(s) is log real minimum wage in regression (1); log HS/COL relative labor supply and log minimum wage in regression (2); log real minimum wage and average annual unemployment rate in regression (3); and all the variables in regression (4).

where $u_t = \rho u_{t-1} + \epsilon_t$, and ϵ_t is white noise. With this quasi-differencing, it is easy to get the following autoregressive distributed lag model, ADL(1,1):

$$y_t = \phi_0(1-\rho) + \phi_1 x_t - \rho\phi_1 x_{t-1} + \rho y_{t-1} + \epsilon_t. \tag{2.11}$$

It is possible to apply Regression (4) in Table 2.13 to this simple ADL(1,1) model, which gives us consistent and robust estimates since, as shown in Table 2.15, Regression (4) is cointegrated between dependent and independent variables. With straightforward manipulations, however, the more useful error correction model (ECM) is obtained as follows:

$$\Delta y_t = \phi_1 \Delta x_t - (1-\rho)\left[y_{t-1} - \phi_0 - \phi_1 x_{t-1}\right] + \epsilon_t. \tag{2.12}$$

The advantage of the ECM over the ADL(1,1) model is that we can see the short-run impact and the long-run impact on the dependent variable with consistent and robust estimates only if the disequilibrium factor (i.e., the equation in the bracket) is stationary, which implies that there exists a long-run relationship (or cointegration). However, it should be noted that the parameters of the long-run relationship are not observable. To solve this problem, I use the Engel and Granger (1987) [29] method as follows:

$$\Delta y_t = \phi_1 \Delta x_t - (1-\rho)\hat{u}_{t-1} + \epsilon_t, \tag{2.13}$$

where $\hat{u}_{t-1}$ indicates one-year lagged residuals from the initial OLS regression as in Equation (2.10). Only if these residuals are stationary, can the ECM be available.

In Table 2.15, Regression (4) is already cointegrated under lag 3, i.e., $\hat{u}_{t-1}$ is stationary. Thus, using the residuals from Regression (4) with the ECM, it is possible to examine what relationship the log real minimum wage has with the log COL/HS wage inequality. Table 2.16 presents the results from the ECM, and clearly, we can confirm that log relative supply has a significantly positive impact on the log wage inequality. Although I assume that there exists the long-run relationship of real minimum wage and unemployment rate with log between-group wage inequality, they do not have a significant short-run impact. It is interesting to see the role of the disequilibrium factor. Its coefficients are always predicted to be negative only if the initial regression is cointegrated ($\rho < 1$). As a result, when the processes of dependent and independent variables are not in the long-run equilibrium, i.e., $\hat{u}_{t-1}$ is non-zero, in the short-run it adjusts properly overstatement or understatement of the dependent variable in the previous period. Then, if the processes come to a long-run equilibrium, the short-run impact of the independent variable is entirely reflected on the dependent variable.

Interpreting the coefficients in Regression (4), a 1% increase in the gross growth

Table 2.16: Dependent variable: Differenced log COL/HS wage inequality

Variable	(1)	(2)	(3)	(4)
Differenced log COL/HS	0.098***	. .	. .	0.130***
relative labor supply	(0.032)	. .	. .	(0.031)
Differenced log real minimum	. .	0.007	. .	0.027
wage	. .	(0.035)	. .	(0.030)
Differenced average annual	. .	. .	-0.274	-0.484***
unemployment rate	. .	. .	(0.183)	(0.163)
Lagged disequilibrium factor[a]	-0.492***	-0.363**	-0.377**	-0.523***
	(0.142)	(0.155)	(0.148)	(0.132)
R-square	0.302	0.132	0.178	0.445
Observations	41	41	41	41

[a]Residuals estimated from regression (4) in Table 2.13. Standard errors in parentheses; and * significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

rate of the relative labor supply, *ceteris paribus*, leads immediately to 0.13% increase in the gross growth rate of wage ratio between college and high school graduates. Similarly, a 1% increase in the gross growth rate of the real minimum wage leads immediately to 0.027% increase in the gross growth rate of the wage ratio, although this coefficient is not significant.

In addition, a one unit increment increase in unemployment rate, *ceteris paribus*, leads to a 48.4% decrease in the gross rate of the wage ratio in the short run, which explains why when the U.S. economy was in recession, the growth rates in wage gap between college and high school graduates slowed down. Together with Figures 2.13, 2.14, and 2.15, the negative relationship might imply that the occurrence of the recession might reduce the wage gap between low-income college graduates and high school graduates in a sense that the wage inequality within college graduates relative to within high school graduates increased in the 1980s. Finally, the coefficient of -0.523 in the disequilibrium factor implies that the effects from a disequilibrium in a current period would not be immediately reflected in the dependent variable, but adjusted by about 50% of the disequilibrium toward the long-run equilibrium across the future periods.

To sum up Tables 2.15 and 2.16, it is unlikely that real minimum wage is an important factor explaining between-group wage inequality. Specifically, with only the real minimum wage, there is no long-run relationship with wage inequality. Although we assume that it has a long-run relationship with the wage inequality to employ the ECM, the wage inequality in the short-run depends primarily on relative labor supply, not on real minimum wage. These results do not support the revisionists' views.

2.5 Concluding Remarks

In labor economics, debates on factors of wage inequality are ceaseless. Revisionists (DiNardo, Fortin, and Lemieux 1996 [28]; Lee 1999 [48]; Card and DiNardo 2002 [20]; and Lemieux 2006 [49]) consider falling real minimum wage an important factor on earnings inequality. However, the real minimum wage appears to have a trend property, and the lower-tail wage inequalities using low education and experience groups were stable when the falling real minimum wage prevailed. Rather, the upper-tail inequalities not affected by the real minimum wage increased over the same period. As a result, it is too suspicious to believe that it is an important factor of the inequality.

Of course, the real minimum wage appears to have a strong negative effect on between-group wage inequality in OLS estimations, but these regressions seem to be spurious. In particular, when the real minimum wage alone is included in the regression model, it is clearly spurious. Robustly, although, along with relative labor supply, it might have a long-run relationship with wage inequality, it does not show a significant short-run impact on wage inequality. Therefore, I conclude that the revisionists' claims are unsupported by the data.

Although additional researches are required to support this conclusion, it may imply that a governmental policy of minimum wage will show a short-run impact on reducing the lower-tail wage inequality, but not a long-run impact. Rather, the frequency in minimum wage policy might lead only to unemployment of workers in the lower-tail of wage distribution, although it may have an economic meaning just as the minimum cost of living for unskilled workers.[18] Instead, governmental policies such as support for job training and education may be more effective in reducing the wage inequality.

[18] I thank Eun-kyung Kim for help comments.

