Three essays on gender wage differentials

Fang, Zheng

2011

Fang, Z. (2011). Three essays on gender wage differentials. Doctoral thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/50622>

<https://doi.org/10.32657/10356/50622>

Three Essays on Gender Wage Differentials

Fang Zheng

School of Humanities and Social Sciences

A thesis submitted to the Nanyang Technological University

in partial fulfillment of the requirement for the degree of Doctor of Philosophy

2011

Acknowledgements

First and foremost, I would like to thank my supervisor Associate Professor Chris Sakellariou for his inspirational guidance and tremendous help in my thesis writing, as well as the support in every aspect of life. In addition, I would like to thank Prof. Nattavudh Powdthavee, Prof. Jie Zhou and two external examiners for invaluable comments and suggestions in improving my thesis. Gratitude also goes to Prof. Kampon Adireksombat, Kong Weng Ho, Wai Mun Chia, Guiying Laura Wu, Qu Feng, Yohanes Eko Riyanto, and Duc Quang Nguyen for their kindness and helpful discussions during the thesis writing; and Prof. Shuntian Yao, Weihong Huang, Joseph Alba, John Lane, and Randolph Tan for teaching me advanced knowledge in Economics.

I am also grateful to the Division of Economics, Nanyang Technological University for providing us this excellent research environment. I have benefited a lot from discussions in the weekly seminars and academic conferences participated by both internal and external renowned researchers and scholars. I am deeply indebted to Prof. Blaise Melly for discussions and suggestions in the early draft of the thesis, and Prof. Audra Bowlus for kindly providing us the data used in the thesis.

Last but not the least, I would also like to take this opportunity to thank all my fellow PhD friends, Jing Wang, Yuxin Zou and Weijing Xu, to name just a few, for the happy time we have spent together; thank my parents and older brother for their incessant encouragement and support; and thank Jie Huang, my fiancé for everything!

Table of Contents

Executive Summary	7
1 Glass Ceilings versus Sticky Floors: New Evidence and an International Update.....	9
1.1 Introduction	9
1.2 Literature review	12
1.3 The origin of gender wage differentials	14
1.3.1 Demand side	14
1.3.2 Supply side	18
1.4 Conceptual framework	20
1.5 Data description.....	21
1.6 Results and discussion	23
1.6.1 The raw gender gap	23
1.6.2 Counterfactual decompositions	25
1.6.3 Counterfactual gender wage gap	28
1.7 Conclusion.....	32
1.8 Appendix	43
2 The Evolution of Gender Wage Differentials and Discrimination in Thailand: 1991-2007---An Application of Unconditional Quantile Regression	64
2.1 Introduction	64
2.2 Conceptual framework	65
2.2.1 Decomposition of the gender wage gap at quantiles	66
2.2.2 Decomposition of changes in gender wage gaps over time.....	69
2.3 Data description and raw gender wage differentials	71
2.3.1 Data description.....	71
2.3.2 Raw gender wage differentials	73
2.4 Unconditional quantile regressions and decomposition of the wage gap.....	74
2.4.1 Unconditional quantile regressions by gender.....	74
2.4.2 The gender wage gap by year.....	75
2.4.3 The evolution of gender wage gaps over time.....	77
2.5 Conclusion.....	80
3 Discrimination in the Equilibrium Search Model with Wage-Tenure Contracts	95

3.1	Introduction	95
3.2	The model.....	100
3.2.1	The environment.....	100
3.2.2	Workers' optimal decision.....	102
3.2.3	Firms' optimal decision	103
3.3	Equilibrium.....	105
3.4	Equilibrium Properties	110
3.5	A special case	113
3.6	A Numerical Example	115
3.7	Application one: Racial wage discrimination	117
3.7.1	Identification.....	119
3.7.2	Estimation.....	120
3.7.3	Comparison.....	123
3.8	Application two: Gender wage discrimination.....	125
3.8.1	Data.....	125
3.8.2	Estimation.....	127
3.9	Conclusion.....	129
3.10	Appendix	133
4	Conclusion	145
	Bibliography	149

List of Tables

Table 1.1:	Glass ceilings vs. sticky floors: an international comparison.....	35
Table 1.A1:	Data sources	43
Table 1.A2:	Descriptive statistics	44
Table 1.A3 (a):	Raw gender wage differentials from pooled data.....	52
Table 1.A3 (b):	Raw gender wage differentials in the public sector	53
Table 1.A3 (c):	Raw gender wage differentials in the private sector	54
Table 1.A4 (a):	Decomposition of gender wage differentials without controlling for occupation: pooled data	55
Table 1.A4 (b):	Decomposition of gender wage differentials without controlling for occupation: by sector	57
Table 1.A5 (a):	Decomposition of gender wage differentials with controlling for occupation: pooled data	59
Table 1.A5 (b):	Decomposition of gender wage differentials with controlling for occupation: by sector	61
Table 1.A6:	Summary of Table A4 and Table A5 for glass ceilings/sticky floors evidence	63
Table 2.1:	Descriptive statistics by time period and gender	82
Table 2.2:	Decomposition of gender wage differentials at selected quantiles.....	84
Table 2.3:	Decomposition of changes in gender wage differentials at selected quantiles	85
Table 2.A1:	Mean real hourly wage (in 2007 Baht)	90
Table 2.A2 (a):	Coefficients of unconditional quantile regressions: 1991/1993	91
Table 2.A2 (b):	Coefficients of unconditional quantile regressions: 1998/2000.....	92
Table 2.A2 (c):	Coefficients of unconditional quantile regressions: 2005/2007	93
Table 3.1:	The mean wage of type <i>B</i> workers	116
Table 3.2:	Summary of NLSY data for male high school graduates, 1985-1988.	119
Table 3.3:	Parameter Estimates.....	121
Table 3.4:	Summary of NLSY data for high school white graduates, 1985-1987.	126
Table 3.5:	Parameter estimates	128

List of Figures

Figure 1.1:	Counterfactual gender wage gap over the wage distribution	37
Figure 2.1:	Log gender wage gap over time	86
Figure 2.2:	Gender wage gap across quantiles.....	86
Figure 2.3:	Decomposition of gender wage gaps.....	87
Figure 2.4:	Decomposition of change in gender wage gaps	89
Figure 2.A:	Coefficients effects over time.....	94
Figure 3.1:	Earnings distributions.....	114
Figure 3.2:	Wage Dynamics	118
Figure 3.3:	Predicted earnings distributions	131
Figure 3.4:	Predicted wage dynamics	131
Figure 3.5:	Wage dynamics	124
Figure 3.6:	Hourly wage distributions	132
Figure 3.7:	Scatter plots of wage increase and hourly pay	132
Figure 3.8:	Hourly wage increase using 1986-1985	132
Figure 3.9:	Predicted wage increase	128

Executive Summary

Gender wage gaps in favor of men have been widely documented across a large number of countries. Such gaps can be partially explained by differences in productivity related characteristics, such as education and experience between men and women; the part not explained by differences in characteristics is often referred to as potential discrimination in the labor market. The issue has been studied extensively in the literature, especially at the mean; however, distributional patterns may be of more interest as they relate to policy-making, when targeted intervention is deemed appropriate. This thesis consists of three self-contained essays which study the gender wage differentials and potential gender discrimination across the earnings distribution.

Within the growing literature on gender wage differentials over the wage distribution, two terms - glass ceilings and sticky floors - are used. Glass ceilings refer to a phenomenon where the counterfactual gender wage gap is wider at the top than at the bottom, while sticky floors refer to a wider gap observed at the bottom relative to the top. The objectives of the first chapter of the thesis are to expand the body of evidence, providing an international update from more than 50 countries in 5 continents and to suggest potential explanations to the stylized facts documented across countries. We find that glass ceilings are present in 22 European countries, while no country in Asia but Kazakhstan and Uzbekistan show evidence of glass ceilings. In 6 Latin American countries, the evidence is mixed. In Africa the estimates from the black populations of South Africa and Lesotho point to a clear sticky floor effect, while glass ceilings are found in Egypt and Morocco. Possible explanations could be differences in labor market institutions such as regulation, presence of minimum wage legislation, availability of childcare and job segregation, as well as societal, cultural practices.

To understand the evolution of gender wage gaps at different points of the distribution and the contribution of individual determinants to the gap, Chapter 2 adopts unconditional quantile regression combined with Oaxaca-Blinder decomposition to study the gender wage inequality in Thailand from 1991 to 2007. We find: (1) a persistent sticky floor effect exists; (2) gender gaps in all these years, both at mean and over the distribution, are attributable to gender differences in returns to characteristics, particularly, differences in experience returns at the middle and educational returns at the two ends; (3) gender wage gaps have been declining over time, especially in the 1990s; however, relative changes in characteristics explain only a very small part of these over time changes.

Chapter 3 is a theoretical piece, which develops a discrimination search model with wage-tenure contracts to study differences in labor market outcomes. Based on the model, we find that (1) minority workers have a higher unemployment rate and a longer duration of unemployment; (2) non-discriminating firms make higher profits than discriminating firms; (3) the lowest acceptable wage for a minority worker is greater than that for a majority worker, while the highest expected wage of a minority worker is lower; (4) in general, the average minority workers earn less than majority workers and their wage increases more slowly than their counterparts'. Furthermore, we put the model to data and are able to distinguish the effect of differences in productivity and discrimination on the wage gaps.

CHAPTER ONE

Glass Ceilings versus Sticky Floors: New Evidence and an International Update¹

1.1 Introduction

The gender wage gap has been extensively studied at the mean; however, the analysis of how it evolves along the wage distribution has only received attention in recent years. For example, Albrecht et al. (2003) found an increasing gender gap along the wage distribution in Sweden. Arulampalam et al. (2007) studied eleven European countries and found the *glass ceiling* effect prevailing for most countries. A glass ceiling is an observed gender gap which is wider at the top of the counterfactual wage distribution compared to the bottom part.² Unlike previous studies which employ ordinary least squares (OLS) and the Oaxaca-Blinder decomposition to investigate the average gender wage gap, they constructed counterfactual distributions following the approach suggested by Machado and Mata (2005) – MM henceforth - and decomposed the gender wage gap at different quantiles of interest.³

In this chapter, we use a newly developed counterfactual decomposition technique combined with quantile regression estimation to explore the gender wage differentials in Latin American and Asian countries. This is because, while there is extensive evidence on European countries, the USA and Australia (see literature review and Table 1.1), country studies for Asian and Latin American countries are generally lacking. The approach used is the extension and refinement of the popular MM (2005) procedure,

¹ This chapter has been presented in 2011 Singapore Economic Review Conference.

² Correspondingly, a wider gap at the bottom of the counterfactual wage distribution is referred to as a “sticky floor”.

³ The Oaxaca-Blinder method decomposes the average gap into two components: one is the explained part, due to differences in human capital and demographical characteristics between men and women and the other is the unexplained part (sometimes referred to as “discrimination”), which is due to differences in returns to these characteristics.

proposed by Melly (2006), who derived analytical estimates of the asymptotic variance covariance matrix of the estimators and showed that estimators obtained by MM (2005) are numerically identical to his as the number of simulations goes to infinity. The purpose of the chapter is to expand the body of evidence in the glass ceilings/sticky floors literature, provide an international update using empirical evidence from more than 50 countries in 5 continents and suggest potential explanations to the stylized facts documented across countries.

First, the raw gender wage gap is reported at both the mean and different quantiles of interest. Second, Melly's (2006) method is employed to decompose the estimated gender wage differentials. In this study, the counterfactual wage distribution is constructed using women's characteristics and men's payoff structure; therefore, the difference between the wage distribution of male workers and the counterfactual wage distribution can be explained by gender specific attributes whereas the difference between the counterfactual distribution and the distribution of female workers measures the unexplained wage gap. In other words, it is a measure of the degree of "discrimination" against women in the labor market. Two alternative specifications are used: in the first, a vector of basic variables is controlled for; subsequently occupation dummies are added into the covariates to assess the effect of occupation on the estimated counterfactual wage gap.⁴ Conclusions concerning glass ceiling or sticky floor effects are hence drawn on the basis of observed profiles of the counterfactual gender wage gap. When possible, the analysis is redone by sector of employment (public vs. private) across countries. As has been widely recognized, wage setting institutions in the private sector

⁴ Albrecht et al. (2003) argued that occupation should not be viewed as a factor accounting for the male-female wage gap, but interestingly, they found a glass ceiling in Sweden even after occupation is considered. In this paper, we present two groups of regressions-with and without controlling for occupation - to assess its impact on the findings of glass ceilings or sticky floors.

are quite different from that in the public sector (see for example, Patrinos et al., 2009). The private sector is more market oriented whereas the public sector is more likely to be constrained by anti-discrimination laws and regulations. Sample selection is not considered in this study due to two reasons: first, research on how to adjust for sample selection within quantile regression is still on-going (Buchinsky, 2001; Albrecht et al., 2009; Huber and Melly, 2011); second, there is a lack of suitable instrumental variables in most of our data sets.

Four alternative patterns are observed for different countries examined. Using the total sample of both private and public sector workers, in the case of Bolivia, Guatemala and the Philippines both glass ceilings and sticky floors are observed; only glass ceilings are found for Argentina, Brazil and Chile; only sticky floors for Mexico, Indonesia and Singapore; neither a glass ceiling nor sticky floor for Cambodia, South Korea and Vietnam. When segregated by sector, for all the nine countries with sector information, glass ceilings are observed in the public sector. With regard to the private sector, a glass ceiling effect is also observed for Argentina, Bolivia, Brazil and Chile. Strong evidence of a sticky floor is only observed in the private sectors of Mexico, Guatemala and the Philippines.

The contribution of this study is that it provides evidence of “glass ceilings” vs. “sticky floors” in those countries where evidence does not previously exist. Consequently, we obtain a comprehensive global picture of the pattern of gender wage gap by combining the new with existing evidence, which could help in pointing to directions of future research aiming at exploring the fundamental reasons for gender wage disparities.

The chapter is organized as follows: Section 1.2 reviews existing empirical evidence on the gender wage gap across the wage distribution; the underlying reasons are

summarized in section 1.3. Subsequently, section 1.4 introduces the conceptual framework and specifies the counterfactual decomposition technique employed in this study. Data sources are described in section 1.5 and results are presented and discussed in section 1.6. The final section concludes.

1.2 Literature review

It is widely documented that, on average, men earn more than women (see for example, Blau and Kahn, 1996; 1997; 2000; 2003; 2006). According to human capital theory developed in late 1950s, the gender wage gap can be attributed to education, experience, on-the-job training, as well as other skills and other productivity related characteristics. Nevertheless, by using the traditional Oaxaca-Blinder decomposition, Altonji and Blank (1999) found that such characteristics could only explain less than one third of the gender wage gap in the United States for the period 1979-1995 (though the gap decreased significantly during this period). The unexplained residual is usually taken as an indication of potential discrimination against women in the labor market.

Recently, quantile regression, developed by Koenker and Bassett (1978), has been increasingly used in the study of gender wage differentials. Some of the first empirical papers which applied quantile regression to the study of wages include Buchinsky (1994) and Chamberlain (1994). Subsequent analyses ventured into the study of changes in the wage distribution (Machado and Mata, 2005; Melly, 2005, 2006), the wage gap between whites and minorities (Chay and Honore, 1998), between men and women (Fortin and Lemieux, 1998) and the effects of educational attainment on wage inequality (Martins and Pereira, 2004), among other applications. This tool of research has also been applied

to many other fields within Economics (Fitzenberger et al., 2002), and other disciplines such as sociology and health (see for example, Wei et al., 2006).

Compared to OLS regression which can be only used to characterize the mean difference in male-female wages, quantile regression allows the depiction of the gender wage gap over the entire earnings distribution. Furthermore, quantile regression relaxes assumptions on error distribution, and it is robust to outliers.⁵

One way to proceed is to estimate a pooled quantile regression on the Mincerian earnings equation to derive coefficient estimates of the gender dummy at various points of the wage distribution, a measure of the gender wage gap under the assumption that returns to labor market characteristics are the same between men and women. More interesting, however, is to compare male-female differences in the returns to all characteristics controlled for in the Mincerian equation (which, in most cases are found to be statistically significant), by estimating separate quantile regressions for each gender. An alternative evaluation of the gender wage gap across the wage distribution is using quantile regression combined with the Oaxaca-Blinder decomposition.

For example, Garcia et al. (2001) found that the unexplained gap is higher at the top of the wage scale in Spain using 1991 data. Montenegro (2001) documented the same result in Chile for the period 1990-1998. Gardeazabal and Ugidos (2005), using a slightly different technique, documented increasing gender wage differentials and unexplained components in Spain using 1995 data. Using a similar approach, Sakellariou (2004a, 2004b) observed that the widest gap attributable to different returns to characteristics is at the lower part of the wage distribution in Singapore, using 1998 data, and the Philippines, using 1999 data. Following the work by Albrecht et al. (2003) who established a glass

⁵ Hao and Naiman (2007) provide a comprehensive discussion of quantile regression.

ceiling effect in Sweden utilizing the MM (2005) procedure, a growing literature on gender wage differentials emerged, making the MM (2005) decomposition the most popular among researchers in the field. Employing a modified method proposed by Melly (2006), Nicodemo (2009) studied the gender pay gap within a family, and Fang and Sakellariou (2011) observed a sticky floor effect in Thailand 2004.

Recently, Arulampalam et al. (2007) utilized harmonized European data (the European Community Household Panel) to study the pattern of gender wage differentials in eleven European countries, and documented consistently a glass ceiling effect for all countries except one. Our study, however, is for a variety of Latin American and East Asian countries which are less uniform in their institutions and cultures; this makes it less likely to observe uniform conclusions relating to the pattern of gender wage differentials. This diversity, though, will allow us to compare across groups of countries, and thus to contribute to the analysis of glass ceiling/sticky floor effects and the stylised facts observed.

1.3 The origin of gender wage differentials

There are many potential explanations on why seemingly identical men and women earn different wages and why the gap varies across the wage distribution. We summarize and divide the explanations into two groups: those from the demand side vs. supply side of the labor market.

1.3.1 Demand side

On the demand side, one could resort to statistical discrimination (Aigner and Cain, 1977). Due to incomplete information, employers cannot observe workers' real productivity and have to pay them their marginal productivity according to the

expectation conditional on a noisy signal and some easily observable characteristic such as gender. The point is that even if men and women had the same distribution of productive characteristics, skilled men would earn more than the apparently identically skilled women, while unskilled women would earn more than the apparently identically unskilled men as long as the signal is more informative for male workers.

Taste-based discrimination is an alternative explanation. Because of employers' distaste for the minority workers, they have to accept a lower wage for equally productive characteristics (Becker, 1971).⁶ The stronger the distaste of employers for female workers, the wider the wage gap would be. However, discriminating employers would be driven out of the market in the long run due to the positive cost of distaste; the prejudice therefore cannot persist in equilibrium unless there is a cost in job search (Black, 1995), or employers are nepotistic rather than discriminating (Goldberg, 1982). Recently, Charles and Guryan (2008) showed a third mechanism for how employer's prejudice could survive in the long run and tested the predictions of Becker's employer discrimination model. Though their paper is about the effect of discrimination on the racial wage gap, one can hypothesize the existence of a similar effect for the gender wage gap, as long as employers have animosity towards female workers.