2.6 Appendix

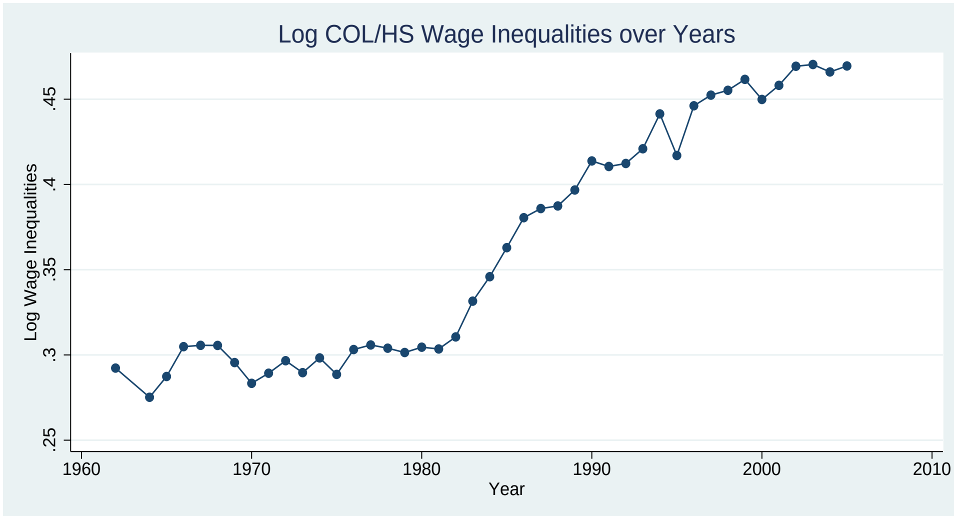

Figure 2.1: Log COL/HS wage inequalities over years

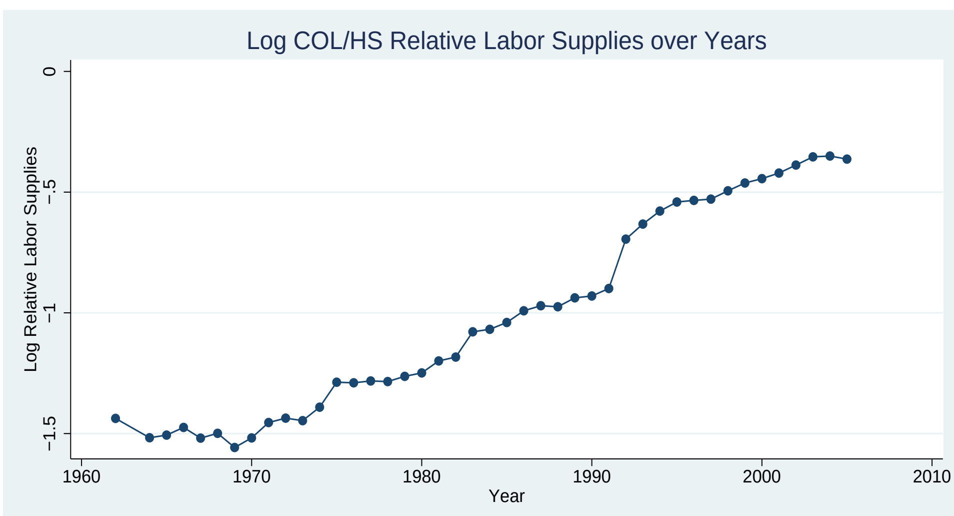

Figure 2.2: Log COL/HS relative labor supplies over years

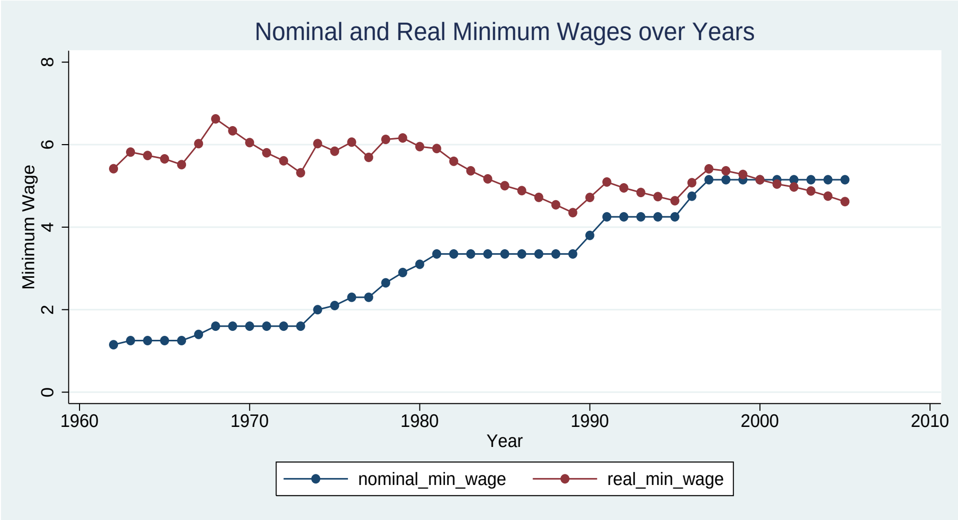

Figure 2.3: Nominal and real minimum wages over years. To get the real minimum wages, the nominal minimum wages are deflated by the personal consumption expenditures: chain-type price index (PCEPI) in terms of 2000 dollars.

Figure 2.4: Log real minimum wages over years. This log real minimum wage is adjusted to start at zero in 1962.

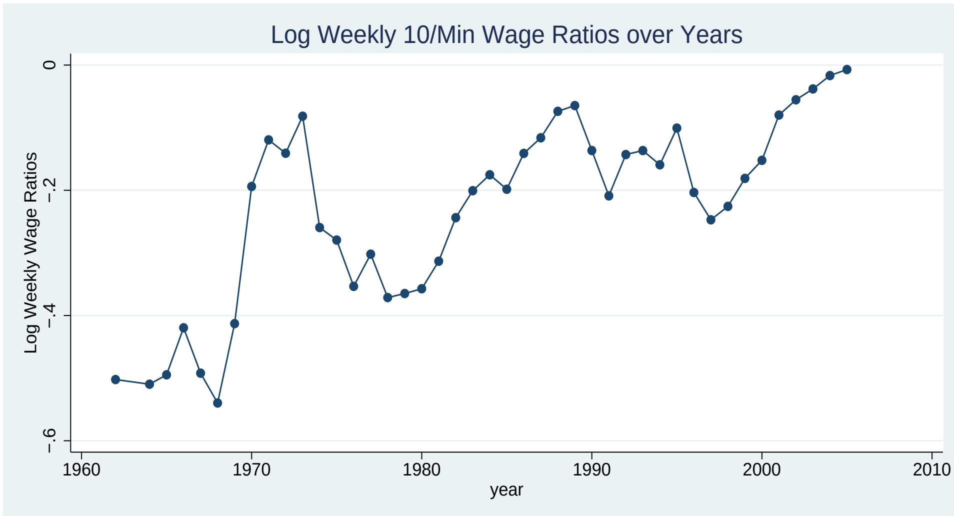

Figure 2.5: Log weekly 10/min wage ratios over years

Figure 2.6: Log 90/10 wage inequalities over years

Figure 2.7: Log 90/50 wage inequalities over years

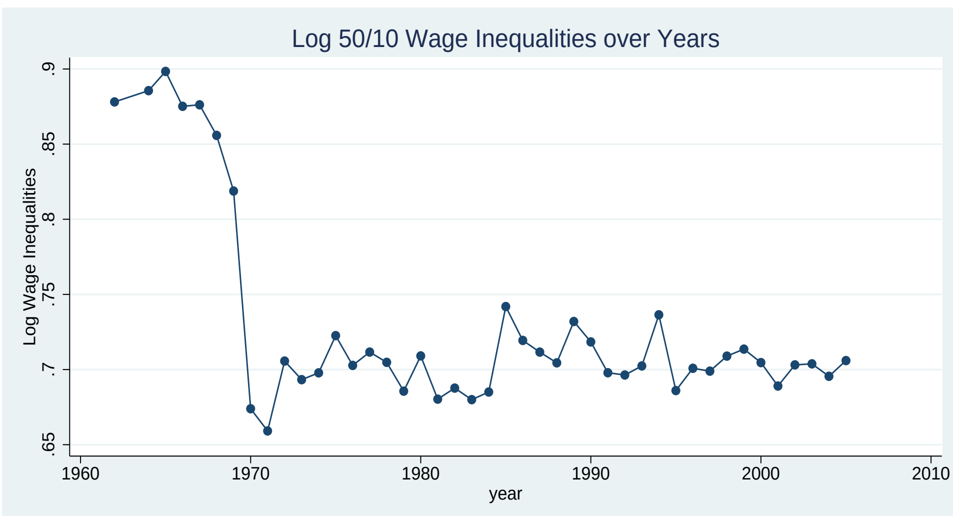

Figure 2.8: Log 50/10 wage inequalities over years

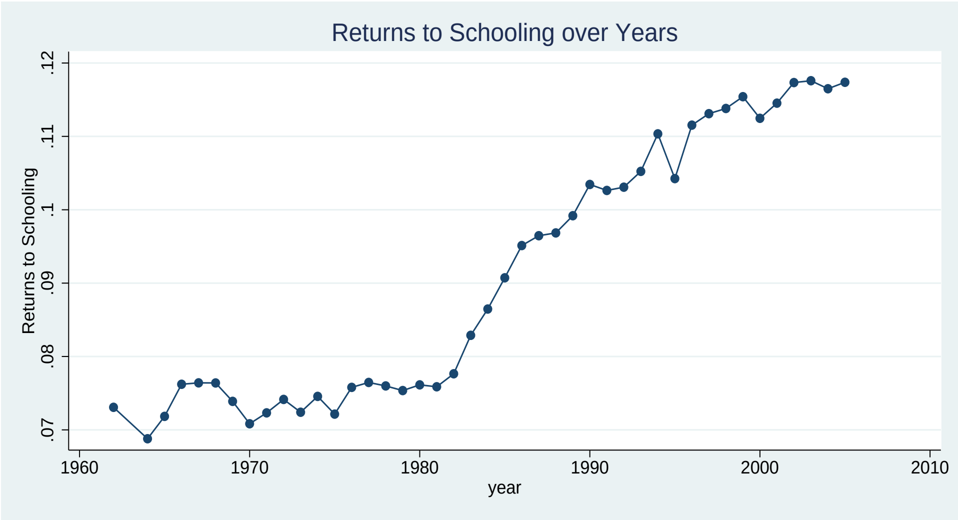

Figure 2.9: Returns to schooling over years

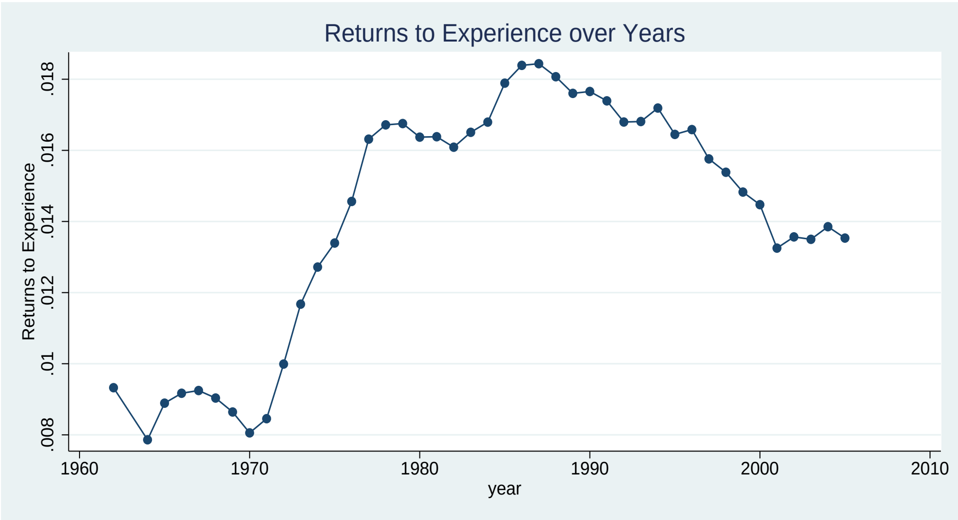

Figure 2.10: Returns to experience over years

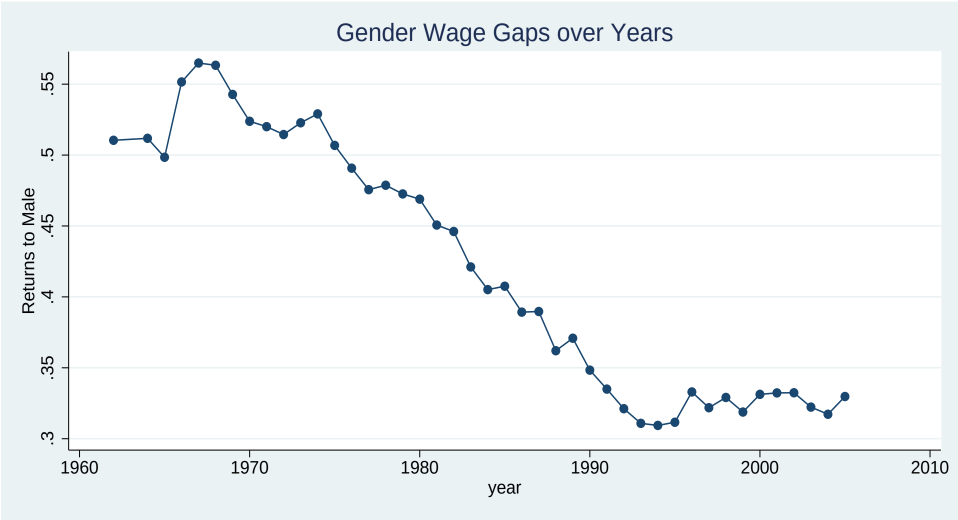

Figure 2.11: Gender wage gaps over years

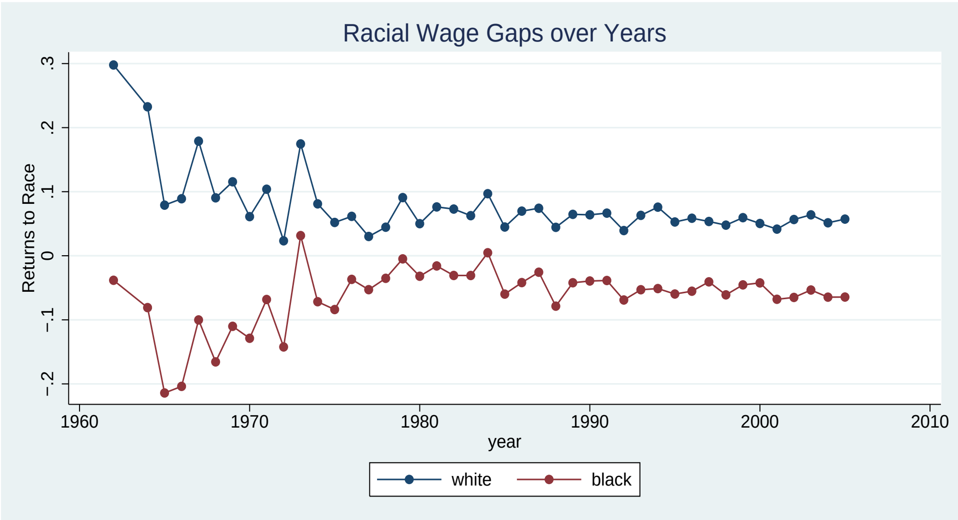

Figure 2.12: Racial wage gaps over years

Figure 2.13: Overall wage dispersions and within-group wage inequalities over years. lwkwage_inequality indicates overall log wage dispersions and lresidual_inequality is the associated within-group wage inequality.

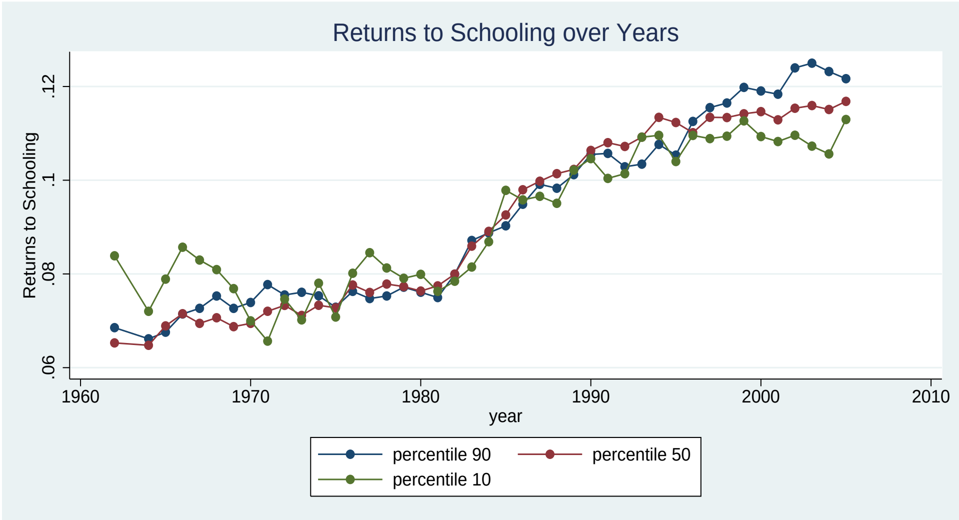

Figure 2.14: Returns to schooling over years for 90th, 50th, and 10th quantiles

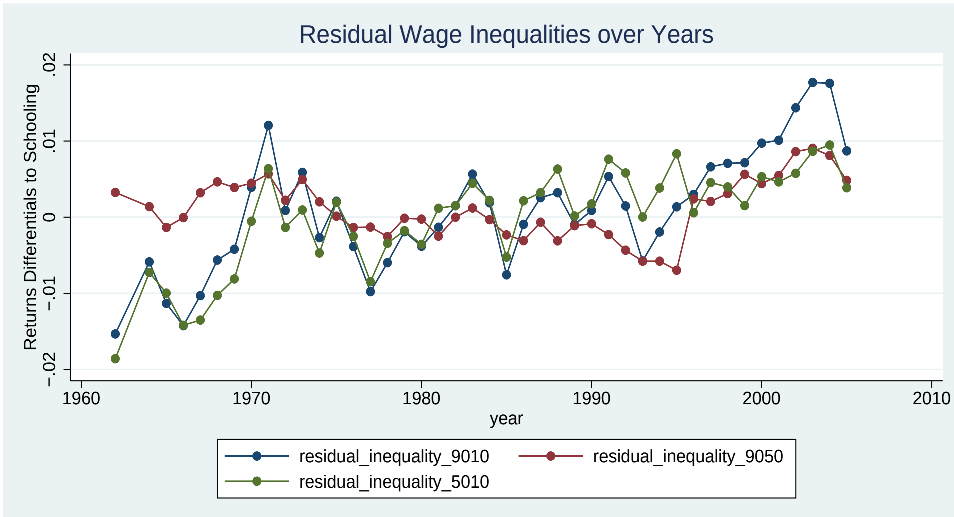

Figure 2.15: Residual wage inequalities over years only in terms of returns to schooling. I measure the residual wage inequality by $\hat{\gamma}_{3r} = \hat{\gamma}_{3\theta} - \hat{\gamma}_{3\theta'}$ by modifying the definition used in Autor et al. (2005) [7].

Figure 2.16: Unemployment rates over years

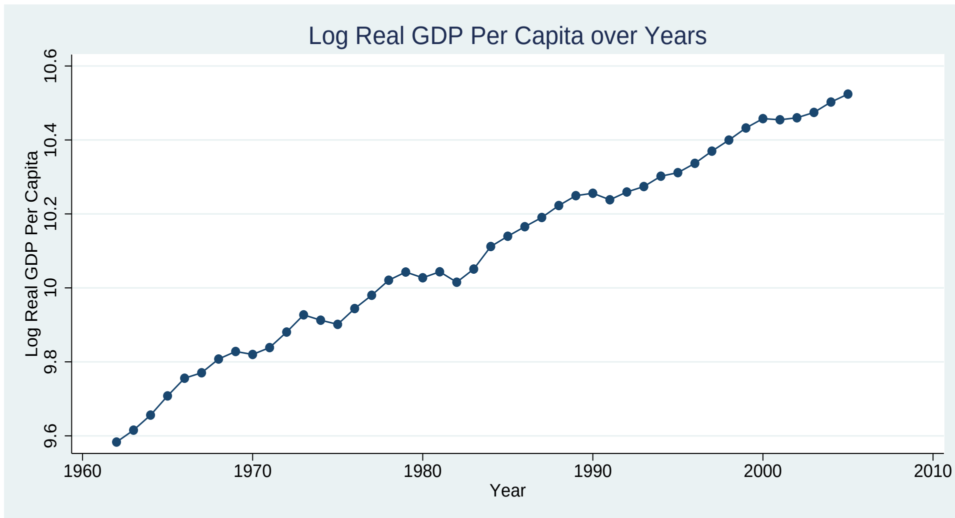

Figure 2.17: Log real GDP per capita over years

Chapter 3

Ability, Human Capital, and Economic Growth

3.1 Introduction

This chapter explores parental choices on educational expenditures and fertility with heterogeneous ability of their children. In this research, I regard human capital as an engine of economic growth. The concept of human capital as an input for production was introduced by Adam Smith. He defined human capital as "an acquired and useful abilities of all the inhabitants or members of the society." Mincer (1958) [52], Schultz (1961) [58], Becker (1962, 1964, 1993) [10] [11] [12], and Ben-Porath (1967) [14] pioneered and contributed greatly to the developments of human capital theory.

People invest in human capital when they educate and train their children (Becker 1993) [12]. He associates the human capital theory with various fields in economics. Specifically, he states that human capital is used to analyze the economics of education, job training theory, economic development and growth, family economics dealing with marriage, fertility, and children's education, and labor economics such as the division of labor.

Stressing human capital as a form of capital, Schultz (1961) [58] states that "direct expenditures on education, health, and internal migration, and attending school and on-the-job training" are investments in human capital. He points out that growth rates in U.S. income are higher than those of land, work hours of workers, and reproducible capital stock, and that the occurrence of this discrepancy between outputs and inputs is due to omission of improvements in human capital. In other words, the discrepancy implies that investments in human capital are an important factor in explaining economic growth. In fact, the economic miracles shown by Hong Kong, Korea, Taiwan, and other Asian countries (the so called Asian tigers), which have few natural resources, highlight the importance of quality of labor as an input to economic growth.

Mincer (1958) [52] shows theoretically that higher wage requires more training. That the distribution of income is right-skewed while the distribution of individual abilities is Gaussian normal distribution leads him to conclude that inter-occupational differentials in income depend on differences in training, and that intra-occupational differentials are related to experiences. Using the optimal control theory, Ben-Porath (1967) [14] examines the optimal path of human capital accumulation and life-cycle earnings.