How does the taste theory relate to the glass ceiling/sticky floor effect? We know that prejudice could manifest itself in more than one way in the labor market, such as in hiring and promotion procedures (Cobb-Clark, 2001). If employers discriminate at the hiring stage, the reservation wage of female workers would be lower and the starting wage would be lower as well, suggestive of a sticky floor; on the other hand, if they

⁶ Evidence on the presence of employers' taste for discrimination includes audit studies such as Pager et al. (2009) and Bertrand and Mullainathan (2004) and experimental studies such as Goldin and Rouse (2000).

discriminate through promotion procedures, men are more likely to be in highly paid positions than women. Women are therefore confronted with a glass ceiling.⁷

But where does the prejudice come from? How is the distaste formed? Is it based on the intrinsic differences between genders or an accumulated result of social custom and conditioning? Recently, a rapidly growing literature that attempts to investigate gender differences has appeared. Niederle and Vesterlund (2007) showed in their experimental study that women are not as likely as men to enter a tournament, suggesting that women are less competitive. Such gender differences emerge early in life, and are even observed in groups of children as early as at the age of 3 years (Sutter and Rutzler, 2010). Besides, field studies show that women are more risk averse than men (Eckel and Grossman, 2003). It seems that gender differences in risk preferences and tastes for competition could plausibly justify the gender stereotypes that women are not suitable for executive occupations, which require substantial risk-taking and competition. But, Atkinson et al. (2003) found that risk-taking behavior and performance of male and female mutual fund managers don't differ significantly, while Gysler et al. (2002) observed that the degree of risk averseness of women diminishes as expertise and knowledge increase. Concerning risk-taking behavior, the seemingly competing findings show that in the general population, men are more risk taking than women, but in a specific subgroup gender differences may be insignificant which could be a result of selection or adaptive behavior of women in that small group (Croson and Gneezy, 2009).

The residual gender wage gap should decline significantly after controlling for psychological factors like attitude towards risk, tastes for competition, feedback

⁷ Though it is illegal to discriminate against women in many countries, employers could use other means to discriminate in a disguised form, such as setting requirements like longer working hours, more travelling duties etc.

preferences etc.⁸ Manning and Swaffield (2008), using survey based data, found that psychological variables could explain almost half of the counterfactual gender wage gap. However, it is hard to tell whether gender differences in psychological measures are intrinsic, or determined by the social environments and cultures. Gneezy et al. (2008) found that women in a matrilineal society are as competitive as men are in a patriarchal society. Booth and Nolen (2009) found that girls in single-sex schools are more competitive than girls in co-ed schools. It does seem, therefore, that gender differences are nurtured rather than because of nature.

The disciplines of sociology and psychology could give us some additional insights into the origin of gender discrimination. The existence of “homosocial preferences” (Lipma-Blumen, 1976) would suggest that workers feel more comfortable surrounded by their own gender.⁹ Thus, male employers are more likely to promote male workers and female employers are more likely to promote female workers. It is also consistent with the gender identity hypothesis (Akerlof and Kranton, 2000), which argues that both genders behave as following certain prescriptions and would feel a loss of identity by deviating from the prescribed behavior modes. In addition, the sex-ratio in the power structure is important in determining the gender differences in attitudes, behaviors and wages. The findings that women in female-led firms earn more than women in male-led firms (Cardoso and Winter-Ebmer, 2007) constitute such evidence. One can, therefore,

⁸ As pointed out by Booth (2009), it’s challenging for labor economists to identify the contributions of discrimination, unobserved characteristics and intrinsic gender differences to the residual wage gap. Therefore, one can expect that if all intrinsic gender differences on which discrimination is based could be accounted for, the residual gender wage gap should shrink significantly. Becker (1971) has argued that it is not discrimination if it’s not from animosity itself; furthermore, intrinsic gender differences and unobserved characteristics actually overlap. Studies which control for psychological factors in the wage gap include Goldsmith et al. (1997), Bowles et al. (2001) and Mueller and Plug (2006).

⁹ Similar ideas have been expressed in Gneezy et al. (2003); Riach and Rich (2002) and Booth and Leigh (2010).

conclude that gender stereotypes rooted in people's perceptions are mainly nurtured in social customs and conditioning but can change slowly over time.

1.3.2 Supply side

One can also explain the presence of gender wage differentials for apparently identical men and women from the supply side. Self-selection theory suggests that, due to the high opportunity cost associated with housework, low skilled women may choose to stay at home rather than work. Furthermore, women are less likely to choose highly competitive occupations (which tend to command higher pay), and may invest less in human capital. They are also expected to be less willing to ask for promotions and bargain for pay rises at the work place (Kee, 2006; de la Rica et al., 2008; Goldin and Rouse, 2000). There could be several possible reasons for this. First, if women are less willing to pursue and accept outside offers compared to men, this would place them at a disadvantage in the bargaining process; second, in the presence of discrimination in the labour market, women would tend to be more appreciative of the position they hold and be less willing to consider the possibility of bargaining for a promotion; finally, bargaining on its own deviates from the prescribed "gender identity" and they may not feel comfortable to appear too "bossy" (Bertrand and Hallock, 2001). The result of such behavioral tendencies in the labor market is the under-representation of women in high-level occupations and a higher gender gap at the top of the earnings distribution.

In addition to gender differences in preferences, gender specific policies can influence the labor supply as well.¹⁰ Albrecht et al. (2003) argued that parental leave policies and day care provisions can encourage more women to enter the labor force. Arulampalam et al. (2007) argued that such policies can on the one hand increase the

¹⁰ See Croson and Gneezy (2009) for a good survey paper on gender differences in preferences.

incentive of women to invest more in human capital, while on the other hand they allow more time out of work; they found that the negative effect dominates at the top of the wage distribution in all the eleven European countries studied. In addition, minimum wage legislation and collective bargaining institutions can compress the wage distribution at the bottom and decrease the sticky floor effect (Dolado et al., 1996; Arulampalam et al., 2007). However, if compliance is unequal between genders, the wage gap at the bottom could also be wider (Booth, 2009).

Although both the demand and the supply side provide some insights into the phenomenon that apparently identical men and women are rewarded differently, theories aiming to explain the glass ceiling/sticky floor effect found in recent empirics are not many. A few exceptions include Bowlus and Eckstein (2002), de la Rica et al. (2008) and Jellal and Nordman (2009) to our knowledge. Bowlus and Eckstein (2002) employed search theory to distinguish the effects of unobserved characteristics and discrimination on the wage gap. Extending Burdett and Mortensen's (1998) model, they demonstrated that the male earning distribution first order dominates the female distribution and that under certain conditions the wage gap decreases along the distribution. De la Rica et al. (2008) modelled the gender difference in outside opportunities as a disutility shock, suggesting a wider gender wage gap at the bottom of the distribution. Jellal and Nordman (2009) considered uncertainty in the productivity of women in a competitive wage determination model and derived a negative risk premium associated with women's wage. Since the negative premium increases with human capital, the gender wage gap is expected to be wider at the top of the wage distribution. Despite these attempts, it seems to us that much remains to be done in reconciling theoretical models with empirical evidence.

1.4 Conceptual framework

In decomposing the gender wage gap over the entire distribution, we utilize (conditional) quantile regression. Following Buchinsky (1998), the quantile regression model is specified as:

$$y_i = X_i' \beta_\theta + u_{\theta i}, \text{Quant}_\theta(y_i | X_i) = X_i' \beta_\theta$$

where y_i is the dependent variable (such as logarithm of the hourly wage), X_i is a $K \times 1$ vector of regressors and $u_{\theta i}$ is an error term. The θ th conditional quantile of the dependent variable for individual i , conditional on X_i is represented by $\text{Quant}_\theta(y_i | X_i)$.

The estimator for β_θ is obtained by solving:

$$\min_{\beta} \left\{ \sum_{i: y_i \geq X_i' \beta} \theta |y_i - X_i' \beta| + \sum_{i: y_i < X_i' \beta} (1 - \theta) |y_i - X_i' \beta| \right\}$$

As θ increases from 0 to 1, the entire conditional distribution of y is traced.

Under certain regularity conditions, the estimator $\hat{\beta}_\theta$ is consistent and asymptotically normally distributed.

To combine quantile regression with Oaxaca-Blinder decomposition, we employ the method proposed by Melly (2006). The decomposition is as follows:

$$\begin{aligned} & \hat{\text{Quant}}_\theta(\ln w_m) - \hat{\text{Quant}}_\theta(\ln w_f) \\ &= [\hat{\text{Quant}}_\theta(\ln w_m) - \hat{\text{Quant}}_\theta(\ln w_c)] + [\hat{\text{Quant}}_\theta(\ln w_c) - \hat{\text{Quant}}_\theta(\ln w_f)] \end{aligned}$$

where: $\hat{\text{Quant}}_\theta(\ln w_m) = \inf \{ \ln w : n_m^{-1} \sum_{i \in m} \hat{F}_m(\ln w | X_i) \geq \theta \}$

$$\hat{\text{Quant}}_\theta(\ln w_f) = \inf \{ \ln w : n_f^{-1} \sum_{i \in f} \hat{F}_f(\ln w | X_i) \geq \theta \}$$

$$\hat{\text{Quant}}_\theta(\ln w_c) = \inf \{ \ln w : n_f^{-1} \sum_{i \in f} \hat{F}_m(\ln w | X_i) \geq \theta \}$$

$\hat{F}_t(\ln w | X_i)$ ($t \in \{m, f\}$) is the estimator of conditional distribution of $\ln w$ for group t , conditional on X_i . It is calculated as:

$$\hat{F}_t(\ln w | X_i) = \int_0^1 I(X_i' \beta_{t\theta} \leq \ln w) d\theta,$$

where $I(\cdot)$ is the index function. It has been shown that the estimator is consistent and asymptotically normally distributed.

The estimated quantile function of the counterfactual log-wage, $\hat{Quant}_\theta(\ln w_c)$, is constructed using female characteristics and male returns to those characteristics. Therefore, the first part of the decomposition denotes the effect of characteristics and the second part denotes the effect of coefficients. In other words, the proportion of the gender wage gap explained by differences in characteristics is measured by the first part; the second part describes the estimated counterfactual gender wage gap at quantile θ . We are more interested in the second part, since the evidence on glass ceilings/sticky floors is drawn from comparisons of the coefficient effects at different quantiles.

1.5 Data description

The data used are from various country surveys and years (ranging from 1998 to 2007), which are given in Table 1.A1 in the appendix. A consistent subsample is used for each country: it consists of wage and salary employees who were: (1) aged between 25 and 65 years; and (2) with valid information on the variables used in the wage equation. It excludes the self-employed and employees in the armed forces.

The dependent variable is the logarithm of the hourly wage derived from hours worked per week or per month, and monthly or yearly earnings available in the data. The education and occupation variables are categorized according to internationally comparable standards, and combined where necessary. The earnings function

specifications include education level, potential experience and its square, other personal characteristics such as marital status and urbanity.¹¹ When available, characteristics such as union membership and tenure were also used.

Two issues often discussed in this literature are self selection and endogeneity. In mean regressions, Heckman's two-step approach is widely used under parametric assumptions; furthermore, semi-parametric and nonparametric approaches have also been developed. However, in quantile regression, little consensus exists on the appropriate correction procedures. Instead, researchers who have evidenced no obvious selection biasness in the mean regression, tend to not consider the issue in quantile regression. In addition, with respect to endogeneity, though instrumental variables can be used to deal with the problem, the choice of appropriate instruments is a thorny issue. Therefore, due to limitations in the data as well as available econometric techniques tackling selection issues in quantile regression, we will not attempt to assess the influence of selectivity and endogeneity on the estimates of gender wage gaps.

Table 1.A2 presents the mean and standard deviation of variables by gender and country. It is found that in our selected subsample: (1) on average, men are more experienced than women; (2) there is a higher proportion of men working in the private sector compared to women (except Cambodia); (3) there is a considerable degree of occupational segregation between genders; for example, female workers are in general more likely to be found in clerical and sales occupations and less likely to be employed as operators, unskilled workers or in occupations with physical strength requirements; (4) in

¹¹ Potential experience is calculated by age-years of education-6. Since female labor market activities would be interrupted by childbirth and child raising, their actual experience is generally less than the potential value. The unexplained gender wage gaps that are estimated using potential experience are therefore likely to be overestimated, especially for those at high quantiles. To mitigate this problem, other working history information (such as tenure), when available, is also included in the wage equation specification.

most countries, women have higher education qualifications compared to men; exceptions are Cambodia, South Korea and Singapore; (5) more men in wage employment are married compared to women. The first four findings are consistent with available evidence from other studies in the literature.

1.6 Results and discussion

1.6.1 The raw gender gap

Table 1.A3 reports the raw gender gap estimated at the mean and five specific percentiles: 10th, 25th, median, 75th and 90th. Both pooled data and segregated data by sector are analyzed, and results are respectively shown in Tables 1.A3 (a), (b) and (c).

Table 1.A3 (a) shows that the pooled raw gender gap is decreasing along the wage distribution in four Latin American countries (Bolivia, Chile, Guatemala and Mexico) and three Asian countries (Indonesia, the Philippines and Singapore). In three cases (Bolivia, Guatemala and Mexico), the gap strongly favored men at lower quantiles and slightly favored women in the higher quantiles. In Indonesia the raw gap is significantly higher at the bottom (men earn 46% more than women). In Singapore, the gap decreases slowly from 35.7% at the 10th percentile to 27.4% at the 90th percentile. Similarly, South Korea also exhibits a high and almost constant gender wage gap (the biggest gap, 49.2%, appears at the median). On the contrary, in Chile and the Philippines female workers earn more than male workers at every quantile, and the superiority is surprisingly more obvious at the top in Chile and at the middle in the Philippines. Brazil has a very small gap, and the highest differential is in the median, at less than 10 log-points. The gender gaps in Argentina and Vietnam are also small and statistically insignificant. From the simple comparison, we can see that patterns of gender wage gap along the distribution

vary across countries. Comparing these results with the mean gap in the first column reveals the advantage of quantile regression against OLS. That is, it uncovers information which would have been hidden under an OLS methodology and reveals a richer picture of the gender wage gap.

Tables 1.A3 (b) and 1.A3 (c) contain the raw gender wage differentials by sector. It has been well recognized that the public sector can be subject to anti-discrimination laws and equal pay regulations and therefore the profile of the gender wage gap can differ significantly from that in the private sector.¹² The results in Table 1.A3 (b) and Table 1.A3 (c) illustrate this point. In the public sector, men on average earn significantly more than women in Argentina, Brazil and Chile. In contrast, in Guatemala, Mexico, the Philippines and Vietnam women earn more than men on average. These patterns along the wage distribution, however, are rather diverse. In addition, the widest pay gaps are observed in Guatemala and Cambodia and the narrowest in Vietnam.¹³

In the private sector, men earn significantly more than women both on average and at different quantiles in all countries except Chile and the Philippines. The gender earnings gap decreases sharply from the 10th to 90th percentile in Bolivia, Guatemala and Mexico. In contrast, it increases slightly across the wage distribution in Argentina, Brazil, Cambodia and Vietnam. Comparing the pay gaps in the private sector to that in the public

¹² Miller (2009) points out another effect sectors might have on the gender wage gap is that the public sector can indulge discrimination taste in wage setting as it does not pursue profit maximization as its goal in general.

¹³ The widest gender pay gap in the public sector is 13.4% at the 25th percentile in Argentina, -15.5% at the median in Bolivia, 28.8% at the median in Brazil, 19.6% at the 90th percentile in Chile, -48.3% at the 10th percentile in Guatemala, -18.2% at the 25th percentile in Mexico, 47.4% at the 90th percentile in Cambodia, -28.2% at the 25th percentile in the Philippines and -7.6% at the median in Vietnam.

sector, larger gaps are observed in the private sector in most countries except Argentina, Brazil and Chile.¹⁴

The finding that wider raw gender wage differentials in the private sector are generally found either at the bottom or at the top (an exception is Cambodia), suggests the existence of glass ceiling or sticky floor effects. Nonetheless, in the public sector, the locations are dispersed and thus the existence of a glass ceiling/sticky floor effect is obscure and needs to be discussed case by case.

1.6.2 Counterfactual decompositions

As described above, quantile regression combined with counterfactual decompositions is employed to decompose the gender wage differentials into their constituent components at quantiles of interest: one due to the differences in characteristics and the other due to the differences in the returns to these characteristics. In the analysis, the counterfactual distribution of wages uses female characteristics and male pay structures. The estimate of the unexplained part (coefficients effect) of the wage gap could be taken as potential discrimination faced by women in the labor market. Table 1.A4 lists the estimates for the wage gap, the effect of characteristics (explained gap) and the effect of coefficients (unexplained gap) without controlling for occupation at 5 quantiles. Estimates with these occupational covariates are shown in Table 1.A5. OLS estimates are reported for the purpose of comparison.

One point worth noting is that the characteristics effect shown in Table 1.A4 (a) is negative for all countries except South Korea and Singapore, which suggests that women in the countries studied in this chapter (with few exceptions) have an advantage in

¹⁴ The widest gender pay gap in the private sector is 9.5% at the 90th percentile in Argentina, 53.9% at the 10th percentile in Bolivia, 15.4% at the median in Brazil, -31.6% at the 90th percentile in Chile, 51.1% at the 10th percentile in Guatemala, 38.2% at the 10th percentile in Mexico, 52.7% at the median in Cambodia, 20.3% at the 10th percentile in the Philippines and 15.4% at the 90th percentile in Vietnam.

productive characteristics not only on average but at every point of the wage distribution. This result may be partly caused by women's self selection into labor market or inaccuracy of the experience proxy. In contrast, in South Korea and Singapore, men have superior characteristics compared to women. Specifically, in South Korea, the gender differences in labor market characteristics explain 16% of the gap on average, ranging from 6.8% at the bottom to 30.2% at the top, while in Singapore, the proportion explained by differences in characteristics is higher, ranging from 9.8% at the bottom to 55.1% at the top.

On the other hand, the coefficients effect is positive at almost every point across all countries, which reinforces the perception of widespread gender discrimination.¹⁵ To be more specific, even assuming men have an identical distribution of characteristics as women, there is a gender wage gap throughout the distribution due to differing returns to those characteristics. Furthermore, when the unexplained (coefficients) component is shown as a share of the estimated raw gender gap (relative "discrimination"), we still find that it generally exceeds 100 percent. This finding suggests that the gender wage differentials in Latin American and Asian countries are mainly due to the differences in the returns to labor market characteristics.

Table 1.A4 (b) shows the decomposition results in the public and the private sector. They are qualitatively similar to those in Table 1.A4 (a): for example, most characteristic effects are negative and most coefficient effects are positive. The distinction is that in Guatemala, Mexico and Cambodia, women in the public sector earn more than men at several points of the wage distribution. Comparing the public sector with the private sector we find that the counterfactual gender wage gap (i.e., coefficients

¹⁵ There are only three exceptions: at the 10th quantile in Argentina (-0.032), 10th quantile in Cambodia (-0.042) and 50th quantile in the Philippines (-0.008).

effect) is higher in the private sector than in the public sector, except in Argentina, Brazil and Chile. As has been discussed earlier, the public sector is less competitive and more likely to have unions which bargain for equal pay compared to the private sector; therefore the gender wage differentials are expected to be smaller in the public sector. It is consistent with evidence in other countries. For example, Miller (2009) also found that in the US, the wage gap in the government sector is smaller than that in the private sector at each decile of the wage distribution. However, one should recognize differences in institutions, social norms and cultures across countries, which might explain the exceptions.

The decomposition of the gender wage differentials after controlling for occupation is reported in Table 1.A5. The results do not change a lot compared with those in Table 1.A4 where occupation is not controlled for. From the pooled data, the higher unexplained gender wage gap is found at the 90th percentile in four countries (Argentina, Brazil, Chile and Vietnam) and in six countries (Bolivia, Guatemala, Mexico, Indonesia, the Philippines and Singapore) is found at the 10th percentile. In the public sector, there are eight countries (Argentina, Bolivia, Brazil, Chile, Guatemala, Cambodia, the Philippines and Vietnam) with the highest counterfactual gender wage gap at the 90th percentile and only one country (Mexico) at the 10th percentile; while in the private sector, there are three countries (Argentina, Brazil and Chile) with the widest gap at the 90th percentile and three countries (Guatemala, Mexico and the Philippines) at the 10th percentile.¹⁶ A highest counterfactual gender wage gap at the 90th percentile indicates the existence of a glass ceiling effect whereas a highest gap at the 10th percentile suggests a sticky floor effect. Hence, for Argentina, Brazil and Chile, there are glass ceiling effects

¹⁶ A minor difference between Table A4 and Table A5 is that in Table 4 there is one more country—Bolivia - that has a highest counterfactual gender wage gap at the 10th percentile in the private sector.

in both the public sector and the private sector; for Mexico there is a sticky floor effect; for the other countries examined, the gender wage differentials vary significantly by sector.

1.6.3 Counterfactual gender wage gap

In this subsection, we will focus on the counterfactual gender wage gap and the evidence for a glass ceiling/sticky floor effect. To illustrate the findings, we plot the counterfactual gender wage differentials estimated from the basic model (excluding occupation) and extended model (including occupation) in Figure 1.1. As stated earlier, positive counterfactual gender wage gaps could be taken as an indication of gender wage discrimination.

[Figure 1.1 about here]

From Figure 1.1, the estimated counterfactual gender wage gap increases as one goes to higher quantiles in Argentina, Brazil and Chile (using a pooled sample as well as using data segregated by sector), suggesting the existence of glass ceilings. In Bolivia, Guatemala and the Philippines, the pattern of the counterfactual gender gap in the public sector is quite different from that in the private sector. First, the average gender gap in the private sector is wider; essentially the plot for the private sector lies above that for the public sector. Second, the counterfactual gender gap increases along the wage distribution in the public sector (mostly at the top of the distribution) but decreases in the private sector (mostly at the bottom of the wage distribution). Moreover, the estimated gaps at the bottom of the distribution of wages in the private sector exceed 0.4 log-points. All these findings suggest that very likely there is a glass ceiling effect in the public sector and a sticky floor effect in the private sectors of Bolivia, Guatemala and the Philippines; the most adversely affected, therefore, are low paid workers in the private

sector. Another finding which applies to Mexico, Indonesia and Singapore, is that the counterfactual gender gap progressively increases as one goes towards the bottom of the wage distribution, indicating a possible sticky floor effect in these countries. Finally, in Cambodia, the gap reaches its largest value in the middle of the distribution; in South Korea, it declines after the 15th percentile; and in Vietnam, the pattern is irregular, however in the private sector it exhibits an increasing pattern.

One could go further and attempt to classify the findings by quantifying what constitutes a glass ceiling and a sticky floor. According to Arulampalam et al. (2007), there is a glass ceiling effect if the gender wage gap at the 90th percentile is 2 percentage points higher than the gender gap at any other point in the wage distribution. Correspondingly, there is a sticky floor effect if the 10th percentile gender wage gap is 2 percentage points higher than the estimated gap at any other point. A looser definition of the glass ceiling effect is associated with a two percentage point gap from the 90th percentile to the 75th percentile or the 50th percentile; similarly a two percentage point gap from the 10th percentile to the 25th percentile or the 50th percentile could also be considered as a sticky floor effect.

Table 1.A6 summarizes the results from Tables 1.A4 and 1.A5 in all three definitions. It's found that glass ceilings exist in the majority of countries, especially in the public sector; sticky floor effects are also common. However, in the cases of Cambodia, South Korea and Vietnam, neither glass ceiling nor sticky floor effects are found, which suggests that the widest counterfactual gender wage gap may appear in the middle of the wage distribution. Conclusions drawn from the extended model are almost the same as that from the basic model, which may suggest that occupation has a consistent effect on the estimated counterfactual gap at all parts of the wage distribution.

Finally, Table 1.1 brings together all the available evidence in the literature (at least to our knowledge), along with the country evidence provided in this study, in an attempt to provide a more complete picture of the glass ceiling/sticky floor puzzle in the form of an international update.

[Table 1.1 about here]

The evidence is classified by continent. In all European countries except possibly Greece, Spain, Ukraine and Switzerland (but not conclusively), glass ceilings are present; the same is the case for Australia and the United States (at least for the private sector). On the other hand, in Asian countries there is no evidence of glass ceilings (except for Kazakhstan and Uzbekistan) and in most cases the presence of sticky floors can be established. In Latin American countries the evidence is mixed, with higher income countries (such as Chile and Argentina) exhibiting glass ceilings and lower income countries (such as Bolivia, Guatemala and Mexico) exhibiting either a sticky floor effect or a mixed pattern. Finally the estimates from the black populations of South Africa and Lesotho point to a clear sticky floor effect, while glass ceilings are found in Egypt and Morocco.

The diversity of patterns in gender wage differentials suggests that the underlying reasons relate to several differences between groups of countries. Such differences include labor market institutions (in the form of regulation, presence of minimum wage legislation, availability of childcare, etc.), differences in female labor force participation rates and job segregation by gender and education attainment. In previous empirical studies, glass ceilings dominated, and almost all countries examined were high income developed countries; hence, the underlying explanations were easier to pinpoint. Thus, in European countries a combination of indicators, such as formal childcare coverage,

maternity leave, flexi-time, etc., have been found to be positively correlated with glass ceilings and negatively correlated with sticky floors (Arulampalam et al. 2007). Similarly for Australia, glass ceilings were found to be largely attributed to the more centralized method for wage fixation, which protects low-wage earnings but not high-wage earnings (Miller, 2005).¹⁷

Plausible explanations for the floor pattern can also be put forward, although they are less established in the literature, as an increasing number of mainly developing countries with a floor pattern (at least in the private sector) has emerged only recently. In the case of countries with low participation of less educated women, sticky floors could be due to statistical discrimination. Less educated women in such countries are associated with frequent career interruptions (due to societal, cultural or religious reasons and practices), employers may use statistical discrimination in wage-setting. As their job tenure expands, however, the underlying reasons behind statistical discrimination are not present, allowing women's wages to converge to male wages, conditional on equal productivity (De la Rica et al., 2008). Another explanation which likely applies to many low income developing countries is that wider gender wage gaps near the bottom of the distribution are due to job segregation along gender lines. We estimated earnings functions within each education level for several countries. We found that the widest gender gap was at low levels of education (less than primary or completed primary at most) in the private sectors of Bolivia, Guatemala, Mexico, Cambodia, Indonesia, the Philippines and Singapore (all cases of an decreasing pattern, at least in the private sector); the opposite was the case for Argentina and Chile, while no discernible

¹⁷ On the other hand in a case such as that of Singapore, a high-income economy, the finding of a clear sticky floor probably relates to the absence of comparable worth or related legislation in the private sector, as flexible labor practices and an attractive investment environment are emphasized.

relationship between gender gap and education level was found for Brazil and Vietnam and Korea. The most likely explanation for this finding is job segregation along gender lines, as there is a more strict division of jobs performed by less skilled/less educated workers.¹⁸ Therefore, policies which aim to enhance workers' educational levels and skills in those countries may have an effect on reducing the gap.

1.7 Conclusion

This chapter investigates the pattern of gender wage differentials in several Latin American and Asian countries and examines the findings in relation to other country studies available in the literature. We first examine the average raw gender wage gap and the gap at different points of the wage distribution. Then quantile regression combined with counterfactual decomposition (using methodology suggested by Melly, 2006) is applied to decompose the gender wage differentials into characteristics and coefficients effects. The findings suggest that in all countries and almost all points of the wage distribution, women have superior characteristics compared to men, while men are better rewarded for their characteristics compared to women. The proportion of the gender wage gap explained by differences in returns to characteristics exceeds 100 percent in most points, indicating that gender wage discrimination might be the main reason for the wage gaps observed in the labor market. A glass ceiling effect is documented in Argentina, Brazil and Chile while the sticky floor effect is observed in Bolivia, Guatemala, Mexico, Indonesia and Singapore from the pooled data and the strictest definitions for glass ceilings/sticky floors.

¹⁸ Siphambe (2000) also found that gender wage gaps in Botswana were highest among those with no education or lower primary education. He concludes that this is probably due to job segregation on a gender basis.

Two sets of results are derived: without and with inclusion of occupation dummies in the wage equations. We find that in general, the inclusion of occupation does not qualitatively change the pattern of the estimated gender wage gap across quantiles; however, the magnitude of estimates varies. Furthermore, the conclusions about the existence of glass ceiling/sticky floor effects are robust to controlling for occupation in wage equations. Finally, results are derived by sector when possible. Except Vietnam where the counterfactual gender gap is insignificant and irregular and Mexico where a strong sticky floor exists, glass ceilings are observed in all the other countries in the public sector, even in the strictest definition. For the private sector, the conclusion varies across countries.

Finally, we provide a global picture of the patterns of gender wage gap. Glass ceilings are present in 22 European countries, while no country in Asia but Kazakhstan and Uzbekistan shows evidence of glass ceilings. In 6 Latin American countries, the evidence is mixed, while in Africa the estimates from the black populations of South Africa and Lesotho point to a clear sticky floor effect, while glass ceilings are found in Egypt and Morocco. Possible underlying reasons for glass ceilings have been already established in the literature; job segregation along gender lines at low levels of education is one of the likely causes of sticky floors.

This research has certain policy implications. It contributes to pinpointing the target group for the legislators who are formulating the policies to close or narrow the gender wage gap. For example, where sticky floors are evidenced, the law of minimum wage may be considered and when already present, its implementation could be reviewed; on the other hand, affirmative action may be taken to address the glass ceilings. Besides direct government interventions on the labor market, universities, employers as well as

social institutions can also play a role in bringing about the narrowing of the gender wage gap. Training courses could be designed in universities to teach women the skills to bargain for better pay and negotiate with potential employers. Occupational training institutes may help prepare less skilled women for good paid jobs. These are only a few examples of many areas where policies could be utilized to improve outcomes. However, policy suggestions can become more targeted using findings from detailed decompositions at quantiles, which is discussed in the next Chapter.

Table 1.1: Glass ceilings vs. sticky floors: an international comparison

Country	Study	Data Year	Findings
<i>Latin America</i>			
Argentina	This study	2003	Increasing; Glass ceiling
Bolivia	This study	2002	Sticky floor in pooled sample
Brazil	This study	2002	Increasing; Glass ceiling
Chile	Montenegro (2001)	1990-1998	Increasing; Glass ceiling
Guatemala	This study	2003	Increasing; Glass ceiling
	This study	2000	Sticky floor in private sector; Glass ceiling in public sector.
Mexico	This study	2002	Sticky floor in pooled sample and private sector
<i>Asia</i>			
Bangladesh	Ahmed and Maitra (2011)	1999-2005	No glass ceiling
Cambodia	This study	2007	Glass ceiling in public sector
China	Millimet and Wang (2006)	1995	Sticky floor in urban China
	Chi and Li (2008)	1987-2004	Sticky floor in urban China
Indonesia	This study	2007	Decreasing; Sticky floor
Kazakhstan	Newell and Reilly (2001)	1996	Glass ceiling
South Korea	This study	2005	Mixed pattern
Pakistan	Hyder and Reilly (2005)	2001-2002	Sticky floor
Philippines	This study	2006	U-shaped pattern
	Sakellariou (2004)	1999	Sticky floor
Singapore	Sakellariou (2004)	1998	Decreasing; Sticky floor
Sri Lanka	Gunewardena et al. (2008)	1996-2004	Decreasing; Sticky floor in both
Thailand	Fang and Sakellariou (2011)	2004	Decreasing; Sticky floor
Uzbekistan	Newell and Reilly (2001)	1995	Glass ceiling
Vietnam	This study	2006	No discernable pattern
	Pham and Reilly (2007)	1993-2002	No glass ceiling
<i>Europe</i>			
Austria	Arulampalam et al.(2007)	1995-2001	Increasing; Glass ceiling
Belarus	Pastore and Verashchagina (2011)	1996-2006	Glass ceiling
Belgium	Arulampalam et al.(2007)	1995-2001	Increasing; Glass ceiling
Britain	Arulampalam et al.(2007)	1995-2001	Increasing; Glass ceiling
	Chzhen and Mumford (2009)	2005-2006	Glass ceiling
Bulgaria	Newell and Reilly (2001)	1995	Glass ceiling
Croatia	Nestić (2010)	1998, 2005	Glass ceiling
Czech Republic	Newell and Reilly (2001)	1984,1992	Glass ceiling
Denmark	Arulampalam et al.(2007)	1995-2001	Increasing; Glass ceiling
Finland	Arulampalam et al.(2007)	1995-2001	Increasing; Glass ceiling
France	Arulampalam et al.(2007)	1995-2001	Glass ceiling
Germany	Arulampalam et al.(2007)	1995-2001	Increasing; Glass ceiling
Greece	Papapetrou(2004)	1999	U-shape

Hungary	Newell and Reilly (2001)	1992	Glass ceiling
Italy	Arulampalam et al.(2007)	1995-2001	Glass ceiling
Ireland	Arulampalam et al.(2007)	1995-2001	Glass ceiling
Latvia	Newell and Reilly (2001)	1996	Glass ceiling
Netherlands	Arulampalam et al.(2007)	1995-2001	Increasing; Glass ceiling
Poland	Newell and Reilly (2001)	1992, 1996	Glass ceiling
Portugal	Mendes (2010)	2000	Glass ceiling
Russia	Newell and Reilly (2001)	1992,1996	Glass ceiling
Spain	Dohmen et al. (2008)	2002	Glass ceiling
	Gardeazabal and Ugidos (2005)	1995	Glass ceiling
	Arulampalam et al.(2007)	1994-2001	Sticky floor in pooled sample
	De la Rica et al. (2008)	1998	Glass ceiling for highly educated
Sweden	Albrecht et al.(2003)	1998	Increasing; Glass ceiling
Switzerland	Bonjour and Gerfin (2001)	1991-1995	Sticky floor
Slovakia	Newell and Reilly (2001)	1992	Glass ceiling
Ukraine	Newell and Reilly (2001)	1996	Sticky floor
Yugoslavia	Ganguli and Terrell(2005)	1986-2003	Glass ceiling
	Newell and Reilly (2001)	1995, 1996	Glass ceiling
<i>Africa</i>			
Egypt	Kandil (2009)	1988-2006	Glass ceiling
Lesotho	Sakellariou (2010)	1999	Decreasing; Sticky floor
Madagascar	Norman and Wolff (2009)	2005	No glass ceiling
Mauritius	Norman and Wolff (2009)	2005	No glass ceiling
Morocco	Norman and Wolff (2009)	2000	Glass ceiling
South Africa	Ntuli (2007)	1995-2004	Sticky floor
<i>Australia</i>			
Australia	Kee(2006)	2001	Glass ceiling in private sector
<i>North America</i>			
The US	Miller (2009)	2000	Sticky floor in public sector

Figure 1.1 Counterfactual gender wage gap over the wage distribution

Brazil

Chile

Guatemala

Mexico

Cambodia

Indonesia-Pooled

1.8 Appendix

Table 1.A1: Data sources

Country	Survey	Year
Latin America		
Argentina	<i>Encuesta Permanente a Hogares (INDEC)</i>	2003
Bolivia	<i>MECOVI</i>	2002
Brazil	<i>PNAD 2001</i>	2002
Chile	<i>Encuesta de Caracterizacion Socioeconomica</i>	2003
Guatemala	<i>EVCovi</i>	2000
Mexico	<i>Encuesta Nacional de Ingresos y Gastos de los</i>	2002
Asia		
Cambodia	<i>Socio-economic Survey of Households</i>	2007
Philippines	<i>Labor Force Survey</i>	2006
Vietnam	<i>Vietnam Household Living Standard Survey</i>	2006
Indonesia	<i>Sakernas</i>	2007
Korea	<i>International Adult Literacy and Skills Survey</i>	2005
Singapore	<i>Labor Force Survey</i>	1998

Table 1.A2: Descriptive statistics

(a) Argentina				
Variables	Male		Female	
	Mean	Std.	Mean	Std.
Experience	24.429	(11.355)	23.756	(11.032)
Married	0.597	(0.491)	0.436	(0.496)
Private	0.632	(0.482)	0.485	(0.500)
Education				
Less than primary	0.084	(0.278)	0.075	(0.264)
Primary	0.474	(0.499)	0.360	(0.480)
Secondary normal	0.254	(0.435)	0.271	(0.445)
Secondary technical	0.056	(0.229)	0.020	(0.139)
University	0.073	(0.260)	0.099	(0.299)
Higher	0.058	(0.234)	0.174	(0.379)
Occupation				
Professional	0.188	(0.390)	0.249	(0.432)
Associate	0.225	(0.418)	0.070	(0.255)
Clerical/Sales	0.277	(0.448)	0.597	(0.490)
Unskilled labor	0.310	(0.463)	0.083	(0.275)
Obs.	5904		5364	

(b) Bolivia				
Variables	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Experience	22.879	(11.548)	19.748	(11.352)
Married	0.630	(0.483)	0.538	(0.499)
Urban	0.759	(0.428)	0.835	(0.372)
Unionized	0.253	(0.435)	0.342	(0.475)
Private	0.723	(0.448)	0.476	(0.500)
Education				
No education	0.027	(0.161)	0.053	(0.224)
Primary	0.401	(0.490)	0.214	(0.410)
Secondary	0.281	(0.449)	0.221	(0.415)
Higher technical	0.131	(0.337)	0.289	(0.454)
University	0.162	(0.368)	0.223	(0.416)
Occupation				
Professional	0.184	(0.387)	0.341	(0.474)
Associate professional	0.107	(0.309)	0.152	(0.359)
Clerical/Sales	0.106	(0.308)	0.240	(0.428)
Unskilled labor	0.603	(0.489)	0.267	(0.443)
Obs.	1540		678	

(c) Brazil

Variables	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Experience	24.508	(10.748)	21.826	(10.306)
Urban	0.955	(0.207)	0.969	(0.174)
Unionized	0.256	(0.436)	0.258	(0.437)
Tenure	6.145	(7.105)	6.218	(6.613)
Private	0.831	(0.375)	0.691	(0.462)
Education				
Less than primary	0.466	(0.499)	0.301	(0.459)
Primary	0.168	(0.374)	0.140	(0.347)
Lower secondary	0.064	(0.245)	0.055	(0.227)
Higher secondary	0.226	(0.418)	0.345	(0.475)
University	0.076	(0.265)	0.160	(0.367)
Occupation				
Professional/Official	0.211	(0.408)	0.484	(0.500)
Manufacture related	0.336	(0.472)	0.124	(0.329)
Clerical/Sales	0.221	(0.415)	0.240	(0.427)
Unskilled labor	0.233	(0.423)	0.152	(0.359)
Obs.	6299		3074	