Among recent studies dealing with human capital, Lucas (1988) [50] introduces social human capital to the production function of final goods to embody the external effects of human capital. In contrast, Tamura (1991) [59] includes the external effects of human capital in the production function for human capital accumulation to explain income convergence with characteristics of returns to scale in next period human capital production for own human capital. In addition, Becker, Murphy, and Tamura (1990) [13] demonstrate that there may exist multiple long-run equilibria in economies with endogenous fertility. First, when human capital is abundant, fertility is low. Human capital grows at a constant rate because the rates of return on investments in human capital are high relative to those on fertility due to high rearing costs with relatively high parental human capital. On the other hand, when human capital is scarce, fertility is high and human capital is zero with the symmetric logic. It is said that the latter is in the Malthusian regime, the former, in the sustained growth regime. de la Croix and Doepke (2003) [27] show that high income inequality causes fertility differentials, leading to a decrease in economic growth. They point out that the policy that equalizes access to education is more efficient than redistributional policies in income.

While many economists have contributed to human capital theory, most of them assume that children's ability is homogeneous. This study differs from the previous studies in that it deals with children's heterogeneous ability. Horowitz and Wang (2004) [39] in their recent study handle children's heterogeneity. Focusing on child labor, they show that when talent heterogeneity is large, children with a comparative advantage to education may work too much. In this case, they argue that partial bans on child labor will improve the efficiency.

This research is motivated by Acemoglu's (1999) [3] notion that there exist two equilibria — pooling and separating equilibria — when a firm in the labor market randomly faces workers whose skills are heterogeneous. In his model, a pooling equilibrium occurs when the firm produces with a recruited worker and chooses the same level of physical capital, regardless of whether the worker is skilled or unskilled. In contrast, the separating equilibrium implies that the firm chooses larger capacity (capital) for a skilled worker, but if it faces an unskilled worker, it turns him down and shuts down. These different choices are determined by the conditions of labor market (e.g., the fraction of skilled workers in the labor market and the degree of productivity differentials between skilled and unskilled workers).

Based on this notion, I show that the heterogeneity of children's ability may make their parents choose different types of investment in education and fertility. First, I assume that parents know that, in an economy, there is a certain fraction of children with high ability and the degree of productivity differentials in human capital accumulation at time t. Using this knowledge, they make a decision about which type of investment they will choose. Given the conditions mentioned above, once they choose a pooling type, they do not care about whether their children have high or low ability. On the other hand, suppose that they choose a separating type. This indicates that, after observing the ability of their children, they will make discriminatory decisions on which child type they will educate, depending upon whether the children's ability is high or low. Once a type of investment in education is chosen, then a parent allocates her time and resources to consumption and education.

As described earlier, the type of investment parents choose depends on the proportion of children with high ability and their productivity in human capital accumulation. The proportion of high ability can be interpreted various ways. Of course, we can simply regard the proportion as a fraction of children with high ability among children born at time t in an economy. Moreover, we might interpret it as a function of social human capital (with positive relationship) because the higher social human capital in an economy, the more likely children are to show high productivity in accumulating their human capital. An interpretation like this might be useful to compare types of investment in education across countries.

Compared to the separating choice, the pooling choice may equalize educational opportunity. A parent who educates her child without considering her child's ability likely intends to provide public or compulsory education for her child. In contrast, the discriminatory separating choice may indicate that once a child is judged to be smart, he will get private education. Otherwise, he will get public education or no formal education. Although I will show later, if the proportion is relatively low given the productivity differential, a parent's equilibrium choice on education is pooling. That is, a parent does not have any incentive to judge her child's ability when the probability of high ability and/or the productivity differential is low. Further, interpreting the proportion as a function of social human capital, the resulting pooling choice is consistent with the Glomm and Ravikumar (1992)'s [34] prediction that societies in which the majority of people have incomes below average will choose public education. Such societies are likely to have low social human capital.

This chapter is organized as follows: Section 3.2 presents a simple model of a parent's choice on educational expenditures to accumulate her child's human capital, along with the probability of high ability. A parental choice on fertility is added to the simple model in Section 3.3. Section 3.4 concludes.

3.2 Simple Model

3.2.1 The Setup

In this section, I consider an overlapping generations model in which each person lives only for two periods. In the child period, she is educated, and in the adult period, she works and educates her child. For simplicity, I define a parent's utility function as a linear form

$$c_t + \beta h_{t+1}, \tag{3.1}$$

where c_t is the parental consumption at time t, h_{t+1}, her child's human capital, and β, a weight on the human capital. The parent cares only about her own consumption and her child's human capital. She does not care about the human capital or utility of the offspring of her child. The objective function in Equation (3.1) implies that a parent has only one child.

The budget constraint given to the parent is defined as follows:

$$c_t + e_{t+1} \leq w_t h_t (1 - \theta). \tag{3.2}$$

The parent's capacity for work is normalized to unity. Assuming that the labor market is competitive, w_t is an equilibrium wage per unit of human capital in the labor market. Thus, the capacity earnings are $w_t h_t$ for a person who has human capital, h_t, at time t. She invests e_{t+1} from her earnings in educating her child at time t. I assume that the time cost required to rear a child is a fraction of time, $\theta \in (0, 1)$, but it does not contribute to accumulating the child's human capital. That is, a parent allocates her time to work and rearing a child, and then allocates her effective earnings from work to her own consumption and the education of her child.

Relying heavily on Acemoglu (1999) [3] for the theoretical analysis of this research, I define the law of motion for human capital accumulation by

$$h_{t+1} = \lambda d^H h_t^\delta e_{t+1}^\alpha \kappa^\gamma + (1 - \lambda) d^L h_t^\delta e_{t+1}^\alpha, \tag{3.3}$$

where $\lambda \in (0, 1)$ is a probability of having a child with high ability. For simplicity, I normalize to unity the productivity of children with low ability in human capital accumulation and then assume that the productivity of children with high ability κ is greater than one. That is, $h_t^\delta e_{t+1}^\alpha \kappa^\gamma$ in Equation (3.3) is the human capital production function for a high ability child, while $h_t^\delta e_{t+1}^\alpha$, for a low ability child. d^j is a decision variable on whether she will invest in educating her child or not for each state, high ability, H, and low ability, L. I simply define the space of the decision variables by zero and one. That is, $d^j \in \{0, 1\}$ for $j = H, L$. For simple algebraic calculations, the human capital of a child who is not educated by the decision of its parent is normalized to zero, irrespective of whether it is born with high or low ability.

Based on Equation (3.3), I reiterate that a parent's choice of how she will invest in education occurs after observing her child's ability. First, my assumption is that a parent knows ex ante only the probability, λ, and the productivity, κ. Considering these two factors, she chooses a type of investment in education. That is, if she decides a pooling choice, she will invest in education without looking at whether her child has high or low ability. On the other hand, if she decides a separating choice, she will invest either only when her child's ability is high or only when her child's ability is low. After choosing a type of investment in education, she allocates her time and effective earnings to her child's education and consumption. The investment in education is irreversible.

In Equation (3.3), the probability of high ability may be considered given simply and exogenously, but as mentioned earlier, I conjecture that it might be positively correlated to social human capital in a society or the parent's human capital. That is, the probability may show an increasing positive externality in accumulating human capital as social human capital increases or the parent's human capital does. Based on the probability, λ, we can see that the law of motion is an expected production function for a child's human capital. In addition, expenditures on education, the parent's human capital, and the child's ability are employed as inputs for producing human capital.

3.2.2 Two Equilibria and Characteristics

Using Equations (3.1), (3.2), and (3.3), the expected value function for household's problem can be expressed as

$$V^* = \max_{\{e_{t+1}, d^H, d^L\}} \Big[w_t h_t (1-\theta) - e_{t+1} \left(\lambda d^H + (1-\lambda) d^L \right) \\ + \beta \left\{ \lambda d^H h_t^{\delta} e_{t+1}^{\alpha} \kappa^{\gamma} + (1-\lambda) d^L h_t^{\delta} e_{t+1}^{\alpha} \right\} \Big] . \qquad (3.4)$$

Since the decision on the investment in education depends on λ and κ, the expected expenditures on education, which are allocated from effective earnings, can be rewritten as a linear combination of the probability of ability and decision variables for each state. As in Acemoglu (1999) [3] and mentioned previously, if a parent's decision on investment in education for her child is independent of whether the child's ability is high or low, call it "pooling". Otherwise, call it "separating". That is, if $d^H = d^L$, then it is called pooling, and if $d^H \neq d^L$, then separating.

For four types of cases, the first order conditions with respect to e_{t+1} from Equation (3.4) are as follows:

(i) $-1 + \beta \alpha h_t^{\delta} e_{t+1}^{\alpha-1} \left[\lambda \kappa^{\gamma} + (1-\lambda) \right]$ for $(d^H, d^L) = (1, 1)$

(ii) No first-order condition for $(d^H, d^L) = (0, 0)$

(iii) $-\lambda + \beta \lambda \alpha h_t^{\delta} e_{t+1}^{\alpha-1} \kappa^{\gamma}$ for $(d^H, d^L) = (1, 0)$

(iv) $-(1-\lambda) + \beta (1-\lambda) \alpha h_t^{\delta} e_{t+1}^{\alpha-1}$ for $(d^H, d^L) = (0, 1)$.