(d) Chile

Variables	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Experience	25.454	(11.643)	22.038	(10.453)
Married	0.612	(0.487)	0.465	(0.499)
Urban	0.652	(0.476)	0.793	(0.406)
Private	0.894	(0.308)	0.676	(0.468)
Education				
No education	0.021	(0.144)	0.007	(0.081)
Less than primary	0.247	(0.431)	0.107	(0.309)
Primary	0.359	(0.480)	0.210	(0.407)
Secondary	0.193	(0.394)	0.261	(0.439)
Secondary technical	0.109	(0.312)	0.223	(0.416)
University	0.071	(0.256)	0.192	(0.394)
Occupation				
Professional	0.072	(0.258)	0.198	(0.399)
Associate professional	0.053	(0.225)	0.121	(0.326)
Clerical/Sales	0.115	(0.319)	0.437	(0.496)
Unskilled labor	0.760	(0.427)	0.244	(0.429)
Obs.	14356		5240	

(e) Guatemala

Variables	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Experience	24.296	(11.847)	22.111	(11.615)
Married	0.860	(0.347)	0.570	(0.495)
Urban	0.642	(0.480)	0.804	(0.398)
Unionized	0.189	(0.391)	0.240	(0.427)
Private	0.788	(0.409)	0.690	(0.463)
Education				
Less than primary	0.172	(0.377)	0.162	(0.369)
Primary	0.415	(0.493)	0.249	(0.432)
Secondary	0.302	(0.459)	0.436	(0.496)
University	0.111	(0.314)	0.154	(0.361)
Occupation				
Professional	0.178	(0.382)	0.329	(0.470)
Associate professional	0.059	(0.236)	0.052	(0.222)
Clerical/Sales	0.202	(0.402)	0.318	(0.466)
Unskilled labor	0.561	(0.496)	0.301	(0.459)
Obs.	2031		845	

(f) Mexico

Variables	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Experience	24.159	(11.685)	22.657	(11.351)
Married	0.701	(0.458)	0.450	(0.498)
Union	0.189	(0.391)	0.231	(0.422)
Private	0.774	(0.418)	0.705	(0.456)
Education				
Less than primary	0.194	(0.396)	0.176	(0.381)
Primary	0.242	(0.428)	0.199	(0.399)
Lower secondary	0.293	(0.455)	0.310	(0.463)
Upper secondary	0.162	(0.368)	0.181	(0.385)
University	0.109	(0.312)	0.135	(0.341)
Occupation				
Professional	0.029	(0.169)	0.039	(0.195)
Associate professional	0.032	(0.175)	0.060	(0.238)
Official	0.084	(0.277)	0.131	(0.337)
Clerical/Sales	0.335	(0.475)	0.591	(0.492)
Unskilled labor	0.520	(0.500)	0.179	(0.383)
Obs.	7543		4263	

(g) Cambodia

Variables	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Experience	22.570	(12.015)	22.188	(11.686)
Married	0.823	(0.382)	0.530	(0.500)
Private	0.492	(0.500)	0.587	(0.493)
Education				
No education	0.027	(0.162)	0.076	(0.265)
Less than primary	0.143	(0.350)	0.209	(0.407)
Primary	0.177	(0.382)	0.223	(0.417)
Lower secondary	0.235	(0.424)	0.220	(0.415)
Upper secondary	0.218	(0.413)	0.149	(0.357)
University	0.200	(0.400)	0.122	(0.328)
Occupation				
Manager/Official	0.096	(0.295)	0.054	(0.227)
Professional	0.250	(0.433)	0.272	(0.445)
Associate professional	0.156	(0.363)	0.090	(0.286)
Clerical/Service	0.239	(0.427)	0.215	(0.411)
Trades	0.102	(0.303)	0.038	(0.192)
Plant machine	0.074	(0.261)	0.261	(0.440)
Unskilled labor	0.083	(0.276)	0.071	(0.257)
Obs.	665		368	

(h) Indonesia

Variables	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Experience	22.337	(10.068)	20.411	(12.275)
Married	0.857	(0.351)	0.742	(0.438)
Urban	0.608	(0.488)	0.648	(0.478)
Education				
Less than primary	0.053	(0.224)	0.061	(0.240)
Primary	0.202	(0.401)	0.175	(0.380)
Lower secondary	0.169	(0.375)	0.100	(0.301)
Upper secondary	0.248	(0.432)	0.185	(0.389)
Voc high	0.125	(0.331)	0.118	(0.322)
Tertiary	0.203	(0.402)	0.360	(0.480)
Occupation				
Professional	0.078	(0.268)	0.026	(0.158)
Manager/Official	0.189	(0.392)	0.383	(0.486)
Sales	0.130	(0.337)	0.178	(0.382)
Laborer	0.092	(0.289)	0.091	(0.288)
Production	0.136	(0.342)	0.111	(0.314)
Transportation	0.136	(0.343)	0.033	(0.178)
Unskilled labor	0.239	(0.427)	0.179	(0.383)
Obs.	6561		2738	

(i) South Korea

Variables	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Experience	22.902	(12.076)	20.25	(11.972)
Urban	0.824	(0.381)	0.799	(0.401)
Standard score	-0.028	(0.973)	0.035	(1.042)
Education				
Primary	0.056	(0.230)	0.077	(0.266)
Lower secondary	0.147	(0.355)	0.142	(0.349)
Upper secondary	0.410	(0.492)	0.493	(0.500)
Tertiary	0.369	(0.483)	0.278	(0.448)
Higher	0.018	(0.132)	0.010	(0.100)
Occupation				
Manager	0.030	(0.171)	0.020	(0.141)
Professional	0.050	(0.219)	0.059	(0.235)
Associate professional	0.097	(0.296)	0.072	(0.259)
Clerk	0.215	(0.411)	0.264	(0.441)
Service/Sales	0.220	(0.414)	0.387	(0.487)
Skilled labor	0.222	(0.416)	0.062	(0.242)
Operator	0.091	(0.287)	0.014	(0.116)
Unskilled labor	0.075	(0.263)	0.122	(0.327)
Obs.	2028		1093	

(j) Philippines

Variables	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Age	38.821	(9.660)	38.042	(9.790)
Married	0.826	(0.379)	0.728	(0.445)
Private	0.790	(0.407)	0.610	(0.488)
Education				
Less than primary	0.066	(0.248)	0.016	(0.124)
Primary	0.097	(0.296)	0.043	(0.202)
Less than high school	0.099	(0.298)	0.031	(0.174)
High school	0.279	(0.448)	0.146	(0.353)
University	0.190	(0.392)	0.147	(0.354)
Higher	0.270	(0.444)	0.618	(0.486)
Occupation				
Manager/Official	0.072	(0.258)	0.074	(0.262)
Professional	0.081	(0.273)	0.330	(0.470)
Associate professional	0.056	(0.230)	0.079	(0.270)
Clerk	0.077	(0.267)	0.227	(0.419)
Service/Sales	0.178	(0.383)	0.108	(0.310)
Trade	0.223	(0.416)	0.073	(0.261)
Operator	0.150	(0.357)	0.036	(0.187)
Unskilled labor	0.164	(0.370)	0.072	(0.259)
Obs.	8088		4699	

(k) Singapore

Variables	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Experience	24.787	(11.473)	23.536	(11.938)
Married	0.819	(0.385)	0.588	(0.492)
Long tenure	0.861	(0.346)	0.843	(0.363)
Education				
Less than primary	0.142	(0.349)	0.155	(0.362)
Primary	0.090	(0.286)	0.061	(0.239)
Secondary	0.373	(0.484)	0.447	(0.497)
Secondary vocational	0.025	(0.155)	0.008	(0.091)
Post secondary	0.046	(0.209)	0.096	(0.294)
Postsecondary vocational	0.022	(0.145)	0.017	(0.130)
Polytechnic	0.128	(0.334)	0.078	(0.268)
University	0.175	(0.380)	0.139	(0.346)
Occupation				
Senior	0.145	(0.352)	0.056	(0.229)
Professional	0.127	(0.333)	0.084	(0.278)
Associate professional	0.203	(0.402)	0.216	(0.411)
Clerical	0.061	(0.239)	0.289	(0.454)
Production	0.315	(0.465)	0.146	(0.354)
Service/Sales	0.094	(0.292)	0.133	(0.340)
Unskilled labor	0.055	(0.227)	0.075	(0.263)
Obs.	3533		1693	

(1) Vietnam

Variables	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Experience	23.450	(10.661)	23.149	(10.455)
Married	0.845	(0.362)	0.783	(0.413)
Urban	0.512	(0.500)	0.572	(0.495)
Tenure	10.013	(8.763)	10.938	(9.241)
Private	0.299	(0.458)	0.289	(0.453)
Education				
No education	0.007	(0.085)	0.009	(0.096)
Less than primary	0.032	(0.175)	0.030	(0.170)
Primary	0.097	(0.296)	0.103	(0.304)
Lower secondary	0.171	(0.377)	0.137	(0.344)
Upper secondary	0.138	(0.345)	0.114	(0.318)
Vocational	0.301	(0.459)	0.315	(0.465)
Tertiary	0.254	(0.436)	0.292	(0.455)
Occupation				
Manager/Official	0.181	(0.385)	0.074	(0.262)
Professional	0.148	(0.355)	0.178	(0.382)
Associate professional	0.161	(0.368)	0.281	(0.450)
Clerical	0.070	(0.255)	0.074	(0.262)
Service/Sales	0.064	(0.245)	0.043	(0.204)
Skilled manual	0.137	(0.344)	0.145	(0.353)
Machinery	0.079	(0.270)	0.039	(0.193)
Unskilled labors	0.160	(0.366)	0.166	(0.372)
Obs.	1228		1081	

Table 1.A3 (a): Raw gender wage differentials from pooled data

	OLS	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
Latin America						
Argentina	-0.007 (0.013)	-0.154*** (0.026)	0 (0.003)	0.010 (0.019)	-0.031 (0.032)	0.028 (0.030)
Bolivia	-0.048 (0.043)	0.413*** (0.075)	0.148** (0.060)	-0.239*** (0.067)	-0.293*** (0.067)	-0.079 (0.066)
Brazil	0.037 (0.050)	0.006 (0.011)	0.075*** (0.021)	0.096*** (0.027)	0.003 (0.037)	0 (0.063)
Chile	-0.181*** (0.012)	-0.079*** (0.015)	-0.119*** (0.012)	-0.174*** (0.022)	-0.342*** (0.026)	-0.261*** (0.027)
Guatemala	0.054 (0.039)	0.462*** (0.071)	0.047 (0.052)	-0.164*** (0.064)	-0.266*** (0.052)	0.045 (0.060)
Mexico	0.121*** (0.017)	0.336*** (0.035)	0.179*** (0.023)	0.063*** (0.024)	-0.042 (0.030)	-0.073** (0.035)
Asia						
Cambodia	0.156*** (0.059)	-0.151* (0.083)	-0.049 (0.056)	0.223*** (0.062)	0.457*** (0.076)	0.174 (0.126)
Indonesia	0.167*** (0.019)	0.466*** (0.033)	0.313*** (0.026)	0.099*** (0.032)	0.018 (0.023)	0.029 (0.023)
Korea	0.449*** (0.027)	0.405*** (0.056)	0.446*** (0.032)	0.492*** (0.036)	0.448*** (0.039)	0.393*** (0.033)
Philippines	-0.155*** (0.011)	0.041 (0.041)	-0.140*** (0.010)	-0.260*** (0.013)	-0.261*** (0.013)	-0.119*** (0.024)
Singapore	0.344*** (0.019)	0.357*** (0.021)	0.344*** (0.032)	0.288*** (0.019)	0.278*** (0.042)	0.274*** (0.073)
Vietnam	-0.014 (0.027)	0 (0.050)	-0.007 (0.041)	-0.062* (0.033)	-0.008 (0.039)	0 (0.033)

Note: Standards errors in parentheses; *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.A3 (b): Raw gender wage differentials in the public sector

	OLS	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
Latin America						
Argentina	0.075 *** (0.019)	0 (0.002)	0.134 *** (0.028)	0.069 ** (0.030)	0.085 * (0.046)	0.118 *** (0.042)
Bolivia	0.070 (0.061)	0.055 (0.127)	-0.136 (0.100)	-0.155 ** (0.065)	0 (0.076)	0.065 (0.101)
Brazil	0.301 *** (0.110)	0 (0.043)	0.161 ** (0.064)	0.288 *** (0.071)	0.128 * (0.075)	0.223 ** (0.104)
Chile	0.072 *** (0.026)	-0.028 (0.032)	0 (0.027)	0.081 (0.051)	0.134 *** (0.032)	0.196 *** (0.035)
Guatemala	-0.159 *** (0.059)	-0.483 *** (0.101)	-0.357 *** (0.061)	-0.264 *** (0.053)	0.049 (0.066)	0.083 (0.076)
Mexico	-0.079 ** (0.033)	-0.153 *** (0.051)	-0.182 *** (0.039)	-0.136 *** (0.041)	-0.085 ** (0.038)	0.021 (0.046)
Asia						
Cambodia	0.099 (0.087)	-0.020 (0.130)	-0.052 (0.116)	-0.026 (0.061)	0.020 (0.113)	0.474 *** (0.172)
Philippines	-0.135 *** (0.018)	-0.201 *** (0.050)	-0.282 *** (0.029)	-0.144 *** (0.021)	0 (0.007)	0.095 *** (0.032)
Vietnam	-0.053 (0.033)	-0.059 (0.061)	-0.075 * (0.045)	-0.076 ** (0.038)	-0.020 (0.043)	-0.015 (0.031)

Note: Standards errors in parentheses; *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.A3 (c): Raw gender wage differentials in the private sector

	OLS	10th percentile	25th percentile	50th percentile	75th percentile	90th percentile
Latin America						
Argentina	0.024 (0.017)	-0.050 (0.049)	0 (0.015)	0 (0.024)	0.027 (0.030)	0.095** (0.038)
Bolivia	0.238*** (0.057)	0.539*** (0.121)	0.485*** (0.074)	0.357*** (0.076)	-0.033 (0.088)	-0.077 (0.147)
Brazil	0.060 (0.057)	0.044 (0.027)	0.105*** (0.022)	0.154*** (0.018)	0.154*** (0.036)	0.095 (0.059)
Chile	-0.113*** (0.013)	-0.041*** (0.007)	-0.049*** (0.014)	-0.080*** (0.011)	-0.182*** (0.017)	-0.316*** (0.033)
Guatemala	0.251*** (0.045)	0.511*** (0.078)	0.288*** (0.058)	0.052 (0.045)	0.077 (0.070)	0.050 (0.093)
Mexico	0.258*** (0.018)	0.382*** (0.044)	0.223*** (0.025)	0.223*** (0.016)	0.160*** (0.021)	0.167*** (0.040)
Asia						
Cambodia	0.322*** (0.069)	0.154* (0.083)	0.355*** (0.075)	0.527*** (0.068)	0.381*** (0.116)	0 (0.201)
Philippines	-0.055*** (0.013)	0.203*** (0.051)	0 (0.023)	-0.113*** (0.019)	-0.133*** (0.018)	-0.167*** (0.023)
Vietnam	0.083* (0.045)	0.087 (0.061)	0.105** (0.043)	0.110*** (0.034)	0.123* (0.064)	0.154 (0.108)

Note: Standards errors in parentheses; *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.A4 (a): Decomposition of gender wage differentials without controlling for occupation: pooled data

Countries	Percentiles	Total Gap	Characteristics Effect	Coefficients Effect
Latin America				
Argentina	OLS	-0.007	-0.085***	0.078***
	P10	-0.083***	-0.051***	-0.032**
	P25	-0.025**	-0.059***	0.034***
	P50	0.006	-0.078***	0.085***
	P75	0.007	-0.104***	0.111***
	P90	0.038	-0.130***	0.167***
Bolivia	OLS	-0.048	-0.193***	0.145***
	P10	0.319***	-0.118*	0.436***
	P25	0.144**	-0.130**	0.274***
	P50	-0.226***	-0.228***	0.003
	P75	-0.283***	-0.311***	0.028
	P90	-0.099*	-0.180***	0.081
Brazil	OLS	0.037	-0.264***	0.301***
	P10	0.005	-0.101***	0.106***
	P25	0.065***	-0.140***	0.205***
	P50	0.117***	-0.188***	0.305***
	P75	0.052*	-0.283***	0.335***
	P90	0.003	-0.394***	0.397***
Chile	OLS	-0.181***	-0.309***	0.129***
	P10	-0.092***	-0.144***	0.052***
	P25	-0.100***	-0.158***	0.059***
	P50	-0.186***	-0.277***	0.091***
	P75	-0.339***	-0.470***	0.131***
	P90	-0.260***	-0.542***	0.282***
Guatemala	OLS	0.054	-0.140***	0.193***
	P10	0.375***	-0.011	0.386***
	P25	0.047	-0.077*	0.124***
	P50	-0.126***	-0.181***	0.055
	P75	-0.182***	-0.239***	0.058
	P90	-0.058	-0.187***	0.129**
Mexico	OLS	0.121***	-0.022**	0.142***
	P10	0.322***	0.014	0.308***
	P25	0.182***	0.007	0.176***
	P50	0.073***	-0.022	0.095***
	P75	-0.036	-0.063***	0.027
	P90	-0.055*	-0.074***	0.019

Table 1.A4 (a): Decomposition of gender wage differentials without controlling for occupation: pooled data (Continued)

Countries	Percentiles	Total Gap	Characteristics Effect	Coefficients Effect
Asia				
Cambodia	OLS	0.156***	0.052	0.104*
	P10	-0.077	-0.035	-0.042
	P25	0.001	-0.029	0.030
	P50	0.187***	0.032	0.154**
	P75	0.314***	0.112	0.202**
	P90	0.269	0.175	0.094
Indonesia	OLS	0.167***	-0.075***	0.242 ***
	P10	0.453***	-0.030	0.484***
	P25	0.311***	-0.049*	0.360***
	P50	0.068**	-0.102***	0.170***
	P75	0.011	-0.091***	0.102***
	P90	0.064***	-0.072***	0.136***
Korea	OLS	0.450***	0.072***	0.377***
	P10	0.451***	0.031	0.420***
	P25	0.493***	0.048	0.445***
	P50	0.467***	0.075**	0.392***
	P75	0.436***	0.097***	0.339***
	P90	0.390***	0.118***	0.272***
Philippines	OLS	-0.155***	-0.240***	0.084***
	P10	0.023	-0.161***	0.184***
	P25	-0.160***	-0.192***	0.032**
	P50	-0.265***	-0.257***	-0.008
	P75	-0.245***	-0.302***	0.057***
	P90	-0.101***	-0.267***	0.166***
Singapore	OLS	0.344***	0.119***	0.225***
	P10	0.334***	0.033*	0.301***
	P25	0.353***	0.073***	0.280***
	P50	0.306***	0.101***	0.205***
	P75	0.312***	0.172***	0.146***
	P90	0.388***	0.205***	0.182***
Vietnam	OLS	-0.014	-0.054***	0.039*
	P10	-0.030	-0.056	0.026
	P25	-0.028	-0.059**	0.031
	P50	-0.014	-0.056**	0.043*
	P75	-0.005	-0.049*	0.044
	P90	0.011	-0.034	0.045

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.A4 (b): Decomposition of gender wage differentials without controlling for occupation: by sector