The first terms in the necessary conditions of (i), (iii), and (iv) indicate the marginal costs of investing one unit of resource in education, while the second terms indicate

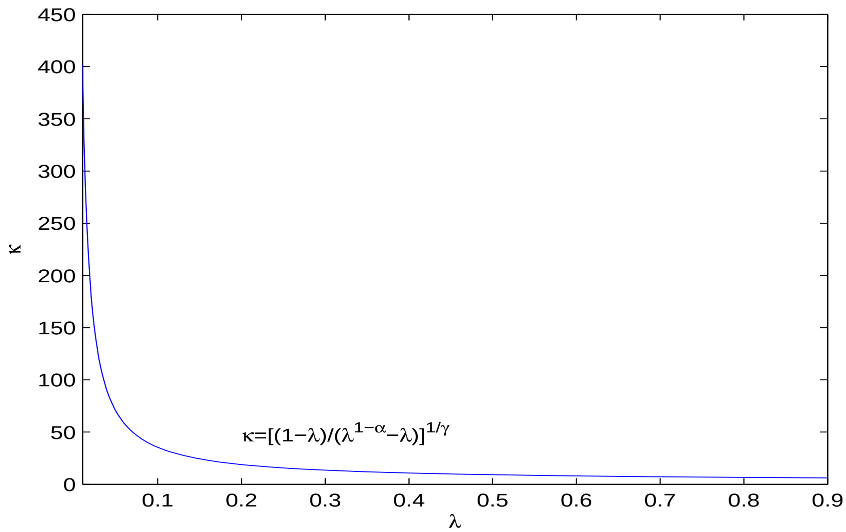

Figure 3.1: Two equilibria and the critical condition. $\alpha = 0.5$ and $\gamma = 0.4$.

the marginal benefits. Equation (3.4) for the second case is independent of expenditures on education, and the maximized expenditures are trivially zero. Since Equation (3.4) is concave in expenditures on education, e_{t+1}, the necessary conditions for (i), (iii), and (iv) satisfy the sufficient second-order conditions.

Proposition 1 *If* $\kappa > \left[\frac{1-\lambda}{\lambda^{1-\alpha}-\lambda}\right]^{\frac{1}{\gamma}}$, *then the equilibrium is unique and separating with* $(d^H, d^L) = (1, 0)$, *where the optimal expenditures on education are* $e^{s*}_{t+1} = \left[\alpha\beta h^{\delta}_t \kappa^{\gamma}\right]^{\frac{1}{1-\alpha}}$. *Otherwise, then it is unique and pooling with* $(d^H, d^L) = (1, 1)$, *where they are* $e^{p*}_{t+1} = \left[\alpha\beta h^{\delta}_t \left\{\lambda\kappa^{\gamma} + (1-\lambda)\right\}\right]^{\frac{1}{1-\alpha}}$.[1]

Proof. See Appendix 3.5.1.

The critical condition, $\kappa = \left[(1-\lambda)/(\lambda^{1-\alpha}-\lambda)\right]^{1/\gamma}$, in Proposition 1 is presented in Figure 3.1. The critical condition in Figure 3.1 shows that the high ability, $\kappa > 1$,

[1]This proposition is similar to Acemoglu (1999) [3].

is downward sloping in the probability λ, as in Acemoglu (1999) [3]. Given $\kappa > 1$, when the probability of getting a child of high ability increases and then exceeds the critical point, a parent's decision on education for her child switches from the pooling to the separating equilibrium. In addition, for $\lambda \in (0, 1)$, expected expenditures on education in the separating equilibrium, λe_{t+1}^{s*}, is greater than, e_{t+1}^{p*}, in the pooling equilibrium if an economy is in the separating equilibrium, and vice versa. In other words, the expected education expenditures are maximal in the choice yielding the equilibrium in each regime. The separating equilibrium may imply higher inequality in education, leading to higher inequality in income, relative to the pooling equilibrium. With respect to the two equilibria, one can see in Barro's (1999) [9] empirical paper that higher inequality in income slows down the growth in poor countries while it accelerates the growth in rich countries, implying that each equilibrium is optimal in its own regime in terms of economic growth.

In Figure 3.2, the red solid line means a standardized expected educational expenditure of a parent's pooling choice of $(d^H, d^L) = (1, 1)$ with the probability while the blue dot-dashed line, of the parent's separating choice of $(d^H, d^L) = (1, 0)$. The point where the two lines intersect is the critical probability, λ^*, which switches regimes from the pooling to the separating one. In Figure 3.2, together with the calibrations of $\alpha\beta h_t^\delta = 1$, $\alpha = 0.5$, $\gamma = 0.4$, and $\kappa = 10$, the critical probability, λ^*, appears to be about 0.43.

As shown in Figure 3.2, the expected educational expenditures increase with the probability, λ, for both cases. In addition, they are higher in each regime than otherwise, although this result is different from that in the model containing fertility in the next section. If the probability, λ, becomes higher, then an increase in the contribution to the value function, Equation (3.4), from the expected expenditures on education for the two equilibria is greater than a decrease in the contribution

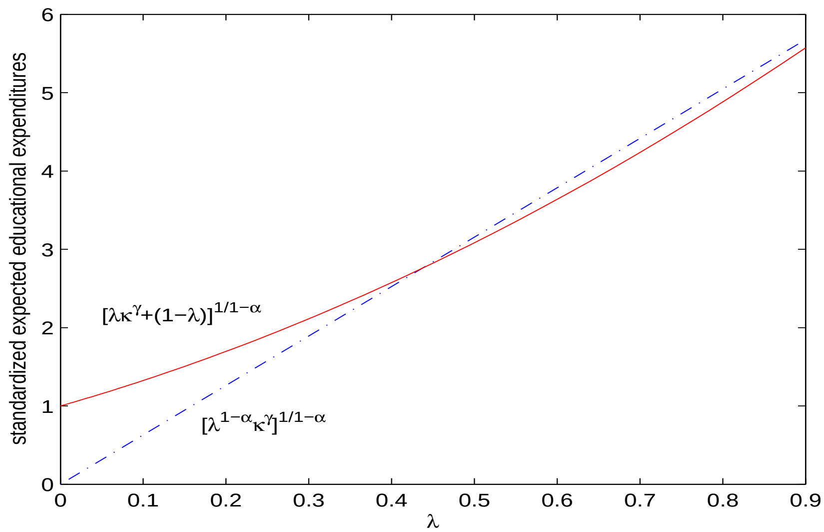

Figure 3.2: Standardized expected educational expenditures. $\alpha\beta h_t^{\delta} = 1$, $\alpha = 0.5$, $\gamma = 0.4$, and $\kappa = 10$.

from the reduced consumption because of $\kappa > 1$. Furthermore, we can see that with the higher probability, the expected expenditures on education in the separating equilibrium are higher than in the pooling equilibrium, suggesting that parents in an economy with high social human capital are more willing to spend resources on education than parents in a low social human capital economy.

Meanwhile, in Proposition 1 we can also see that the expected expenditures on education for both cases increase with a level of high ability and its intensity, κ^{γ}. An increase in κ makes the production of human capital more productive, leading to an increase in parental expenditures on education. With Proposition 1, the higher ability is or productivity differentials are, the higher the differentials in the expected educational expenditures between the two equilibria as shown in Equation (3.5). This implies that the differentials in human capital accumulation get bigger, leading to higher inequality between the two equilibria.

$$\frac{\partial}{\partial \kappa^{\gamma}}\left(\frac{\lambda e^{*s}_{t+1}}{e^{*p}_{t+1}}\right) = \frac{1}{1-\alpha}\left[\frac{\lambda^{1-\alpha}\kappa^{\gamma}}{\lambda\kappa^{\gamma}+(1-\lambda)}\right]^{\frac{\alpha}{1-\alpha}} \frac{1-\lambda}{\left(\lambda\kappa^{\gamma}+(1-\lambda)\right)^{2}} > 0 \tag{3.5}$$

In other words, a higher dispersion of children's ability leads to higher educational expenditures in the separating equilibrium than in the pooling equilibrium. As a result, income inequality increases between the two equilibria, which may help explain the increasing inequality between developed and undeveloped countries.

In Proposition 1, the expected educational expenditures in both equilibria increase with the elasticity of human capital production with respect to investments in education, α, the weight on utility from the child's human capital, β, and a parent's human capital and its intensity, h_t^{δ}. Besides, the rearing costs, θ, in Equation (3.4) play no role in determining the expenditures. Fertility is normalized to one in Equation (3.4) even though the given parent's time cost, θ, has effects on fertility because, in turn, fertility affects educational expenditures. Though it will be presented in the next section, I will point out here that an increase in rearing costs makes rearing children more expensive to parents with high human capital relative to those with low human capital. Thus, increased rearing costs give more incentives to parents with high human capital to reduce the number of children. This result is well presented in Becker, Murphy, and Tamura (1990) [13].

3.2.3 Characteristics in Dynamics of Two Equilibria

Substituting the optimal educational expenditures into Equation (3.3), we can examine the dynamics of human capital for each equilibrium. Under pooling and separating

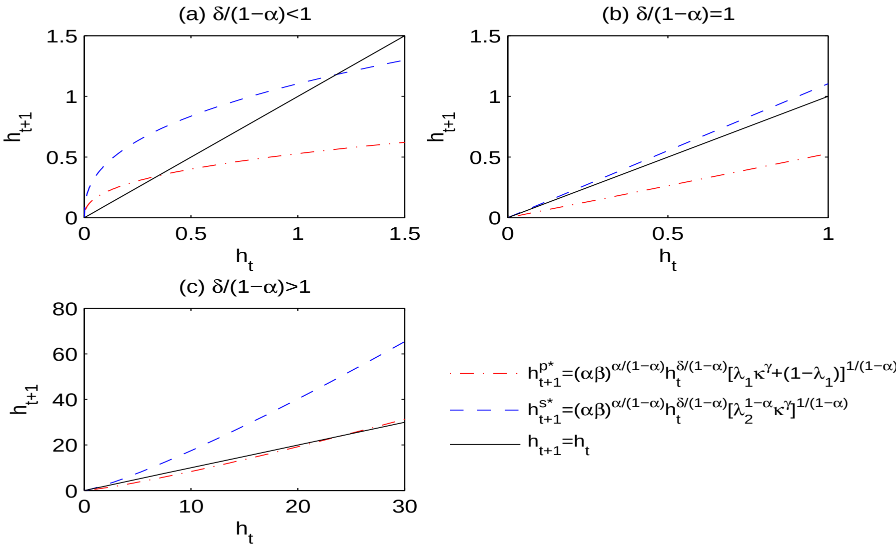

Figure 3.3: Dynamics of human capital. $\alpha = 0.5$, $\beta = 0.5$, $\gamma = 0.4$, $\kappa = 10$, $\lambda_1 = 0.3$, and $\lambda_2 = 0.7$.

regimes, the laws of motion for human capital are expressed as

$$h_{t+1}^{p*} = (\alpha\beta)^{\frac{\alpha}{1-\alpha}} h_t^{\frac{\delta}{1-\alpha}} \left[\lambda\kappa^{\gamma} + (1-\lambda)\right]^{\frac{1}{1-\alpha}}, \tag{3.6}$$

$$h_{t+1}^{s*} = (\alpha\beta)^{\frac{\alpha}{1-\alpha}} h_t^{\frac{\delta}{1-\alpha}} \left[\lambda^{1-\alpha}\kappa^{\gamma}\right]^{\frac{1}{1-\alpha}}. \tag{3.7}$$

Provided that $\delta/(1-\alpha) < 1$, the first-order difference equations in terms of human capital have a unique and stable steady-state equilibrium, respectively. If $\delta/(1-\alpha) = 1$ and neither $(\alpha\beta)^{\frac{\alpha}{1-\alpha}} [\lambda\kappa^{\gamma} + (1-\lambda)]^{\frac{1}{1-\alpha}}$ nor $(\alpha\beta)^{\frac{\alpha}{1-\alpha}} [\lambda^{1-\alpha}\kappa^{\gamma}]^{\frac{1}{1-\alpha}}$ is unitary, we have no steady-state point. On the other hand, if $\delta/(1-\alpha) > 1$, we have steady-state points for both the regimes, but they are unstable, which causes multiple long-run equilibria in terms of human capital accumulation. These are presented in Figure 3.3. Together with $\alpha = 0.5$, $\beta = 0.5$, $\gamma = 0.4$, $\kappa = 10$, $\lambda_1 = 0.3$, and $\lambda_2 = 0.7$, Panel (a) shows the case of $\delta/(1-\alpha) < 1$, Panel (b), $\delta/(1-\alpha) = 1$, and Panel (c), $\delta/(1-\alpha) > 1$. Interestingly, along with these calibrations of parameters, Panel

(b) shows that the long-run equilibrium of human capital is zero under the pooling choice due to low probability while it is infinity under the separating choice due to high probability. This implies that the probability may result in different long-run equilibria of human capital. Figure 3.3 shows that the rate of growth of human capital in the separating equilibrium is higher than that in the pooling equilibrium because of a higher probability of high ability in the separating regime.

Equations (3.6) and (3.7) show that given $\kappa > 1$, when the probability of high ability is sufficiently low, it is reasonable for a parent to choose a pooling decision, leading to higher growth rate of human capital than the separating decision. However, as the probability gets sufficiently high, a parent's discriminatory education decision across children's ability is efficient, leading to switching to the separating equilibrium and thus to higher economic growth. That is, it is inefficient for a parent to invest the same amount of educational expenditures, irrespective of her child's ability when the probability is sufficiently high — or social human capital is high.

3.3 The Model with Fertility

3.3.1 The Setup

In this section, I add fertility to the simple model in the previous section. So I define a parent's utility function as follows:

$$c_t + \beta n_t^{1-\epsilon} h_{t+1}^{\epsilon}, \tag{3.8}$$

where n_t indicates a parental fertility at time t, and I assume that $0 < \epsilon < 1$. The second term of Equation (3.8) which has a Cobb-Douglas form shows that quantity and quality of children are complementary to a parent's utility. The budget constraint below is similar to that in the previous section except for fertility:

$$c_t + n_t e_{t+1} \leq w_t h_t (1 - \theta n_t). \tag{3.9}$$

Since the costs of rearing children are θ per child, the total time costs by a parent are θn_t. I assume that children's ability within a household is homogeneous. In this case, it is efficient that the parent, a head in the given household, treats her children equally. Thus, I do not assume that she differentiates between her children. She only makes investment decisions on education for her children among four types of decisions, depending upon λ and κ. I employ the same law of motion for human capital as I did in the previous section, i.e., Equation (3.3).

3.3.2 Two Equilibria and Characteristics

Using Equations (3.3), (3.8) and (3.9) as in the previous section, the expected value function for household's problem can be expressed as

$$\begin{aligned} V^* = \max_{\{e_{t+1}, n_t, d^H, d^L\}} & \Big[w_t h_t (1 - \theta n_t) - n_t e_{t+1} \left(\lambda d^H + (1 - \lambda) d^L \right) \\ & + \beta n_t^{1-\epsilon} \left\{ \lambda d^H h_t^\delta e_{t+1}^\alpha \kappa^\gamma + (1 - \lambda) d^L h_t^\delta e_{t+1}^\alpha \right\}^\epsilon \Big] \end{aligned} \tag{3.10}$$

I explore the necessary conditions, case by case, for four types of decisions on education. I assume that the parental fertility, n_t, is always positive to avoid getting trivial corner solutions. The first order conditions with respect to e_{t+1} and n_t from Equation (3.10) are as follows:

(i) $(d^H, d^L) = (1,1)$:

$$-n_t + \beta\alpha\epsilon n_t^{1-\epsilon} h_t^{\delta\epsilon} e_{t+1}^{\alpha\epsilon-1} \left[\lambda\kappa^\gamma + (1-\lambda)\right]^\epsilon = 0, \tag{3.11}$$

$$-\theta w_t h_t - e_{t+1} + \beta(1-\epsilon) n_t^{-\epsilon} h_t^{\delta\epsilon} e_{t+1}^{\alpha\epsilon} \left[\lambda\kappa^\gamma + (1-\lambda)\right]^\epsilon = 0 \tag{3.12}$$

(ii) $(d^H, d^L) = (0,0)$:

No first-order condition with respect to e_{t+1} and a trivial solution of $n_t^* = 0$.

(iii) $(d^H, d^L) = (1,0)$:

$$-\lambda n_t + \beta\alpha\epsilon n_t^{1-\epsilon} h_t^{\delta\epsilon} e_{t+1}^{\alpha\epsilon-1} \lambda^\epsilon \kappa^{\gamma\epsilon} = 0, \tag{3.13}$$

$$-\theta w_t h_t - \lambda e_{t+1} + \beta(1-\epsilon) n_t^{-\epsilon} h_t^{\delta\epsilon} e_{t+1}^{\alpha\epsilon} \lambda^\epsilon \kappa^{\gamma\epsilon} = 0 \tag{3.14}$$

(iv) $(d^H, d^L) = (0,1)$:

$$-(1-\lambda) n_t + \beta\alpha\epsilon n_t^{1-\epsilon} h_t^{\delta\epsilon} e_{t+1}^{\alpha\epsilon-1} (1-\lambda)^\epsilon = 0, \tag{3.15}$$

$$-\theta w_t h_t - (1-\lambda) e_{t+1} + \beta(1-\epsilon) n_t^{-\epsilon} h_t^{\delta\epsilon} e_{t+1}^{\alpha\epsilon} (1-\lambda)^\epsilon = 0 \tag{3.16}$$

The first terms in Equations (3.11), (3.13), and (3.15) represent the marginal costs from increasing one unit of educational expenditures, while the second terms represent the marginal benefits contributing to the value functions. Likewise, The first and second terms in Equations (3.12), (3.14), and (3.16) indicate the marginal costs of having a child, the costs of rearing and educating a child on the margin, while the third terms indicate the marginal benefits. The expected value function shown in Equation (3.10) is concave in educational expenditures, e_{t+1}, and the number of children, n_t, which implies that the sufficient conditions hold. Solving the first-order conditions for each type, we get the following solutions:

(i) $(d^H, d^L) = (1,1)$:

$$e_{1t+1}^{p*} = \frac{\alpha\epsilon\theta w_t h_t}{1-\epsilon-\alpha\epsilon}, \tag{3.17}$$

$$n_{1t}^{p*} = \left[\left(\frac{1-\epsilon-\alpha\epsilon}{\alpha\epsilon\theta w_t}\right)^{1-\alpha\epsilon} \alpha\beta\epsilon h_t^{\epsilon(\alpha+\delta)-1}\right]^{\frac{1}{\epsilon}} [\lambda\kappa^\gamma + (1-\lambda)] \tag{3.18}$$

(ii) $(d^H, d^L) = (0,0)$:

$e_{2t+1}^{p*} = 0$ and $n_{2t}^{p*} = 0$, which is conflicting with the assumption of $n_t > 0$.