Countries	Percentile	<i>Public Sector</i>			<i>Private Sector</i>		
		Total Gap	Char. Effect	Coef. Effect	Total Gap	Char. Effect	Coef. Effect
Latin America							
Argentina	OLS	0.075***	-0.026*	0.101***	0.024	-0.022*	0.046***
	P10	0.019	0.010	0.010	-0.029	0.017	-0.046*
	P25	0.081***	-0.013	0.094***	-0.012	0.006	-0.019
	P50	0.079***	-0.025	0.104***	0.033*	-0.014	0.047***
	P75	0.089***	-0.033	0.122***	0.046**	-0.040*	0.085***
	P90	0.126***	-0.050	0.176***	0.057*	-0.076**	0.133***
Bolivia	OLS	-0.070	-0.085**	0.015	0.238***	-0.044	0.282***
	P10	0.028	-0.083	0.111	0.510***	0.047	0.464***
	P25	-0.141*	-0.103	-0.038	0.482***	0.004	0.479***
	P50	-0.166***	-0.087	-0.079	0.299***	-0.033	0.332***
	P75	-0.006	-0.063	0.057	-0.040	-0.111	0.070
	P90	0.095	-0.085	0.180*	-0.069	-0.163*	0.095
Brazil	OLS	0.301***	-0.209***	0.510***	0.060	-0.156***	0.216***
	P10	0.069*	-0.093***	0.162***	0.026	-0.061***	0.086***
	P25	0.167***	-0.116***	0.283***	0.097***	-0.085***	0.182***
	P50	0.230***	-0.145***	0.375***	0.158***	-0.107***	0.265***
	P75	0.176***	-0.195***	0.372***	0.177***	-0.154***	0.332***
	P90	0.225**	-0.285***	0.510***	0.122**	-0.247***	0.369***
Chile	OLS	0.072***	-0.102***	0.174***	-0.113***	-0.220***	0.107***
	P10	-0.006	-0.071***	0.065***	-0.045**	-0.100***	0.055***
	P25	-0.023	-0.113***	0.090***	-0.047***	-0.101***	0.054***
	P50	0.066*	-0.151***	0.217***	-0.072***	-0.176***	0.104***
	P75	0.121***	-0.095***	0.216***	-0.199***	-0.299***	0.100***
	P90	0.215***	-0.057*	0.272***	-0.304***	-0.455***	0.151***
Guatemala	OLS	-0.159***	-0.080*	-0.080	0.251***	-0.065**	0.316***
	P10	-0.430***	-0.138	-0.291**	0.602***	0.030	0.572***
	P25	-0.381***	-0.144**	-0.236***	0.296***	-0.004	0.300***
	P50	-0.265***	-0.152***	-0.113***	0.090**	-0.054	0.144***
	P75	0.005	-0.034	0.040	0.045	-0.147**	0.192***
	P90	0.120	0.015	0.105	0.070	-0.140*	0.210***
Mexico	OLS	-0.079**	-0.109***	0.030	0.258***	0.058***	0.199***
	P10	-0.092	-0.149**	0.058	0.402**	0.057	0.345**
	P25	-0.161***	-0.145***	-0.016	0.264***	0.051	0.213***
	P50	-0.164***	-0.124***	-0.041	0.201***	0.051**	0.150***
	P75	-0.082**	-0.074***	-0.008	0.176***	0.053**	0.123***
	P90	0.029	-0.017	0.046	0.145	0.060	0.085

Table 1.A4 (b): Decomposition of gender wage differentials without controlling for occupation: by sector (Continued)

Countries	Percentile	<i>Public Sector</i>			<i>Private Sector</i>		
		Total Gap	Char. Effect	Coef. Effect	Total Gap	Char. Effect	Coef. Effect
Asia							
Cambodia	OLS	0.099	0.119*	-0.020	0.322***	0.126***	0.196***
	P10	-0.016	0.041	-0.057	0.174**	0.008	0.165**
	P25	-0.041	0.093	-0.134	0.324***	0.080	0.243***
	P50	-0.007	0.092	-0.100	0.461***	0.153*	0.308***
	P75	0.002	0.017	-0.015	0.399***	0.203*	0.196*
	P90	0.555***	0.178	0.377**	0.026	0.206	0.180
Philippine	OLS	-0.135***	-0.181***	0.045***	-0.055***	-0.166***	0.111***
	P10	-0.236***	-0.236***	0.000	0.224***	-0.101***	0.325***
	P25	-0.300***	-0.256***	-0.044**	-0.014	-0.096***	0.082***
	P50	-0.161***	-0.167***	0.006	-0.110***	-0.140***	0.030**
	P75	0.002	-0.121***	0.122***	-0.168***	-0.216***	0.049**
	P90	0.104***	-0.093***	0.196***	-0.189***	-0.314***	0.124***
Vietnam	OLS	-0.053	-0.083***	0.031	0.083*	0.017	0.066
	P10	-0.088	-0.122	0.034	0.067	0.034	0.034
	P25	-0.085*	-0.108***	0.023	0.066	0.021	0.045
	P50	-0.062	-0.084***	0.022	0.107**	0.027	0.080
	P75	-0.025	-0.061***	0.036	0.117*	0.025	0.092
	P90	0.010	-0.035	0.045	0.069	0.002	0.068

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.A5 (a): Decomposition of gender wage differentials with controlling for occupation: pooled data

Countries	Percentiles	Total Gap	Characteristics Effect	Coefficients Effect
Latin America				
Argentina	OLS	-0.007	-0.088***	0.081***
	P10	-0.080***	-0.048**	-0.032*
	P25	-0.025*	-0.057***	0.032**
	P50	0.006	-0.082***	0.088***
	P75	0.008	-0.110***	0.117***
	P90	0.036*	-0.132***	0.168***
Bolivia	OLS	-0.048	-0.209***	0.161***
	P10	0.315***	-0.079	0.394***
	P25	0.132**	-0.111*	0.243***
	P50	-0.211***	-0.249***	0.038
	P75	-0.298***	-0.356***	0.058
	P90	-0.099*	-0.230***	0.131**
Brazil	OLS	0.037	-0.366***	0.403***
	P10	0.016	-0.137***	0.153***
	P25	0.069***	-0.188***	0.258***
	P50	0.114***	-0.263***	0.377***
	P75	0.047	-0.423***	0.470***
	P90	-0.010	-0.559***	0.550***
Chile	OLS	-0.181***	-0.362***	0.182***
	P10	-0.087***	-0.165***	0.078***
	P25	-0.099***	-0.187***	0.088***
	P50	-0.193***	-0.358***	0.165***
	P75	-0.332***	-0.543***	0.211***
	P90	-0.275***	-0.603***	0.328***
Guatemala	OLS	0.054	-0.190***	0.243***
	P10	0.374***	-0.029	0.404***
	P25	0.065	-0.108***	0.173***
	P50	-0.108**	-0.243***	0.135***
	P75	-0.204***	-0.325***	0.121***
	P90	-0.045	-0.223***	0.178***
Mexico	OLS	0.121***	-0.032***	0.153***
	P10	0.340**	0.040	0.299**
	P25	0.180**	0.024	0.155**
	P50	0.075***	-0.019	0.094***
	P75	-0.034	-0.102***	0.068***
	P90	-0.059	-0.122*	0.063

Table 1.A5 (a): Decomposition of gender wage differentials with controlling for occupation: pooled data (Continued)

Countries	Percentiles	Total Gap	Characteristics Effect	Coefficients Effect
Asia				
Cambodia	OLS	0.156***	0.023	0.133**
	P10	-0.059	-0.115**	0.056
	P25	-0.008	-0.105***	0.097***
	P50	0.173***	0.015	0.158***
	P75	0.314***	0.134**	0.180***
	P90	0.281***	0.172**	0.109
Indonesia	OLS	0.167***	-0.076***	0.243***
	P10	0.450***	-0.026	0.476***
	P25	0.319***	-0.053**	0.373***
	P50	0.074***	-0.125***	0.199***
	P75	-0.007	-0.103***	0.097***
	P90	0.072***	-0.040**	0.112***
Korea	OLS	0.450***	0.073***	0.377***
	P10	0.419***	0.041	0.378***
	P25	0.503***	0.069**	0.434***
	P50	0.461***	0.076***	0.385***
	P75	0.433***	0.100***	0.333***
	P90	0.384***	0.113***	0.272***
Philippines	OLS	-0.155***	-0.284***	0.129***
	P10	0.023	-0.192***	0.215***
	P25	-0.153***	-0.228***	0.075***
	P50	-0.273***	-0.319***	0.046***
	P75	-0.250***	-0.342***	0.092***
	P90	-0.106***	-0.313***	0.208***
Singapore	OLS	0.344***	0.162***	0.182***
	P10	0.348***	0.038*	0.310***
	P25	0.352***	0.070***	0.282***
	P50	0.303***	0.136***	0.168***
	P75	0.321***	0.251***	0.071***
	P90	0.388***	0.305***	0.083***
Vietnam	OLS	-0.014	-0.080***	0.065***
	P10	-0.028	-0.095***	0.067*
	P25	-0.030	-0.078***	0.048*
	P50	-0.019	-0.074***	0.055**
	P75	-0.005	-0.072***	0.066**
	P90	0.016	-0.051	0.067*

Note: *,** and ***denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.A5 (b): Decomposition of gender wage differentials with controlling for occupation: by sector

Countries	Percentile	Public Sector			Private Sector		
		Total Gap	Char. Effect	Coef. Effect	Total Gap	Char. Effect	Coef. Effect
Latin America							
Argentina	OLS	0.075***	-0.026*	0.100***	0.024	-0.018	0.042**
	P10	0.018	0.011	0.007	-0.029	0.020	-0.049*
	P25	0.077***	-0.006	0.083***	-0.005	0.022	-0.027
	P50	0.077***	-0.026	0.104***	0.036*	0.001	0.036**
	P75	0.088***	-0.036	0.125***	0.048*	-0.027	0.075***
	P90	0.133***	-0.044	0.177***	0.051	-0.077**	0.128***
Bolivia	OLS	-0.070	-0.117***	0.047	0.238***	-0.038	0.275***
	P10	-0.022	-0.096	0.074	0.524***	0.123	0.401***
	P25	-0.128	-0.159**	0.031	0.468***	0.064	0.403***
	P50	-0.141**	-0.144**	0.003	0.282***	-0.012	0.295***
	P75	-0.016	-0.091	0.075	-0.055	-0.143*	0.088
	P90	0.076	-0.099	0.174*	-0.057	-0.212**	0.155*
Brazil	OLS	0.301***	-0.282***	0.583***	0.060	-0.248***	0.309***
	P10	0.068	-0.102***	0.170***	0.034	-0.098***	0.132***
	P25	0.182***	-0.143***	0.325***	0.098***	-0.134***	0.232***
	P50	0.224***	-0.211***	0.435***	0.155***	-0.179***	0.333***
	P75	0.162***	-0.309***	0.471***	0.018***	-0.276***	0.454***
	P90	0.255***	-0.343***	0.598***	0.120**	-0.385***	0.505***
Chile	OLS	0.072***	-0.142***	0.214***	-0.113***	-0.273***	0.160***
	P10	-0.015	-0.129	0.115	-0.044***	-0.121***	0.077***
	P25	-0.021	-0.171	0.150***	-0.046***	-0.124***	0.078***
	P50	0.057*	-0.193***	0.250***	-0.085***	-0.236***	0.151***
	P75	0.112***	-0.117***	0.229***	-0.184***	-0.375***	0.191***
	P90	0.228***	-0.069	0.297***	-0.301***	-0.534***	0.233***
Guatemala	OLS	-0.159***	-0.153***	-0.006	0.251***	-0.095***	0.345***
	P10	-0.389***	-0.222**	-0.167*	0.598***	0.039	0.559***
	P25	-0.399***	-0.301***	-0.098	0.292***	-0.020	0.312***
	P50	-0.235***	-0.218***	-0.017	0.103**	-0.063	0.167***
	P75	-0.009	-0.068*	0.060	0.070	-0.176***	0.246***
	P90	0.119	-0.008	0.127	0.057	-0.229*	0.286**
Mexico	OLS	-0.079**	-0.134***	0.055**	0.258***	0.063***	0.195***
	P10	-0.084	-0.176***	0.093	0.421***	0.098**	0.322***
	P25	-0.177***	-0.160***	-0.017	0.262***	0.085***	0.177***
	P50	-0.168***	-0.15***	-0.018	0.196***	0.063***	0.133***
	P75	-0.066	-0.091***	0.024	0.175***	0.044**	0.131***
	P90	0.007	-0.039	0.046	0.162***	0.019	0.143***

Table 1.A5 (b): Decomposition of gender wage differentials with controlling for occupation: by sector (Continued)

Countries	Percentile	Public Sector			Private Sector		
		Total Gap	Char. Effect	Coef. Effect	Total Gap	Char. Effect	Coef. Effect
Asia							
Cambodia	OLS	0.099	0.038	0.062	0.322***	0.117*	0.205***
	P10	-0.046	-0.002	-0.044	0.186***	-0.027	0.213**
	P25	-0.029	-0.065	0.036	0.332***	0.080	0.252***
	P50	-0.003	-0.028	0.025	0.450***	0.189**	0.260***
	P75	0.080	-0.004	0.084	0.387***	0.224**	0.164
	P90	0.498***	0.143	0.354**	0.088	0.194	-0.105
Philippine	OLS	-0.135***	-0.218***	0.083***	-0.055***	-0.191***	0.136***
	P10	-0.270***	-0.335***	0.065**	0.182***	-0.110***	0.292***
	P25	-0.294***	-0.322***	0.028*	-0.013	-0.118***	0.105***
	P50	-0.163***	-0.202***	0.040***	-0.105***	-0.172***	0.067***
	P75	0	-0.110***	0.110***	-0.178***	-0.257***	0.079***
	P90	0.096***	-0.094***	0.190***	-0.188***	-0.333***	0.144***
Vietnam	OLS	-0.053	-0.109***	0.056**	0.083*	0.016	0.067
	P10	-0.088	-0.156***	0.068	0.073	0.003	0.070
	P25	-0.089*	-0.129***	0.040	0.061	0.010	0.051
	P50	-0.064*	-0.106***	0.043	0.116***	0.034	0.081**
	P75	-0.022	-0.079**	0.057*	0.118**	0.029	0.089
	P90	0.017	-0.054	0.071	0.071	0.015	0.056

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 1.A6: Summary of Table A4 and Table A5 for glass ceilings/sticky floors evidence

	Basic Model						Extended Model					
	Glass Ceilings			Sticky Floors			Glass Ceilings			Sticky Floors		
	90 th - all	90 th - 75 th	90 th - 50 th	10 th - all	10 th - 25 th	10 th - 50 th	90 th - all	90 th - 75 th	90 th - 50 th	10 th - all	10 th - 25 th	10 th - 50 th
A. Pooled Data												
Argentina	✓	✓	✓				✓	✓	✓			
Bolivia		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Brazil	✓	✓	✓				✓	✓	✓			
Chile	✓	✓	✓				✓	✓	✓			
Guatemala		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Mexico				✓	✓	✓				✓	✓	✓
Cambodia												
Indonesia		✓		✓	✓	✓				✓	✓	✓
South Philippines		✓	✓		✓	✓		✓	✓		✓	✓
Singapore		✓		✓	✓	✓				✓	✓	✓
Vietnam								✓				
B. Public Sector												
Argentina	✓	✓	✓				✓	✓	✓			
Bolivia	✓	✓	✓		✓	✓	✓	✓	✓		✓	✓
Brazil	✓	✓	✓				✓	✓	✓			
Chile	✓	✓	✓				✓	✓	✓			
Guatemala	✓	✓	✓				✓	✓	✓			
Mexico		✓	✓		✓	✓		✓	✓		✓	✓
Cambodia	✓	✓	✓				✓	✓	✓			
Philippines	✓	✓	✓		✓		✓	✓	✓		✓	✓
Vietnam			✓						✓		✓	✓
C. Private Sector												
Argentina	✓	✓	✓				✓	✓	✓			
Bolivia		✓				✓		✓				✓
Brazil	✓	✓	✓				✓	✓	✓			
Chile	✓	✓	✓				✓	✓	✓			
Guatemala			✓	✓	✓	✓		✓	✓	✓	✓	✓
Mexico				✓	✓	✓				✓	✓	✓
Cambodia												
Philippines		✓	✓	✓	✓	✓		✓	✓	✓	✓	✓
Vietnam												

CHAPTER TWO

The Evolution of Gender Wage Differentials and Discrimination in Thailand:

1991-2007---An Application of Unconditional Quantile Regression¹⁹

2.1 Introduction

Thailand is being regarded as a new industrialized economy, and has experienced rapid economic growth before the Asian Financial Crisis. According to Mammen and Paxon (2000), real GDP per capita in Thailand has increased by 125% from \$2178 in 1980 to \$4891 in 1995. During the same period, income inequality also increased significantly (Motonishi, 2006). However, how the wage inequality between men and women has evolved is seldom documented. One exception is Nakavachara (2010), who finds the main sources of the decline in gender earnings gap during 1985-2005 are increases in female education and changes in unobserved characteristics. Another exception is Fang and Sakellariou (2011) who document a sticky floor in Thailand 2004. Questions such as: How the wage differentials have changed across the wage distribution and what are the main contributors to these changes? Whether sticky floors are persistent in Thailand?--are still open for discussion. Using Thai Labor Force Survey in 1991-2007, this study investigates these questions in detail.

The method used in the study is a quantile decomposition which combines recently developed unconditional quantile regression (Firpo, Fortin and Lemieux, 2009) and the traditional Oaxaca-Blinder decomposition. Using it, we are able to trace the individual determinants of the gender wage gap at various points of the wage distribution. In addition, we propose a double decomposition approach, a simple extension of the single quantile decomposition, to explore the reasons underlying the

¹⁹ This chapter has been presented in 12th East Asian Economic Association Conference.

distributional change in gender wage differentials. Our main findings are as follows. First, the counterfactual gender wage differentials at the lower part of the wage distribution are wider than those at the upper part over the entire 1991-2007 period, indicating a persistent sticky floor effect. Second, gender gaps in all these years, both at the mean and (almost) over the whole distribution, are attributable to gender differences in returns to characteristics (coefficients effect).²⁰ The experience premium is a main contributor to the wage differentials at the middle part of the distribution; while a gender gap in educational returns seems more relevant at both sides. Third, there is a declining trend in gender wage inequality across the entire distribution (except for the very top part), especially in the 1990s. Only a small proportion of the decline can be explained by gender characteristics changes (mainly in occupation and industry); while changes in experience premiums seem to account for a sizable part of the overall change.

This chapter is organized as follows: The methodology is discussed in section 2.2; section 2.3 describes the data and provides an overview of the raw gender wage differentials. Results from single and double decompositions are discussed in section 2.4. Section 2.5 gives a summary of the findings.

2.2 Conceptual framework

The decomposition methodology used in this chapter is based on unconditional quantile regression. As is widely known, the traditional Oaxaca-Blinder (Blinder 1973; Oaxaca 1973) technique can decompose the mean gender wage gap into two components, one due to gender differences in characteristics (characteristics effect) and the other due to gender differences in returns to those characteristics (coefficients

²⁰ In the 1990s, gender differences in characteristics explained a very small part of the wage gap at the lower part of the earnings distribution.

effect). To carry out the decomposition at different points of the wage distribution, one has to combine the Oaxaca-Blinder technique with (conditional) quantile regression (Koenker and Bassett 1978). There are many approaches proposed in the literature, and so far the most popular one may be Machado and Mata (2005) who construct the counterfactual wage distribution by randomly sampling the quantiles and observations.²¹ Empirical applications using this approach include Albrecht et al. (2003), Arulampalam et al. (2007), De la Rica et al. (2008), Kee (2006) and Ganguli and Terrell (2005), among several others. However, all these methods share the same problem, namely, they cannot account for the contribution of individual covariates in the characteristics effect or coefficients effect.