(iii) $(d^H, d^L) = (1,0)$:

$$e_{3t+1}^{s*} = \frac{\alpha\epsilon\theta w_t h_t}{\lambda(1-\epsilon-\alpha\epsilon)}, \tag{3.19}$$

$$n_{3t}^{s*} = \left[\left(\frac{1-\epsilon-\alpha\epsilon}{\alpha\epsilon\theta w_t}\right)^{1-\alpha\epsilon} \alpha\beta\epsilon h_t^{\epsilon(\alpha+\delta)-1}\right]^{\frac{1}{\epsilon}} \lambda^{1-\alpha}\kappa^\gamma \tag{3.20}$$

(iv) $(d^H, d^L) = (0,1)$:

$$e_{4t+1}^{s*} = \frac{\alpha\epsilon\theta w_t h_t}{(1-\lambda)(1-\epsilon-\alpha\epsilon)}, \tag{3.21}$$

$$n_{4t}^{s*} = \left[\left(\frac{1-\epsilon-\alpha\epsilon}{\alpha\epsilon\theta w_t}\right)^{1-\alpha\epsilon} \alpha\beta\epsilon h_t^{\epsilon(\alpha+\delta)-1}\right]^{\frac{1}{\epsilon}} (1-\lambda)^{1-\alpha}. \tag{3.22}$$

Proposition 2 *If* $\kappa > \left[\frac{1-\lambda}{\lambda^{1-\alpha}-\lambda}\right]^{\frac{1}{\gamma}}$*, then the equilibrium is unique and separating with* $(d^H, d^L) = (1,0)$*, where the optimal expenditures on education and parental fertility are* $e_{t+1}^{s*} = \frac{\alpha\epsilon\theta w_t h_t}{\lambda(1-\epsilon-\alpha\epsilon)}$ *and* $n_t^{s*} = \left[\left(\frac{1-\epsilon-\alpha\epsilon}{\alpha\epsilon\theta w_t}\right)^{1-\alpha\epsilon} \alpha\beta\epsilon h_t^{\epsilon(\alpha+\delta)-1}\right]^{\frac{1}{\epsilon}} \lambda^{1-\alpha}\kappa^\gamma$*. Otherwise, then it is unique and pooling with* $(d^H, d^L) = (1,1)$*, where they are* $e_{t+1}^{p*} = \frac{\alpha\epsilon\theta w_t h_t}{1-\epsilon-\alpha\epsilon}$ *and* $n_t^{p*} = \left[\left(\frac{1-\epsilon-\alpha\epsilon}{\alpha\epsilon\theta w_t}\right)^{1-\alpha\epsilon} \alpha\beta\epsilon h_t^{\epsilon(\alpha+\delta)-1}\right]^{\frac{1}{\epsilon}} [\lambda\kappa^\gamma + (1-\lambda)]$*.*

Proof. See Appendix 3.5.2.

As in Proposition 1, if given $\kappa > 1$, the probability that a child with high ability is born rises and then exceeds the critical point due to the downward-sloping critical condition, a parent's educational decision for her child switches from the pooling to the separating equilibrium. In Proposition 2, we can see that a parent's expected expenditures on education per child, λe_{t+1}^{s*} and e_{t+1}^{p*}, are identical in the pooling and separating equilibria, regardless of the probability, λ. Instead, we get the result that optimal fertility is higher in its own regime. That is, when the probability of high ability is sufficiently low, leading to a pooling equilibrium, the pooling choice for fertility is higher than the separating one. In contrast, when the probability is sufficiently high, leading to a separating equilibrium, the separating choice for fertility is higher than the pooling choice. However, a parent's total expected expenditures on education, $\lambda n_t^{s*} e_{t+1}^{s*}$ are higher in the separating equilibrium than, $n_t^{p*} e_{t+1}^{p*}$, in the pooling equilibrium.

Intuitively, when the probability that a born child has high ability is low, a parent's separating choice implies that fertility is low relative to her pooling choice, because if it is more likely that her children's ability is low, she is forced to take a risk of not educating them under the separating choice in the pooling regime. As a result, in an economy with this low probability, it is more efficient that a parent makes a pooling choice, not considering children's ability. Note that the pooling choice of fertility is modestly increasing in the probability, λ. In contrast, if the probability is sufficiently high, the marginal benefits of getting a child are increasing rapidly relative to the pooling choice, leading to a rapid increase in fertility because $\kappa > 1$ implies that the separating choice has a higher positive externality from having children, compared to the pooling. Thus, in this case the separating choice is an equilibrium. It is worth noting that in either of the two equilibria, fertility is increasing in probability. That is, as the probability goes up, a parent has an incentive to have more children since the risk of having children with low ability is decreasing and she can have positive externality from children with high ability in terms of her value function.

Consider educational and fertility choices in each equilibrium from Proposition 2 with respect to some exogenous variables. From the results in Proposition 2, first we have a constraint, $0 < \epsilon < 1/(1+\alpha)$, to avoid getting zero or negative educational expenditures and fertility. In addition, it should be noted that the optimal educational expenditures are increasing in ϵ and θ. Since ϵ is an exponential weight in human capital, it appears to be natural to be positively correlated with the expenditures. More importantly, the rearing costs, θ, are also positively correlated to the expenditures but negatively correlated with fertility. Increased rearing costs make children more expensive; thus parents have incentives to spend more on education for more expensive children. Meanwhile, if $\delta < 1$, the fertility choices in each regime are negatively correlated to parental human capital. Consistent with previous literature, this result is because the time costs of a parent with high human capital are large relative to low parental human capital from rearing children. On the other hand, it is straightforward to see that educational expenditures for both the regimes are positively correlated to the parental human capital.

Provided that the probability of high ability is due to social human capital and $0 < \epsilon < 1/(1+\alpha)$, the effects of social human capital and parental human capital on fertility are conflicting. Moreover, assuming that parental human capital is homogeneous at time t, whether or not fertility will increase as an economy grows is ambiguous. But empirically, fertility appears to decrease when an economy takes off from Malthusian stagnation to sustained economic growth (Galor, 2004) [31].

3.3.3 Characteristics in Dynamics of Two Equilibria

Plugging the optimal educational expenditures into Equation (3.3) as in the previous section, we can look through dynamics of human capital for each regime. Under pooling and separating regimes, the laws of motion for human capital are as follows:

$$h_{t+1}^{p*} = \left(\frac{\alpha\epsilon\theta w_t}{1-\epsilon-\alpha\epsilon}\right)^{\alpha} h_t^{\alpha+\delta}\left[\lambda\kappa^{\gamma}+(1-\lambda)\right], \tag{3.23}$$

$$h_{t+1}^{s*} = \left(\frac{\alpha\epsilon\theta w_t}{1-\epsilon-\alpha\epsilon}\right)^{\alpha} h_t^{\alpha+\delta}\lambda^{1-\alpha}\kappa^{\gamma}. \tag{3.24}$$

Similar to the previous section, if $\alpha+\delta<1$, then the first-order difference equations for human capital show that they both have a unique and stable steady-state equilibrium. If $\alpha+\delta=1$ and neither $\left(\frac{\alpha\epsilon\theta w_t}{1-\epsilon-\alpha\epsilon}\right)^{\alpha}\left[\lambda\kappa^{\gamma}+(1-\lambda)\right]$ nor $\left(\frac{\alpha\epsilon\theta w_t}{1-\epsilon-\alpha\epsilon}\right)^{\alpha}\lambda^{1-\alpha}\kappa^{\gamma}$ is one, then there is no steady-state point. On the other hand, although if $\alpha+\delta>1$, then we have steady-state points for both the regimes, we can see that they are unstable, leading to multiple long-run equilibria in terms of human capital accumulation.

Letting $A\equiv\left(\frac{\alpha\epsilon\theta w_t}{1-\epsilon-\alpha\epsilon}\right)^{\alpha}$, we see that the growth rate of human capital is higher in each own regime, regardless of the size of $\alpha+\delta$. However, note that due to higher probability, the growth rate of human capital in the separating equilibrium is higher than that in the pooling equilibrium as in the previous section. That is, as the probability of high ability goes up, parents switch their choices from the pooling to the separating one, and then the growth rate of output in the separating equilibrium is higher than in the pooling equilibrium.

3.4 Concluding Remarks

This chapter deals with parental choices about expected educational expenditures and fertility when children's ability is heterogeneous. Together with the heterogeneity in ability and the probability of high ability, a parent's choices create pooling and separating equilibria. When the probability of high ability is sufficiently low, the parent's pooling choice is optimal. In contrast, when it is sufficiently high, the separating choice is optimal. That is, as heterogeneity and probability increase, the parent switches her choice from pooling to separating.

Assuming that a parent has only one child, expected educational expenditures for the pooling choice are larger than those for the separating choice when an economy is in the pooling equilibrium. Likewise, expenditures for the separating choice are larger when it is in the separating equilibrium. However, due to the higher probability, the growth rate of human capital in the separating equilibrium is higher than that in the pooling equilibrium.

In the model with fertility, the results are slightly different from the simple model. Expected expenditures on education are the same in the two equilibria. However, similar to what I mention above, fertility for the pooling and separating choices in each own regime is higher than otherwise. Considering the higher probability, the fertility is higher in the separating equilibrium than in the pooling equilibrium, leading to higher expected expenditures on education for all children in the separating equilibrium. Finally, fertility has two conflicting forces in probability and parental human capital. Which force is greater is ambiguous, but empirically, negative effects of parental human capital on fertility likely dominate.

Although this chapter contributes to exploring a parent's educational and fertility choice for the heterogeneity of children's ability, it is pointed out that there are unrealistic problems with the model. Unlike Acemoglu's (1999) [3] model, if a parent is altruistic, she is unlikely to abandon her child, even when she observes the born child's low ability. In practice she will not give up educating her low-ability child. In other words, it may seem difficult to observe a parent's separating choice in a real world, and thus this unrealistic problem undercuts the conclusions in this chapter. Therefore, further research is required. Ideally, this research will study parents in the real world making choices about fertility and the education of children with heterogeneous ability.[2]

[2] I am grateful to Robert F. Tamura for helpful comments.

3.5 Appendix

3.5.1 *Proof of Proposition 1*

We can prove Proposition 1 by comparing the value functions for each state. Plugging the optimal expenditures on education from the necessary conditions into Equation (3.4), those for each state are presented below:

$$\text{(i) } V_1^{p*} = w_t h_t(1-\theta) + \tfrac{1-\alpha}{\alpha}\left[\alpha\beta h_t^{\delta}\left\{\lambda\kappa^{\gamma} + (1-\lambda)\right\}\right]^{\frac{1}{1-\alpha}} \quad \text{for } (d^H, d^L) = (1,1)$$

$$\text{(ii) } V_2^{p*} = w_t h_t(1-\theta) \quad \text{for } (d^H, d^L) = (0,0)$$

$$\text{(iii) } V_3^{s*} = w_t h_t(1-\theta) + \tfrac{1-\alpha}{\alpha}\lambda\left[\alpha\beta h_t^{\delta}\kappa^{\gamma}\right]^{\frac{1}{1-\alpha}} \quad \text{for } (d^H, d^L) = (1,0)$$

$$\text{(iv) } V_4^{s*} = w_t h_t(1-\theta) + \tfrac{1-\alpha}{\alpha}(1-\lambda)\left[\alpha\beta h_t^{\delta}\right]^{\frac{1}{1-\alpha}} \quad \text{for } (d^H, d^L) = (0,1).$$

To compare the value functions for each state, it is sufficient to examine the following conditions because the value function in (ii) is minimal: $\frac{\lambda\kappa^{\gamma}+(1-\lambda)}{\lambda^{1-\alpha}\kappa^{\gamma}}$, $\frac{\lambda\kappa^{\gamma}+(1-\lambda)}{(1-\lambda)^{1-\alpha}}$, and $\frac{\lambda^{1-\alpha}\kappa^{\gamma}}{(1-\lambda)^{1-\alpha}}$. First, consider the condition for $V_1^{p*} < V_3^{s*}$ with $\lambda \in (0,1)$. For this condition to hold, the first condition, $\frac{\lambda\kappa^{\gamma}+(1-\lambda)}{\lambda^{1-\alpha}\kappa^{\gamma}} < 1$, should be satisfied. Simplifying this inequality gives us the following condition: $\kappa > \left[\frac{1-\lambda}{\lambda^{1-\alpha}-\lambda}\right]^{\frac{1}{\gamma}}$. Then, consider the condition for $V_1^{p*} > V_4^{s*}$ with $\lambda \in (0,1)$, and then $\frac{\lambda\kappa^{\gamma}+(1-\lambda)}{(1-\lambda)^{1-\alpha}} > 1$ should hold. This inequality simplifies to $\kappa > \left[\frac{(1-\lambda)^{1-\alpha}-(1-\lambda)}{\lambda}\right]^{\frac{1}{\gamma}}$.

If the condition $\kappa > \left[\frac{1-\lambda}{\lambda^{1-\alpha}-\lambda}\right]^{\frac{1}{\gamma}}$ holds, it implies $\kappa > \left[\frac{(1-\lambda)^{1-\alpha}-(1-\lambda)}{\lambda}\right]^{\frac{1}{\gamma}}$ for all $\lambda \in (0,1)$. That is, we can see that $V_4^{s*} < V_1^{p*} < V_3^{s*}$. Then, the equilibrium is a separating one with $(d^H, d^L) = (1,0)$ under the condition $\kappa > \left[\frac{1-\lambda}{\lambda^{1-\alpha}-\lambda}\right]^{\frac{1}{\gamma}}$.

In contrast, under the condition $1 < \kappa < \left[\frac{1-\lambda}{\lambda^{1-\alpha}-\lambda}\right]^{\frac{1}{\gamma}}$, there exists a pooling equilibrium with $(d^H, d^L) = (1,0)$ for all $\lambda \in (0,1)$. On the other hand, $\kappa <$

$\left[\frac{(1-\lambda)^{1-\alpha}-(1-\lambda)}{\lambda}\right]^{\frac{1}{\gamma}}$ is impossible since $\frac{(1-\lambda)^{1-\alpha}-(1-\lambda)}{\lambda} < 1$ for all $\lambda \in (0,1)$, but $\kappa > 1$. Thus, the separating one with $(d^H, d^L) = (0,1)$ cannot be an equilibrium. Q.E.D.

3.5.2 *Proof of Proposition 2*

As in Appendix 3.5.1, I compare the expected value functions for the four types of states to determine equilibria. The optimal educational expenditures and parental fertility give us the following value functions:

(i) $V_1^{p*} = w_t h_t \left[1 + n_{1t}^{p*}\left(\frac{\epsilon\theta}{1-\epsilon-\alpha\epsilon}\right)\right]$ for $(d^H, d^L) = (1,1)$

(ii) $V_2^{p*} = w_t h_t$ with trivial fertility $n_{2t}^{p*} = 0$ for $(d^H, d^L) = (0,0)$

(iii) $V_3^{s*} = w_t h_t \left[1 + n_{3t}^{s*}\left(\frac{\epsilon\theta}{1-\epsilon-\alpha\epsilon}\right)\right]$ for $(d^H, d^L) = (1,0)$

(iv) $V_4^{s*} = w_t h_t \left[1 + n_{4t}^{s*}\left(\frac{\epsilon\theta}{1-\epsilon-\alpha\epsilon}\right)\right]$ for $(d^H, d^L) = (0,1)$.

The value function in (ii) cannot be an equilibrium since it is the smallest, so to compare the value functions, it is sufficient to compare the optimal fertilities for the three remaining states. Thus, the key conditions from Equations (3.18), (3.20), and (3.22) are as follows: $\frac{n_{1t}^{p*}}{n_{3t}^{s*}} = \frac{\lambda\kappa^{\gamma}+(1-\lambda)}{\lambda^{1-\alpha}\kappa^{\gamma}}$, $\frac{n_{1t}^{p*}}{n_{4t}^{s*}} = \frac{\lambda\kappa^{\gamma}+(1-\lambda)}{(1-\lambda)^{1-\alpha}}$, and $\frac{n_{3t}^{s*}}{n_{4t}^{s*}} = \frac{\lambda^{1-\alpha}\kappa^{\gamma}}{(1-\lambda)^{1-\alpha}}$. These conditions are exactly the same as those in Appendix A. Therefore, the critical condition for distinguishing the pooling from the separating equilibrium is $\kappa = \left[\frac{1-\lambda}{\lambda^{1-\alpha}-\lambda}\right]^{\frac{1}{\gamma}}$. Q.E.D.

Chapter 4

Summary and Conclusions

Chapter 4 is a summary and conclusion of Chapters 2 and 3. First, to identify the relationship between the wage inequality and the real federal minimum wage in Chapter 2, I calculate the between-group and quantile wage inequalities by using the OLS and quantile regressions.

The main results from the OLS show that the rates of return to schooling are stable in the 1960s and 1970s[1], increase sharply in the 1980s, and then weaken in the 1990s and 2000s. The returns to experience rise rapidly in the 1970s, weaken in the 1980s, and then decline in the late 1980s. The gender wage differentials, which decline in the 1970s and 1980s, become stable from the mid 1990s. The racial wage gaps, having declined until the 1970s, get stable from the 1980s. These results seem consistent with previous studies.

Meanwhile, predicted log wages evaluated at sample means of high school dropouts and graduates with six quantile regressions show that those for the 10th quantile are below the nominal minimum wage. In addition, using the predicted log wages at six quantiles, the static OLS regressions of percentile wage inequalities show

[1]The returns to schooling in the 1970s are slightly smaller than in the 1960s.

that residuals from the regressions are significantly positive autocorrelated, leading t-ratio to be biased. The robust method to prevent the bias does not show any significant economic meaning of the federal minimum wage on the percentile wage inequality.

In fact, real minimum wage may seem to have a strong negative effect on between-group wage inequality in OLS regressions. In the time-series analysis for the inequality, however, I find that labor market factors are still important in determining inequality, but minimum wage is not. Minimum wage alone has neither any long-run relationship with inequality nor even a short-run impact on it with the long-run specification including the relative labor supply in the error correction model. Thus, I conclude in Chapter 2 that the data are inconsistent with the revisionists' view.

Together with this conclusion, Chapter 2 on the relationship between wage inequality and minimum wage requires further future research. First, the chapter does not separate the CPS sample by sex. Doing so in a future study may allow us to examine more obvious relationships between inequality and minimum wage because patterns of employment and earnings between male and female workers may differ. Second, since the effects of minimum wage on wage inequality may differ across regions, in particular, the South in the United States, it would be interesting to analyze the effects with the sample only in the South. Third, it should be noted that the sectors bound by minimum wages are different across industries. Thus, by controlling for industries and occupations, we might obtain more meaningful estimation results on wage inequality and minimum wage. Fourth, although I do not control for relative labor supply in Tables 2.10, 2.11, and 2.12, it might be useful to include COL/HS relative labor supply in the model to estimate the impacts of real minimum wage on percentile wage ratios. Finally, the possibility of errors in measurement still exists. This leads to a potential attenuation bias in the effects of minimum wages on wage inequality, so the extent of the attenuation bias should be examined in future research.[2]

In Chapter 3, building on Acemoglu's (1999) [3] model and the overlapping generations model, I examine a parent's choices on investments in human capital for her children and fertility when the children's ability is heterogeneous. Using this framework, I find that when a fraction of children with high ability is sufficiently low in an economy, a parent chooses pooling, while when sufficiently high, she chooses separating. That is, as the fraction of high ability grows given the ability differentials, a parent switches her choice from the pooling to the separating equilibrium. It should be noted that the separating choice may lead to a more unequal economy than the pooling one. Suppose that the separating choices which are optimal in the separating equilibrium are mainly found in developed countries whereas the pooling choices are found in undeveloped countries. This may imply that inequality in the developed countries and equality in the undeveloped countries are optimal, respectively. This implication may be consistent with Barro's (1999) [9] empirical paper showing that the relationship between inequality and growth in rich countries is positive while the relationship in poor countries is negative.

The main results in a simple model are that expected educational expenditures in each equilibrium are greater than otherwise. The growth rate of the economy in the separating equilibrium is higher than in the pooling equilibrium, due to the higher fraction of high ability. In the meantime, the model with fertility shows that the expected educational expenditures are identical in the two equilibria. Fertility for the pooling and separating choices in each own regime is, however, higher than otherwise. Besides, the fertility in the separating equilibrium is higher than in the

[2]I thank all my dissertation committe members, Daniel K. Benjamin, Curtis J. Simon, Robert F. Tamura, and John T. Warner, for helpful comments.

pooling equilibrium, due to the higher fraction of high ability, implying higher expected expenditures on children's education in the separating equilibrium.

As aforementioned in Section 3.4, the model has an unrealistic problem with the parental separating choice. Therefore, future research requires a more realistic model considering the heterogeneity of children's ability.

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