To mitigate the problem, we use unconditional quantile regression methodology recently developed by Firpo et al. (2009). As an estimate from unconditional quantile regression provides the average partial effect of a small location shift of an independent variable on the unconditional quantile of the dependent variable, one can proceed with the decomposition of the gender wage gap (or the wage gap between any two groups) in a similar fashion to the standard Oaxaca-Blinder decomposition.²²

2.2.1 Decomposition of the gender wage gap at quantiles

Consider wage equations for male and female employees:

²¹ Other approaches include Juhn, Murphy and Pierce (1993), DiNardo, Fortin and Lemieux (1996), Fortin and Lemieux (1998), and Melly (2006).

²² In the FFL procedure, to estimate the effect of changes in the distribution of X , one uses a first order linear approximation of the effect; the procedure results in two terms: the first order linear approximation term and the remaining approximation error. The first order term is estimated using a mean regression method which exploits the law of iterated expectations and the assumption of linearity of the term. However, the estimand is still an approximation of the effect and the approximation error does not vanish. Recently, Chernozhukov, Fernandez-Val and Melly (2009) proposed an approach which directly estimates the exact effect without an approximation error. In another recent paper, Rothe (2010) proposed a method to evaluate the effect of counterfactual changes in the unconditional distribution of a single covariate on the unconditional distribution of an outcome variable of interest. He showed that such effects are point identified if the covariate affected is continuously distributed; on the other hand, if the distribution of the covariate is discrete, the effects are only partially identified. He, then, derived informative bounds for these effects.

$$\ln W_m = g_m(X_m, \varepsilon_m); \ln W_f = g_f(X_f, \varepsilon_f)$$

where $\ln W_i (i = m, f)$ denotes the logarithm of hourly wage for individual i , $X_i (i = m, f)$ is a vector of explanatory variables and $\varepsilon_i (i = m, f)$ the error term. The wage differential at quantile τ can be decomposed into two parts:

$$Q_\tau(\ln W_m) - Q_\tau(\ln W_f) = [Q_\tau(\ln W_m) - Q_\tau(\ln W_c)] + [Q_\tau(\ln W_c) - Q_\tau(\ln W_f)],$$

where $\ln W_c$ is the counterfactual log hourly wage. In this chapter, we use female's characteristics and male's wage structure to construct the counterfactual wage distribution. Hence, the first component measures the wage gap due to gender differences in characteristics (characteristics effect) and the second component the wage gap due to differences in returns to those characteristics (coefficients effect). The coefficients effect is also indicative of the degree of gender discrimination in the labor market.

To estimate the two components of the decomposition, a reweighting approach (Firpo et al., 2007; Dinardo et al., 1996) is used; hence, no specific functional forms or parametric distributions are assumed in the overall decomposition. In deriving the re-weighting functions, the probability that a person belongs in the “female” group conditional on X (propensity score) is estimated from a logit regression.

Next, to get the estimates of the effects of each individual variable on the wage gap, we use the decomposition method based on unconditional quantile regression recently developed by Firpo et al. (2009). The estimation of unconditional quantile regression consists of two steps. The first step is to derive the re-centered influence function (RIF) of the dependent variable, hence the name RIF regression; the second step involves estimating an OLS regression of the generated RIF variable on

covariates.²³ As shown in Firpo et al. (2009), the estimated coefficients are in fact unconditional partial effects of small location shifts of the covariates. Therefore, it is as easy to decompose the gender wage gap at quantiles as decomposing at the mean using Oaxaca-Blinder methodology.

Specifically, the RIF of variable Y at quantile τ is:

$$RIF(Y; Q_\tau, F_Y) = Q_\tau + \frac{\tau - I(Y \leq Q_\tau)}{f_Y(Q_\tau)},$$

where Q_τ can be estimated by the sample quantile and $f_Y(\cdot)$ can be estimated using Kernel density. If the specification of unconditional quantile regression is linear, i.e., $RIF(Y; Q_\tau, F_Y) = X\beta + \varepsilon$, then the OLS estimate of β (namely, RIF-OLS estimator) provides a consistent estimator of the marginal effect on the unconditional quantile of a small location shift in the distribution of X , holding all else constant. However, if the unconditional quantile regression is not linear, RIF-OLS estimates may not be consistent. Instead, an alternative non-parametric estimator may be used (see Firpo et al., 2009 for further discussion).

As $\widehat{Q}_\tau(Y) = \bar{X}\widehat{\beta}_\tau$, the decomposition of gender wage differentials can be rewritten as

$$Q_\tau(\ln W_m) - Q_\tau(\ln W_f) = [(\bar{X}_m - \bar{X}_f)\widehat{\beta}_{m\tau} + R_X] + [\bar{X}_f(\widehat{\beta}_{m\tau} - \widehat{\beta}_{f\tau}) + R_S],$$

where R_X and R_S are approximation errors which will appear in practice because of the first order approximations and the way the counterfactual wage distribution is constructed.²⁴

In contrast with other counterfactual decompositions in the literature (see, Machado and Mata, 2005 and Melly, 2006 for example), one of the advantages of the

²³ The influence function is widely used in the robust estimation of statistical and econometric models. It reflects the influence of an observation on the specific distributional statistic. The re-centered influence function is obtained by adding back the statistic to the influence function and its expectation equals precisely the statistic.

²⁴ As $E[RIF(Y; Q_\tau, F_Y)|X] = X\beta$ and $E[RIF(Y; Q_\tau, F_Y)] = Q_\tau$, taking expectations on both sides yields $Q_\tau(Y) = \bar{X}\beta$. So, $\widehat{Q}_\tau(Y) = \bar{X}\widehat{\beta}_\tau$.

RIF decomposition is that it cannot only decompose the unconditional gender wage gap at any quantile of the wage distribution, but also allows the characterization of the contribution of any single covariate on each component. The identification problem in this sort of detailed decompositions as pointed out by Oaxaca and Ransom (1999) is that the coefficients effect is not invariant to the choice of reference group; this problem is dealt with using the averaging approach proposed by Yun (2005).²⁵ Another advantage of RIF decomposition is its computational efficiency as it only requires OLS regression estimation on the RIF variable. Therefore, we choose the technique of RIF-decomposition to analyze the gender wage differentials in Thailand in 1991-2007.

2.2.2 Decomposition of changes in gender wage gaps over time

We propose a method of “double decomposition” to explore the determinants of distributional changes in gender wage gaps. It is called “double-decomposition” because there are two differences in both the explained and unexplained components.

Denoting $Q_\tau(\ln W_m) - Q_\tau(\ln W_f)$ as ΔQ_τ , the change in gender wage gaps can be decomposed as:

$$(\Delta Q_\tau)_1 - (\Delta Q_\tau)_0 = \{[(\Delta \bar{X})_1 - (\Delta \bar{X})_0]\beta_{m\tau}^1 + (\Delta \bar{X})_0(\beta_{m\tau}^1 - \beta_{m\tau}^0)\} + \{\bar{X}_f^{-1}[(\Delta \beta_\tau)_1 - (\Delta \beta_\tau)_0] + (\bar{X}_f^{-1} - \bar{X}_f^0)(\Delta \beta_\tau)_0\},$$

where:

$$\Delta \bar{X} = \bar{X}_m - \bar{X}_f; \quad \Delta \beta_\tau = \beta_{m\tau} - \beta_{f\tau}$$

The change in wage gaps at quantile τ is decomposed into four parts. The first two parts altogether correspond to the change in characteristics effects, and the last

²⁵ Other solutions to the identification problem in the detailed wage decompositions include Nielsen (2000) and Gardeazabal and Ugidos (2005). But Nielsen (2000)’s method cannot distinguish the constant term from dummy variables; and, Gardeazabal and Ugidos (2005)’s approach, though producing identical results in zero normalization, may be not so attractive as Yun (2005)’s from a practical point of view. The idea of Yun (2005) is to get “estimates with every possible specification of reference groups and take the average of the estimates with various reference groups as the ‘true’ contributions of individual variables to wage differentials”. STATA procedure *Devcon* can be employed for this purpose.

two parts measure the change in coefficients effects. This chapter focuses only on the direct effects changing characteristics and coefficients have on the overall gap change, as measured by the first and third components. The remaining two components represent reference effects.²⁶ Similar to the single RIF decomposition, there are approximation errors as well. We are particularly interested in the third component, as it indicates a trend in potential discrimination. If it is positive, it suggests women are more unequally treated than before; if it is negative, it suggests an improvement of gender inequality.

This approach has several advantages. First, it allows us to decompose the change in gender wage gaps at quantiles. Previous studies on the evolution of gender wage gaps, either choose individual cross-sections and decompose the gap at quantiles by year (Chi and Li, 2008) or only decompose the change in gender wage gaps at the mean (D énurger, Fournier and Chen, 2007; Ng, 2007; Wellington, 1993; Smith and Welch, 1989). Pham and Reilly (2007), while attempting to decompose the change in gender wage gaps at quantiles, could not provide an intuitive interpretation of the decomposition components, because the characteristics gap has to be conditional on a specific quantile of the wage distribution. In contrast, the unconditional quantile regression-based double decomposition is relatively easy to interpret. Recent application on a similar approach includes Kassenbohmer and Sinning (2010). We will use this double decomposition to investigate how the gender wage differentials in 2005/2007 are different from those in the early 1990s and late 1990s, and to what extent these changes can be attributable to characteristics change or coefficients change.

²⁶ The second part measures the effect of changing the reference point from period 1 to period 0 with respect to changes in the characteristics effect, while the last part measures the effect of changing the reference point from period 1 to period 0 with respect to changes in coefficients effect; both components are thus named as the reference effects in the table reported.

2.3 Data description and raw gender wage differentials

2.3.1 Data description

The data used are from the Labor Force Surveys (LFS) of Thailand for years 1991-2007. The LFS has been undertaken by the National Statistical Office (NSO) since 1963. Three rounds had been conducted every year during 1984-1997; since 1998, one additional round was added; after 2000 and starting from 2001, the LFS is conducted monthly. For the purpose of consistency, we make use of Round One during 1991-2000 and February data during 2001-2007. To explore sources of the over time change in gender wage differentials, we choose three representative time points: 1991-1993, 1998-2000 and 2005-2007. The years-grouping can help to reduce the effect of any unusual event in a specific year and exhibit a stable trend of gender wage gaps.

The LFS contains detailed demographic characteristics and employment information. In this study, we keep observations aged 25-65 years old, with valid values on gender, region, urbanity, marital status, educational attainment, and job characteristics such as wage, sector, occupation and industry. Employers, the self-employed and unpaid family workers are dropped from the sample. The dependent variable is the logarithm of the real hourly wage, generated from wage type, wage rate, wage per day or salary and regional CPI. Explanatory variables, as well as real hourly wage, are summarized in Table 2.1 by year and gender.²⁷ The proportion of workers with only primary education or less has decreased over time, with a corresponding increase in workers with secondary education. And, the gender gap in educational attainment at the primary and secondary levels is closing, consistent with Knodel

²⁷ Age is used as a proxy for experience in this chapter. It bears the same problem as potential experience that unexplained wage gaps might be overestimated due to the job interruption experienced by women.

(1997)'s observation. The proportion with university education increased from 13.6 to 16.6 percent for men and from 20.2 to 25 percent for women in the last decade; however, it declined slightly in recent years (by 2.6 percentage points for men and 1 percentage point for women).²⁸ Regarding occupational segregation, women seem to be more likely to be working as professionals, clerks, service and sales workers, while men are more likely to be officials, managers, or in trade-related occupations. Besides, women are more likely to be engaged in manufacturing, social work and other low-paying industries, while men are more likely working in the industry of construction.²⁹

[Table 2.1 about here]

This study does not address the issue of sample selection for three reasons. First, adjusting for the selection bias in the framework of quantile regression involves too much complexity, and it is still an open question in the econometric theory.³⁰ Second, there are no good instruments for participation equations in the data. Finally, the rate of female labor participation in Thailand has been historically high (Mammen and Paxon, 2000), so we speculate that sample selection is not a major problem in this study.

²⁸ By observing the trend of percentage of men and women with university education, we find a huge jump in 1998-2000. This could be caused by a soured job market after the Asian financial crisis where only a few vacancies are available for graduates. They have no choices but to enter university or higher degree program for further study.

²⁹ There are changes in education, occupation and industry codes after the year 2000. I have done a rematch to keep classifications as consistent as possible with the latest coding. However, the large changes observed in the relative employment levels in the *Professional*, *Associate Professional* and *Unskilled Workers* as well as in the *Public Administration*, *Social Work* and *Other* industries are generally caused by the reclassification of occupation and industry categories.

³⁰ For example, Buchinsky (1998) utilizes higher order series to adjust for sample selection when he investigates the female wage structure in the US, but finds the constant term unidentified. Albrecht et al. (2009) follows the assumptions of Buchinsky (1998) and proposes a method to address the selection bias in the framework of quantile decomposition. However, the estimates are inconsistent when there is heterogeneity (Huber and Melly, 2011).

2.3.2 Raw gender wage differentials

Figure 2.1 depicts the evolution of raw gender wage gaps over the 1991-2007 period. It shows that the wage gap between men and women has been converging over time, both on average and on a distributional perspective. The smallest gap is observed in 1998; and at the 90th percentile that year, women even earned more than men. Furthermore, from the relative position of the three lines indicating the log gaps at the 10th percentile, median and 90th percentile, the wage differential seems to be more serious at the bottom part of the earnings distribution.

[Figure 2.1 and 2.2 about here]

The pattern is more obvious in Figure 2.2, where the wage gap is plotted against percentiles in the three representative years. In 1991/1993, the gap declines significantly from 32% at the 5th percentile to 8% at the 95th percentile; the gaps in 1998/2000 and 2005/2007, though smaller in magnitude, also show a decreasing trend over the entire distribution. While there is a converging trend in the gender wage gap, it seems to change little after 1998.

Looking at the average real hourly wage by different groups in Table 2.A1, one can have a preliminary impression of which group of people has a substantial gender wage gap and how the gap has evolved over the years in different groups of people. For example, there is a wide wage gap among workers aged 55-65 years old, with primary or lower secondary education, and working in manufacturing or construction firms. The gap gets narrowed in almost all groups, except in some higher educational groups. In addition, the real hourly wage in 2005/2007, is higher compared to early 1990s, but a little lower compared to late 1990s, except for workers who are either very low or very high in the education/occupation ladder.

2.4 Unconditional quantile regressions and decomposition of the wage gap

2.4.1 Unconditional quantile regressions by gender

Table 2.A2 reports the estimates of coefficients of unconditional quantile regressions by gender at the 10th percentile, median and 90th percentile in 1991/1993, 1998/2000 and 2005/2007. The estimated returns to characteristics are generally different between men and women at all quantiles and time periods. For example, in 1991/1993, the gender difference in the premium to university education (compared to no education) increases from 0.15 at the 10th percentile to 0.65 at the 90th percentile. Specifically, men with university education earned 63 percent more than men without any education at the lower part of the wage distribution and 136 percent more at the upper part; on the other hand, women with university education earned 48 percent more than women without education at the lower part and only 72 percent more at the upper part of the wage distribution. Therefore, one can expect that in 1991/1993, different rewards to university education contributed positively to the unexplained gender wage gap at both the bottom and the top, and more so at the top of the wage distribution.

Looking at university premiums over time, in 2005/2007 men with university education earned 50 percent more than men without education at the 10th percentile, while women at the same percentile earned 78 percent more than women without any education. So at the 10th percentile, the gender difference in returns to university education relative to no education as reflected by the estimated coefficient has increased from 0.15 in favor of men in 1991/1993 to 0.28 in favor of women in 2005/2007. On the other hand, the situation at the 90th percentile is quite different, as the premium to university education is consistently higher for men and the gender difference has increased over time. Consequently, one can expect that the changes in

differential returns to education between genders reduced the wage gap at the 10th percentile but widened the gap at the 90th percentile.

Estimates of other coefficients can be similarly explained. Specifically, they can shed some light on the decomposition results and sources of the over-time change in gender wage differentials in the next sections.

2.4.2 The gender wage gap by year

Table 2.2 presents our first main results. It reports the decomposition of gender wage gaps at the 10th percentile, median and 90th percentile in three periods. Looking at the top of the table, gender differences in characteristics can explain only a small fraction of the total gap at the 10th percentile, whereas at the upper half of the wage distribution the entire gap is due to gender differences in returns to those characteristics. Coefficients effects in the overall decomposition are decreasing with quantiles (at least in 2005/2007), indicating a sticky floor effect in Thailand.

[Table 2.2 about here]

As explained before, one of the benefits of unconditional quantile regression is that it not only allows the decomposition of gender wage differentials into a characteristics effect and a coefficients effect but also the determination of the contribution of each individual covariate in each component of the gender gap. We group all the explanatory variables into seven categories: age, marital status, region, sector, education, occupation and industry; the residual in the last row of each part corresponds to the approximation error. We observe that most approximation errors are not statistically significantly different from zero, suggesting the validity of model specification.

We find that at the lower part of the wage distributions, gender differences in occupation and industry composition play an important role in explaining the wage

differentials; on the other hand, among coefficients effects, the major contributor at the median is age (a proxy for experience), at the top the main contributor is education, while at the bottom, it is unobservable characteristics associated with the constant.

Note that the effect of the constant in gender wage differentials tends to be large, which may reflect the effect of gender differences in some hard-to-measure characteristics and attributes such as competitiveness, risk preference and other psychological factors. For example, Manning and Swaffield (2008) find that gender differences in psychological variables can explain almost half of the counterfactual gender wage gap. However, it is hard to tell whether gender differences in the psychological measures are intrinsic, or determined by the social environments and cultures. If gender differences in these measures are associated with nurture rather than nature, studies on discrimination should not control for them. In fact, existing findings indeed support the nurture view. For example, Gneezy et al. (2009) find that women in the matrilineal societies are as competitive as men in the patriarchal societies. Booth and Nolen (2009) observe that girls in single-sex schools are more competitive than girls in co-ed schools. Therefore, no matter which psychological differences the constant term represents, it is probably more appropriate to include it in the “discrimination” component.

[Figure 2.3 about here]

Figures 2.3 (a), 2.3 (b) and 2.3 (c) plot the decomposition of gender wage differentials in 1991/1993, 1998/2000 and 2005/2007, respectively. In each figure, there are three plots: the first depicts the decomposition of gender wage differentials into two parts, characteristics and coefficients effects, and the other two plots graph the contribution of each group of variables in the characteristics and coefficients effects (not including the constant). It is easily seen from these figures that age is the

most influential determinant of gender wage differentials, while gender differences in returns to other productivity related or demographic characteristics do not contribute substantially to the wage gaps. Finally, in each year-group, the coefficients effects generally decrease along the wage distributions, indicating the persistent existence of a sticky floor effect in Thailand.

2.4.3 The evolution of gender wage gaps over time

As observed earlier, gender wage differentials in 2005/2007 have declined dramatically (especially at the lower half of the wage distribution) compared to that in early 1990s. However, it seems that the pattern has changed little after the 1997 Asian financial crisis. Using decompositions based on RIF-regressions, we graph the coefficients effect at the mean and coefficients effects at the 10th percentile, median and 90th percentile in each year, so that we can observe the evolution of potential gender discrimination more clearly.³¹ As shown in Figure 2.A, the average discrimination has declined only a little, except for 1998 where it drops about 8 percentage points. Moreover, it shows that women at the lower part of the wage distribution faced more severe discrimination than women at the upper part.

What are the forces behind these changes in gender wage differentials (inasmuch as they reflect discrimination)? In this subsection, we attempt to answer these questions by means of the double-decomposition technique introduced in Section 2.2. Gender wage differentials in 2005/2007 are compared with those in 1991/1993 and in 1998/2000. Table 2.3 presents the double-decomposition results at three specific points of the wage distribution, i.e., 10th percentile, median and 90th percentile.

³¹ The evolution of the characteristics effects was also graphed but not presented in the paper. It essentially shows that on average, the characteristics effect hardly explains any of the gender wage differentials over the last two decades.

First, let's look at the comparison between 2005/2007 and 1991/1993. Relative to the early 1990s, gender wage differentials have decreased by five percentage points on average (calculated as $(47.644-44.879)/44.879-(41.487-37.345)/37.345$ using the data in Table 2.A1); however the estimates vary at different points of the wage distributions. For example, the gender wage gap decreased by 4.6 percentage points at the 10th percentile and 8.1 percentage points at the median. Decomposing the change into two major parts, changing characteristics and changing coefficients effects, we can identify the underlying forces. Take the 90th percentile as an example. The gender wage differential at the 90th percentile has decreased by 5.2 percentage points, of which 6.9 percentage points can be attributed to changes in gender differences in characteristics. On the other hand, changes in gender differences in wage structures have an opposing effect, contributing to an increase in the gap by 1.7 percentage points - which suggests that women at the top of the wage distribution are facing more severe discrimination compared to the early 1990s.

Use of unconditional quantile regression allows an easy and intuitive decomposition of changes at the individual variable level. For example, comparing the 2005/2007 period to the early 1990s, the over-time changes in industry composition of men and women have contributed 0.7 percentage points to the decrease in gender gap at the 10th percentile; however, the payoff structure relating to industry affiliation has worsened. Still looking at changes at the 10th percentile and comparing the same time periods, the change in gender differences in returns to industry affiliation contributes 7.4 percentage points to the increase of gender wage gap.

[Table 2.3 about here]

Similarly, we can analyze changes in gender wage differentials between 2005/2007 and the late 1990s. It is found that after the 1997 Asian financial crisis, gender discrimination is deteriorated rather than improved. For example, discrimination increased by 8.7 percentage points at the 10th percentile and 6.7 percentage points at the 90th percentile; most of the over-time change is due to changes in the constant, which is reflective of the gender discrimination as well as differences in unobserved characteristics.

[Figure 2.4 about here]

Figure 2.4 shows the double-decomposition results in more detail. Decompositions of the changes between gender wage gaps in 2005/2007 and gender wage gaps in 1991/1993 across quantiles are plotted in Figure 2.4 (a), while those between 2005/2007 and 1998/2000 are shown in Figure 2.4 (b). Generally speaking, gender discrimination in the middle part of the wage distribution has improved since the early 1990s; however, the circumstances at the bottom, after improving at the early 1990s, have deteriorated after the 1997 financial crisis. What is worse, at the top of the wage distribution, the situation has deteriorated compared to either the early 1990s or the late 1990s, suggesting a tendency for glass ceilings to appear.

From the first plot in Figure 2.4 (a), we see that the gender wage gap has narrowed at almost every point of the wage distribution, with the most significant change occurring between the 20th and the 40th percentiles. However, the closing of gender wage gap is not due to changes in gender differences in characteristics, but due to changes in gender differences in wage structures. Furthermore, the change in wage structures at the upper half of the wage distribution has made women worse-off (the line for the unexplained gap lies above zero after the 70th percentile). Looking at the other two plots, the main contributor to the narrowing of the gender wage gap is the

change in gender differences in the return to age/experience. Among the changing characteristics effects, industry and occupation also contribute, but in a much smaller scale. Finally, the two plots showing the contributions of individual variables to the wage change between 2005/2007 and 1998/2000 in Figure 2.4 (b) also point to the same conclusions. What is different is the pattern shown in the overall double decomposition. The gaps get wider at both ends of the distribution and all changes are accounted for by the unexplained part. In other words, compared to the late 1990s, discrimination becomes more severe among people with low income as well as people with high income.

2.5 Conclusion

Using a methodology which combines unconditional quantile regressions with the Oaxaca-Blinder decomposition technique, we explore in detail the evolution of gender wage differentials in Thailand over the 1991-2007 period. We find that on average, the raw gender wage differentials declined in the early 1990s and changed little after the 1997 Asian financial crisis. Using Oaxaca-Blinder decomposition, we also find that most of the differentials are due to “discrimination”.

From the distributional perspective, the pattern of the overall gender gap is V-shaped in each year, with the left side much steeper. Moreover, the gap dropped at almost every point of the wage distributions in the early 1990s and increased at both tails after the 1997 financial crisis. Using decomposition techniques combined with unconditional quantile regression methodology, persistent sticky floors are documented and all gaps are attributable to discrimination, with the exception of the bottom in the early 1990s. We also find that the gender differences in returns to

experience seem to be the most important factor in determining the wage gap, especially in the 1990s.

Finally, using double decomposition, the current wage gaps are compared with the early 1990s and the late 1990s. Our findings suggest that gender inequality in the labor market generally improved compared to the 1990s, with a small contribution from changes in relative characteristics between men and women. Changing returns to experience seem to be the most influential factor that accounts for the narrowing gap. However, “discrimination” at the top of the wage distribution seems to be getting no better than the 1990s.

These results suggest policy-makers in Thailand who aim to close the gender pay gap to focus on reducing differences in returns to experience, especially for low-income groups.

Table 2.1: Descriptive statistics by time period and gender

	1991/1993				1998/2000				2005/2007			
	Male		Female		Male		Female		Male		Female	
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.
Real hourly wage	0.415	(0.409)	0.373	(0.384)	0.501	(0.486)	0.483	(0.481)	0.476	(0.490)	0.449	(0.465)
Age	36.491	(9.202)	35.570	(8.654)	37.817	(9.404)	36.602	(8.843)	38.591	(9.511)	37.499	(9.076)
Age squared/100	14.163	(7.497)	13.401	(6.962)	15.186	(7.729)	14.179	(7.122)	15.797	(7.831)	14.885	(7.358)
Married	0.818	(0.386)	0.669	(0.471)	0.798	(0.401)	0.667	(0.471)	0.766	(0.423)	0.675	(0.468)
Urban	0.427	(0.495)	0.478	(0.500)	0.425	(0.494)	0.491	(0.500)	0.387	(0.487)	0.441	(0.496)
Private	0.749	(0.434)	0.769	(0.422)	0.750	(0.433)	0.780	(0.414)	0.790	(0.408)	0.793	(0.405)
Education Dummies												
No education	0.024	(0.153)	0.053	(0.225)	0.019	(0.136)	0.042	(0.200)	0.022	(0.148)	0.040	(0.195)
Less than primary	0.552	(0.497)	0.521	(0.500)	0.392	(0.488)	0.377	(0.485)	0.267	(0.443)	0.249	(0.432)
Primary	0.074	(0.262)	0.055	(0.229)	0.177	(0.382)	0.152	(0.359)	0.243	(0.429)	0.207	(0.405)
Lower secondary	0.102	(0.303)	0.053	(0.225)	0.135	(0.341)	0.084	(0.278)	0.135	(0.342)	0.105	(0.307)
Upper secondary	0.041	(0.198)	0.028	(0.165)	0.057	(0.231)	0.043	(0.202)	0.139	(0.346)	0.109	(0.311)
Diploma	0.070	(0.256)	0.087	(0.282)	0.054	(0.226)	0.053	(0.223)	0.052	(0.221)	0.048	(0.214)
University	0.136	(0.343)	0.202	(0.402)	0.166	(0.372)	0.250	(0.433)	0.140	(0.347)	0.241	(0.428)
Occupation dummies												
Official/manager	0.041	(0.198)	0.023	(0.150)	0.048	(0.214)	0.031	(0.173)	0.050	(0.218)	0.019	(0.136)
Professional	0.102	(0.302)	0.185	(0.388)	0.123	(0.329)	0.214	(0.410)	0.069	(0.253)	0.120	(0.325)
Assoc. professional	0.003	(0.052)	0.002	(0.046)	0.002	(0.048)	0.003	(0.058)	0.072	(0.258)	0.101	(0.301)
Clerical	0.091	(0.287)	0.124	(0.330)	0.074	(0.262)	0.109	(0.311)	0.047	(0.212)	0.107	(0.309)
Service/sales	0.088	(0.283)	0.095	(0.293)	0.106	(0.308)	0.114	(0.318)	0.064	(0.245)	0.100	(0.300)
Agric. Worker	0.174	(0.379)	0.231	(0.421)	0.160	(0.366)	0.173	(0.378)	0.065	(0.246)	0.061	(0.239)
Trades	0.312	(0.463)	0.225	(0.418)	0.290	(0.454)	0.222	(0.416)	0.254	(0.435)	0.113	(0.317)
Operator	0.111	(0.314)	0.026	(0.160)	0.116	(0.320)	0.024	(0.154)	0.156	(0.363)	0.104	(0.305)
Unskilled worker	0.080	(0.271)	0.089	(0.285)	0.081	(0.272)	0.110	(0.312)	0.223	(0.416)	0.274	(0.446)
Industry dummies												
Agric./mining	0.186	(0.389)	0.230	(0.421)	0.162	(0.368)	0.173	(0.378)	0.173	(0.379)	0.164	(0.370)
Manufacturing	0.189	(0.391)	0.262	(0.440)	0.205	(0.404)	0.290	(0.454)	0.209	(0.407)	0.302	(0.459)

Electricity/gas/water	0.018	(0.135)	0.006	(0.078)	0.021	(0.142)	0.007	(0.084)	0.011	(0.103)	0.002	(0.049)
Construction	0.201	(0.401)	0.060	(0.238)	0.181	(0.385)	0.049	(0.216)	0.194	(0.396)	0.049	(0.217)
Sales	0.073	(0.260)	0.070	(0.255)	0.086	(0.280)	0.087	(0.281)	0.109	(0.312)	0.098	(0.297)
Hotels/transportation	0.061	(0.239)	0.019	(0.138)	0.055	(0.227)	0.018	(0.134)	0.064	(0.244)	0.064	(0.244)
Finance	0.034	(0.180)	0.034	(0.182)	0.043	(0.202)	0.047	(0.211)	0.050	(0.218)	0.054	(0.225)
Public admin.	0.185	(0.388)	0.177	(0.382)	0.189	(0.392)	0.168	(0.374)	0.094	(0.292)	0.061	(0.239)
Social work	0.022	(0.148)	0.056	(0.231)	0.024	(0.153)	0.062	(0.241)	0.091	(0.288)	0.176	(0.381)
Other	0.031	(0.173)	0.084	(0.277)	0.034	(0.182)	0.100	(0.300)	0.004	(0.061)	0.030	(0.171)
Region dummies												
Bangkok	0.204	(0.403)	0.251	(0.434)	0.187	(0.390)	0.248	(0.432)	0.157	(0.364)	0.195	(0.396)
Central	0.272	(0.445)	0.310	(0.462)	0.278	(0.448)	0.302	(0.459)	0.295	(0.456)	0.325	(0.468)
North	0.190	(0.392)	0.182	(0.386)	0.175	(0.380)	0.166	(0.372)	0.170	(0.376)	0.166	(0.372)
Northeast	0.233	(0.423)	0.175	(0.380)	0.261	(0.439)	0.196	(0.397)	0.270	(0.444)	0.201	(0.401)
South	0.101	(0.301)	0.082	(0.275)	0.098	(0.298)	0.089	(0.284)	0.108	(0.311)	0.114	(0.317)
Obs.	25963		17880		50321		38785		24543		20885	

Table 2.2: Decomposition of gender wage differentials at selected quantiles

	1991/1993			1998/2000			2005/2007		
	10th	50th	90th	10th	50th	90th	10th	50th	90th
Total gap	0.255*** (0.018)	0.171*** (0.012)	0.017 (0.014)	0.119*** (0.004)	0.107*** (0.008)	-0.048* (0.026)	0.208*** (0.015)	0.090*** (0.012)	-0.035 (0.026)
Char. Effects	0.052*** (0.008)	-0.049*** (0.013)	-0.049*** (0.011)	0.007** (0.003)	-0.087*** (0.008)	-0.064*** (0.014)	0.010 (0.011)	-0.048*** (0.011)	-0.118*** (0.027)
Coef. Effects	0.203*** (0.017)	0.220*** (0.012)	0.066*** (0.015)	0.112*** (0.005)	0.195*** (0.007)	0.016 (0.020)	0.199*** (0.017)	0.138*** (0.011)	0.083*** (0.030)
Characteristics Effects									
Age	-0.001 (0.001)	0.006*** (0.001)	0.029 (0.018)	0.001 (0.001)	0.010*** (0.001)	-0.053** (0.026)	0.000 (0.002)	0.009*** (0.002)	-0.078** (0.037)
Marriage	0.005 (0.003)	0.012*** (0.002)	0.026 (0.017)	0.005*** (0.002)	0.005*** (0.002)	0.000 (0.005)	0.001 (0.002)	0.001 (0.001)	-0.020* (0.010)
Region	-0.024*** (0.003)	-0.036*** (0.003)	-0.013 (0.008)	-0.020*** (0.002)	-0.036*** (0.003)	0.035** (0.015)	-0.025*** (0.003)	-0.027*** (0.003)	0.017 (0.011)
Sector	0.007*** (0.002)	0.009*** (0.002)	0.014* (0.008)	0.005*** (0.001)	0.010*** (0.002)	-0.013* (0.007)	0.001 (0.001)	0.001 (0.002)	-0.003 (0.005)
Education	-0.006** (0.003)	-0.020*** (0.003)	-0.062** (0.031)	-0.010*** (0.002)	-0.033*** (0.003)	0.024 (0.023)	-0.012*** (0.003)	-0.036*** (0.003)	0.106 (0.073)
Occupation	0.023*** (0.006)	0.004 (0.004)	-0.072* (0.042)	0.007*** (0.003)	-0.007*** (0.003)	0.031 (0.023)	0.020*** (0.004)	-0.002 (0.004)	0.018 (0.027)
Industry	0.045*** (0.006)	-0.013*** (0.004)	0.029 (0.024)	0.018*** (0.004)	-0.016*** (0.003)	-0.036** (0.016)	0.025*** (0.007)	0.010** (0.005)	-0.043** (0.018)
Residual	0.004 (0.008)	-0.011* (0.006)	0.000 (0.018)	0.001 (0.005)	-0.020*** (0.005)	-0.053** (0.026)	-0.000 (0.006)	-0.004 (0.008)	-0.115* (0.064)
Coefficients Effects									
Age	0.001 (0.253)	0.571*** (0.170)	-0.563 (0.419)	-0.314* (0.182)	0.583*** (0.131)	0.522 (0.374)	-0.465* (0.271)	0.227* (0.132)	0.996 (0.674)
Marriage	-0.008 (0.005)	0.009** (0.004)	0.007 (0.006)	0.004 (0.003)	0.008*** (0.002)	-0.026* (0.014)	-0.005 (0.006)	-0.004 (0.003)	0.003 (0.016)
Region	-0.020*** (0.005)	-0.008 (0.005)	0.006 (0.007)	-0.012*** (0.003)	-0.007* (0.004)	-0.001 (0.005)	-0.003 (0.005)	-0.001 (0.003)	0.009 (0.010)
Sector	-0.052*** (0.014)	-0.012 (0.012)	-0.056 (0.044)	-0.025*** (0.007)	-0.034*** (0.011)	-0.010 (0.025)	0.014 (0.016)	-0.025** (0.010)	-0.074 (0.061)
Education	0.035** (0.016)	0.062*** (0.015)	0.009 (0.013)	0.036*** (0.008)	0.005 (0.007)	0.037*** (0.014)	-0.014 (0.012)	-0.003 (0.007)	0.044*** (0.017)
Occupation	-0.023 (0.029)	0.041 (0.028)	0.158 (0.103)	0.051*** (0.014)	0.067*** (0.017)	0.047 (0.043)	0.011 (0.011)	0.026*** (0.006)	0.013 (0.031)
Industry	-0.001 (0.019)	-0.012 (0.018)	0.026 (0.032)	0.002 (0.008)	-0.001 (0.010)	0.035 (0.029)	-0.006 (0.021)	-0.042*** (0.012)	-0.004 (0.058)
_cons	0.273 (0.263)	-0.445*** (0.172)	0.479 (0.375)	0.371** (0.182)	-0.446*** (0.132)	-0.542 (0.396)	0.667** (0.274)	-0.045 (0.132)	-0.946 (0.667)
Residual	-0.001 (0.009)	0.014** (0.006)	0.001 (0.016)	-0.001 (0.005)	0.020*** (0.005)	-0.045 (0.037)	0.001 (0.007)	0.006 (0.008)	0.043 (0.057)

Note: In parentheses are bootstrap errors with 50 repetitions. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.3: Decomposition of changes in gender wage differentials at selected quantiles

	2005/2007-1991/1993			2005/2007-1998/2000		
	10 th	50 th	90 th	10 th	50 th	90 th
Total change	-0.046* (0.024)	-0.081*** (0.018)	-0.052* (0.031)	0.089*** (0.016)	-0.017 (0.013)	0.012 (0.028)
Changing Characteristics	-0.042** (0.018)	0.002 (0.014)	-0.069** (0.033)	0.002 (0.014)	0.040*** (0.014)	-0.054* (0.029)
Changing Coefficients	-0.004 (0.023)	-0.082*** (0.018)	0.017 (0.035)	0.087*** (0.018)	-0.057*** (0.015)	0.067** (0.028)
Explained						
Age	-0.000 (0.000)	0.001 (0.001)	0.011 (0.009)	-0.000 (0.001)	-0.001 (0.002)	-0.008 (0.012)
Marriage	-0.001 (0.001)	-0.001 (0.001)	-0.012*** (0.003)	-0.001 (0.001)	-0.000 (0.001)	-0.009*** (0.002)
Region	0.002 (0.002)	0.002 (0.003)	-0.010*** (0.003)	0.004* (0.002)	0.005** (0.002)	-0.003 (0.003)
Sector	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)
Education	0.002 (0.002)	0.002 (0.003)	-0.010*** (0.003)	0.004* (0.002)	0.005** (0.002)	-0.003 (0.003)
Occupation	-0.010*** (0.004)	-0.010** (0.004)	-0.006 (0.011)	-0.011*** (0.003)	-0.013*** (0.003)	-0.026*** (0.009)
Industry	-0.007* (0.004)	-0.004 (0.004)	0.005 (0.011)	-0.010*** (0.003)	-0.011*** (0.004)	-0.020** (0.009)
Reference	-0.014 (0.018)	-0.024** (0.012)	-0.038 (0.025)	-0.019* (0.010)	-0.003 (0.008)	0.042 (0.028)
Residual	-0.015 (0.022)	0.034** (0.015)	-0.008 (0.031)	0.035*** (0.013)	0.057*** (0.014)	-0.028 (0.032)
Unexplained						
Age	-0.480 (0.445)	-0.361 (0.230)	-0.428 (0.638)	-0.157 (0.350)	-0.362** (0.158)	-0.466 (0.606)
Marriage	0.003 (0.009)	-0.013** (0.005)	-0.009 (0.011)	-0.009 (0.006)	-0.012*** (0.004)	-0.017 (0.013)
Region	0.004 (0.017)	-0.004 (0.012)	-0.011 (0.017)	-0.016 (0.013)	0.001 (0.009)	-0.009 (0.022)
Sector	-0.003 (0.012)	-0.001 (0.008)	0.044*** (0.012)	-0.014 (0.011)	0.009 (0.006)	0.020 (0.015)
Education	0.004 (0.017)	-0.004 (0.012)	-0.011 (0.017)	-0.016 (0.013)	0.001 (0.009)	-0.009 (0.022)
Occupation	0.070** (0.031)	-0.056* (0.029)	0.127* (0.072)	0.029 (0.027)	0.007 (0.019)	0.039 (0.074)
Industry	0.074*** (0.027)	-0.029 (0.026)	0.060 (0.074)	0.046* (0.026)	0.006 (0.016)	-0.014 (0.075)
_cons	0.394 (0.444)	0.400* (0.235)	0.467 (0.629)	0.297 (0.353)	0.400** (0.164)	0.404 (0.610)
Reference	0.003 (0.024)	-0.045* (0.024)	0.026 (0.020)	-0.013 (0.008)	0.014** (0.007)	0.067*** (0.021)
Residual	-0.074 (0.083)	0.030 (0.065)	-0.247* (0.126)	-0.059 (0.063)	-0.122*** (0.047)	0.052 (0.118)

Note: In parentheses are bootstrap errors with 50 repetitions. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Figure 2.1: Log gender wage gap over time

Figure 2.2: Gender wage gap across quantiles

Figure 2.3: Decomposition of gender wage gaps

(a) Decomposition of gender wage gaps in 1991/1993

(b) Decomposition of gender wage gaps in 1998/2000

(c) Decomposition of gender wage gaps in 2005/2007

Figure 2.4: Decomposition of change in gender wage gaps

(a) Decomposition of change in gender wage gaps: 2005/2007-1991/1993

(b) Decomposition of change in gender wage gaps: 2005/2007-1998/2000

Table 2.A1: Mean real hourly wage (in 2007 Baht)

	1991/1993		1998/2000		2005/2007	
	Male	Female	Male	Female	Male	Female
Mean	41.487	37.345	50.079	48.323	47.644	44.879
Age group						
25≤age<35	33.448	32.946	39.993	39.865	37.464	37.187
35≤age<45	45.997	42.387	52.262	52.488	46.594	45.369
45≤age<55	57.394	46.510	64.483	63.162	64.387	61.066
55≤age≤65	49.680	31.453	66.553	57.166	59.670	48.678
Education						
No education	19.758	15.610	25.938	21.794	26.048	22.197
Less than primary	26.265	19.183	31.866	29.223	30.584	23.939
Primary	32.744	23.272	31.895	27.058	29.492	23.989
Lower secondary	46.066	38.122	49.907	40.231	37.406	28.807
Upper secondary	45.830	46.672	47.565	41.334	48.906	39.888
Diploma	63.041	61.766	72.945	69.112	62.955	52.806
University	95.852	81.747	108.780	93.934	117.992	95.823
Occupation						
Official/manager	101.066	107.379	106.079	115.819	106.256	125.155
Professional	92.933	81.892	108.068	93.974	121.480	110.006
Assoc. professional	53.631	57.951	91.970	44.872	81.741	64.567
Clerical	59.486	52.228	62.902	52.684	64.695	58.828
Service/sales	40.331	21.812	47.765	29.202	42.037	29.929
Agric. worker	18.213	15.918	23.877	22.298	28.396	28.498
Trades	31.564	21.365	37.181	36.601	34.998	21.468
Operator	33.252	26.618	39.815	28.030	35.574	26.735
Unskilled worker	26.762	21.392	31.019	25.328	27.314	23.829
By industry						
Agric./mining	19.305	15.981	24.951	22.694	28.032	25.215
Manufacturing	38.416	26.162	48.531	40.834	40.982	31.294
Electricity/gas/water	80.571	88.863	93.222	117.911	119.510	122.339
Construction	28.526	20.567	31.966	25.854	34.309	31.081
Sales	42.296	37.476	48.027	43.209	39.846	37.962
Hotels/transportation	51.491	64.612	66.125	78.064	55.487	41.420
Finance	71.895	74.450	79.982	85.301	75.891	75.451
Public admin.	67.780	76.378	75.882	86.841	69.588	74.668
Social work	56.794	61.210	63.608	66.380	86.443	79.190
Other	31.722	19.161	38.445	26.238	29.778	19.216

Table 2.A2 (a): Coefficients of unconditional quantile regressions: 1991/1993 (Standard errors in parentheses)

	10 th percentile				50 th percentile				90 th percentile			
	Male		Female		Male		Female		Male		Female	
Age	0.023***	(0.008)	0.030***	(0.010)	0.046***	(0.005)	0.023***	(0.007)	0.067***	(0.008)	0.099***	(0.007)
Age squared	-0.030***	(0.010)	-0.048***	(0.013)	-0.048***	(0.006)	-0.029***	(0.008)	-0.042***	(0.010)	-0.086***	(0.008)
Married	0.033	(0.023)	0.083***	(0.022)	0.082***	(0.015)	0.026	(0.016)	0.174***	(0.022)	0.133***	(0.019)
Urban	0.040***	(0.015)	0.087***	(0.021)	0.117***	(0.013)	0.124***	(0.018)	0.049**	(0.023)	0.036	(0.025)
Private	-0.342***	(0.029)	-0.147***	(0.026)	-0.459***	(0.026)	-0.414***	(0.035)	-0.716***	(0.067)	-0.509***	(0.058)
Less than prim	0.250***	(0.084)	0.185***	(0.067)	0.132***	(0.029)	0.102***	(0.035)	0.132***	(0.035)	0.111***	(0.019)
Primary	0.413***	(0.089)	0.314***	(0.081)	0.304***	(0.037)	0.355***	(0.055)	0.405***	(0.046)	0.330***	(0.033)
Lower sec.	0.446***	(0.086)	0.485***	(0.075)	0.367***	(0.036)	0.556***	(0.055)	0.450***	(0.048)	0.285***	(0.039)
Upper sec.	0.482***	(0.091)	0.556***	(0.076)	0.385***	(0.043)	0.587***	(0.060)	0.451***	(0.058)	0.426***	(0.058)
Diploma	0.536***	(0.086)	0.522***	(0.075)	0.565***	(0.039)	0.722***	(0.054)	0.725***	(0.062)	0.495***	(0.059)
University	0.625***	(0.088)	0.480***	(0.076)	0.665***	(0.039)	0.721***	(0.054)	1.362***	(0.070)	0.715***	(0.054)
Official/manager	-0.586***	(0.058)	-0.291***	(0.060)	0.104***	(0.036)	0.246***	(0.057)	1.466***	(0.080)	1.457***	(0.111)
Professional	-0.183***	(0.033)	-0.155***	(0.046)	0.356***	(0.032)	0.390***	(0.054)	1.065***	(0.069)	0.838***	(0.059)
Assoc. prof.	0.022	(0.074)	-0.151	(0.217)	0.392***	(0.114)	0.527***	(0.190)	0.354*	(0.208)	1.560***	(0.400)
Clerical	-0.129***	(0.032)	-0.177***	(0.042)	0.382***	(0.030)	0.330***	(0.049)	0.221***	(0.050)	0.057	(0.044)
Serv./sale worker	-0.204***	(0.036)	-0.546***	(0.057)	0.085***	(0.030)	-0.081*	(0.044)	0.049	(0.033)	0.047	(0.035)
Agric. worker	-0.473***	(0.073)	-0.024	(0.076)	-0.118**	(0.050)	-0.151	(0.114)	0.138***	(0.046)	0.144	(0.122)
Trades operators	-0.040	(0.031)	-0.279***	(0.034)	0.239***	(0.025)	0.084**	(0.040)	0.065**	(0.027)	0.009	(0.027)
Agric/mining	-0.131***	(0.036)	-0.099*	(0.060)	0.205***	(0.028)	0.172**	(0.069)	-0.005	(0.030)	0.025	(0.046)
Manufacturing	-0.229***	(0.078)	0.326***	(0.088)	0.041	(0.056)	0.307***	(0.119)	0.050	(0.060)	-0.047	(0.123)
Elec./gas/water	0.111**	(0.047)	0.399***	(0.053)	0.102***	(0.038)	0.418***	(0.047)	0.146***	(0.048)	0.102***	(0.039)
Construction	-0.062	(0.055)	0.428***	(0.061)	-0.017	(0.056)	0.276***	(0.086)	0.215*	(0.120)	0.384**	(0.166)
Sales	0.348***	(0.049)	0.798***	(0.057)	0.024	(0.040)	0.102*	(0.053)	0.107**	(0.047)	0.119***	(0.041)
Hotels/transpt.	0.104**	(0.051)	0.420***	(0.058)	0.102***	(0.039)	0.344***	(0.042)	0.110**	(0.048)	0.150***	(0.039)
Finance	-0.118**	(0.057)	0.381***	(0.064)	-0.053	(0.043)	0.263***	(0.068)	0.174***	(0.060)	0.134	(0.091)
Public admin.	0.129***	(0.049)	0.483***	(0.050)	0.204***	(0.041)	0.541***	(0.050)	0.035	(0.074)	0.310***	(0.074)
Social work	-0.049	(0.053)	0.443***	(0.056)	0.107**	(0.044)	0.416***	(0.054)	-0.688***	(0.080)	-0.253***	(0.067)
Central	0.013	(0.064)	0.447***	(0.057)	0.160***	(0.051)	0.442***	(0.057)	-0.642***	(0.094)	-0.478***	(0.078)
North	-0.040**	(0.016)	-0.018	(0.020)	-0.167***	(0.016)	-0.188***	(0.020)	-0.104***	(0.029)	-0.077***	(0.026)
Northeast	-0.319***	(0.024)	-0.395***	(0.032)	-0.526***	(0.017)	-0.509***	(0.023)	-0.165***	(0.031)	-0.203***	(0.029)
South	-0.395***	(0.024)	-0.453***	(0.034)	-0.481***	(0.017)	-0.452***	(0.024)	-0.159***	(0.031)	-0.157***	(0.031)
_cons	0.077***	(0.023)	-0.054*	(0.030)	-0.243***	(0.022)	-0.342***	(0.029)	-0.211***	(0.034)	-0.132***	(0.037)
	2.164***	(0.184)	1.435***	(0.215)	2.298***	(0.115)	2.441***	(0.143)	2.562***	(0.176)	1.980***	(0.159)

Table 2.A2 (b): Coefficients of unconditional quantile regressions: 1998/2000 (Standard errors in parentheses)

	10 th percentile		50 th percentile		90 th percentile	
	Male	Female	Male	Female	Male	Female
Age	0.017*** (0.005)	0.040*** (0.008)	0.044*** (0.004)	0.020*** (0.005)	0.077*** (0.008)	0.101*** (0.010)
Age squared	-0.020*** (0.006)	-0.057*** (0.010)	-0.044*** (0.005)	-0.022*** (0.006)	-0.044*** (0.010)	-0.069*** (0.012)
Married	0.039*** (0.014)	0.018 (0.015)	0.040*** (0.013)	-0.005 (0.012)	0.084*** (0.026)	-0.002 (0.029)
Urban	0.043*** (0.008)	0.081*** (0.014)	0.110*** (0.010)	0.132*** (0.011)	0.059*** (0.018)	0.087*** (0.022)
Private	-0.179*** (0.021)	-0.090*** (0.015)	-0.339*** (0.023)	-0.215*** (0.022)	-0.403*** (0.069)	-0.444*** (0.071)
Less than prim	0.186*** (0.058)	0.169*** (0.054)	0.031 (0.031)	0.080*** (0.026)	0.031 (0.035)	0.157*** (0.023)
Primary	0.223*** (0.060)	0.246*** (0.059)	0.126*** (0.034)	0.099*** (0.032)	0.537*** (0.042)	0.575*** (0.039)
Lower sec.	0.330*** (0.059)	0.441*** (0.059)	0.301*** (0.034)	0.323*** (0.036)	0.459*** (0.045)	0.441*** (0.045)
Upper sec.	0.362*** (0.062)	0.519*** (0.059)	0.351*** (0.039)	0.428*** (0.044)	0.568*** (0.052)	0.461*** (0.047)
Diploma	0.417*** (0.059)	0.495*** (0.058)	0.545*** (0.037)	0.627*** (0.040)	0.690*** (0.060)	0.611*** (0.065)
University	0.490*** (0.060)	0.458*** (0.059)	0.684*** (0.036)	0.685*** (0.039)	1.364*** (0.064)	0.845*** (0.067)
Official/manager	-0.440*** (0.037)	-0.138*** (0.038)	-0.002 (0.030)	0.341*** (0.037)	1.158*** (0.073)	1.178*** (0.113)
Professional	-0.102*** (0.022)	-0.061* (0.032)	0.254*** (0.025)	0.382*** (0.034)	0.986*** (0.065)	0.799*** (0.061)
Assoc. prof.	-0.074 (0.053)	0.015 (0.113)	0.140 (0.099)	0.651*** (0.121)	0.848*** (0.317)	0.815*** (0.100)
Clerical	-0.011 (0.021)	-0.067** (0.031)	0.358*** (0.027)	0.341*** (0.034)	0.037 (0.045)	0.046 (0.043)
Service/sales	-0.132*** (0.025)	-0.279*** (0.040)	0.052** (0.025)	-0.013 (0.032)	0.066** (0.033)	0.086*** (0.029)
Agric. worker	-0.191*** (0.046)	0.056 (0.073)	-0.115*** (0.034)	-0.054 (0.066)	0.103** (0.042)	0.067 (0.065)
Trades	0.063*** (0.020)	-0.196*** (0.028)	0.168*** (0.021)	0.035 (0.028)	0.055** (0.025)	0.328*** (0.040)
operators	-0.030 (0.022)	0.065 (0.045)	0.177*** (0.025)	0.015 (0.046)	-0.015 (0.033)	0.027 (0.039)
Agric/mining	-0.164*** (0.050)	0.272*** (0.078)	0.103** (0.040)	0.251*** (0.068)	0.140** (0.058)	0.228*** (0.071)
Manufacturing	0.078*** (0.029)	0.388*** (0.037)	0.121*** (0.032)	0.284*** (0.033)	0.226*** (0.051)	0.234*** (0.045)
Elec./gas/water	-0.017 (0.040)	0.384*** (0.042)	0.018 (0.050)	0.221*** (0.057)	0.756*** (0.140)	0.848*** (0.189)
Construction	0.206*** (0.031)	0.594*** (0.048)	-0.027 (0.033)	0.133*** (0.039)	0.129*** (0.050)	0.225*** (0.042)
Sales	0.047 (0.032)	0.342*** (0.041)	0.072** (0.034)	0.167*** (0.029)	0.198*** (0.054)	0.138*** (0.038)
Hotels/transpt.	-0.060* (0.036)	0.303*** (0.046)	0.013 (0.039)	0.121*** (0.040)	0.330*** (0.069)	0.145 (0.112)
Finance	0.091*** (0.035)	0.406*** (0.037)	0.093** (0.038)	0.252*** (0.036)	0.176** (0.073)	0.312*** (0.077)
Public admin.	0.018 (0.034)	0.444*** (0.037)	0.162*** (0.038)	0.270*** (0.035)	-0.426*** (0.081)	-0.203*** (0.073)
Social work	0.046 (0.046)	0.423*** (0.039)	0.131*** (0.044)	0.208*** (0.037)	-0.379*** (0.096)	-0.466*** (0.093)
Central	-0.035*** (0.010)	-0.037** (0.016)	-0.160*** (0.016)	-0.123*** (0.017)	-0.230*** (0.039)	-0.443*** (0.045)
North	-0.254*** (0.015)	-0.396*** (0.025)	-0.409*** (0.018)	-0.361*** (0.018)	-0.212*** (0.040)	-0.462*** (0.044)
Northeast	-0.240*** (0.014)	-0.350*** (0.024)	-0.426*** (0.017)	-0.394*** (0.018)	-0.303*** (0.039)	-0.471*** (0.044)
South	-0.021 (0.014)	-0.090*** (0.025)	-0.165*** (0.020)	-0.210*** (0.021)	-0.292*** (0.042)	-0.504*** (0.045)
_cons	2.344*** (0.113)	1.574*** (0.164)	2.449*** (0.101)	2.606*** (0.110)	2.124*** (0.195)	1.838*** (0.224)

Table 2.A2 (c): Coefficients of unconditional quantile regressions: 2005/2007 (Standard errors in parentheses)

	10 th percentile		50 th percentile		90 th percentile	
	Male	Female	Male	Female	Male	Female
Age	0.021** (0.008)	0.048*** (0.012)	0.031*** (0.005)	0.022*** (0.005)	0.108*** (0.014)	0.152*** (0.014)
Age squared	-0.024** (0.010)	-0.062*** (0.015)	-0.027*** (0.006)	-0.020*** (0.006)	-0.052*** (0.017)	-0.097*** (0.017)
Married	0.013 (0.022)	0.044* (0.025)	0.011 (0.014)	0.032*** (0.012)	0.212*** (0.045)	0.222*** (0.039)
Urban	0.046*** (0.014)	0.158*** (0.021)	0.069*** (0.011)	0.050*** (0.012)	0.143*** (0.036)	-0.024 (0.037)
Private	-0.267*** (0.026)	-0.315*** (0.038)	-0.332*** (0.023)	-0.247*** (0.023)	-0.707*** (0.116)	-0.963*** (0.099)
Less than prim	0.189** (0.079)	0.412*** (0.099)	0.032 (0.035)	0.051 (0.035)	-0.390*** (0.074)	-0.345*** (0.070)
Primary	0.270*** (0.080)	0.512*** (0.105)	0.096*** (0.035)	0.104*** (0.036)	0.497*** (0.079)	0.489*** (0.075)
Lower sec.	0.341*** (0.080)	0.652*** (0.112)	0.205*** (0.037)	0.208*** (0.040)	0.435*** (0.083)	0.565*** (0.087)
Upper sec.	0.429*** (0.081)	0.731*** (0.114)	0.339*** (0.038)	0.362*** (0.041)	0.687*** (0.091)	0.573*** (0.086)
Diploma	0.452*** (0.080)	0.779*** (0.119)	0.489*** (0.042)	0.520*** (0.045)	1.051*** (0.118)	0.651*** (0.119)
University	0.495*** (0.081)	0.776*** (0.120)	0.569*** (0.040)	0.617*** (0.043)	2.624*** (0.141)	1.521*** (0.116)
Official/manager	0.016 (0.049)	0.043 (0.072)	0.181*** (0.034)	0.350*** (0.044)	1.799*** (0.139)	2.220*** (0.251)
Professional	0.062* (0.033)	0.066 (0.055)	0.279*** (0.029)	0.343*** (0.033)	1.695*** (0.174)	1.789*** (0.129)
Assoc. prof.	0.158*** (0.031)	0.009 (0.067)	0.378*** (0.025)	0.404*** (0.031)	0.581*** (0.131)	0.411*** (0.093)
Clerical	0.178*** (0.035)	0.085 (0.052)	0.310*** (0.029)	0.367*** (0.031)	0.188* (0.107)	0.099 (0.075)
Serv./sale worker	0.040 (0.049)	0.026 (0.060)	0.062** (0.029)	0.116*** (0.027)	0.069 (0.081)	-0.077 (0.055)
Agri. worker	0.142** (0.058)	0.308*** (0.081)	0.025 (0.028)	0.216*** (0.035)	-0.038 (0.045)	-0.012 (0.058)
Trades	0.216*** (0.029)	-0.566*** (0.061)	0.212*** (0.020)	-0.036 (0.026)	-0.025 (0.050)	0.090 (0.061)
operators	0.165*** (0.035)	0.220*** (0.044)	0.160*** (0.021)	0.053* (0.029)	-0.040 (0.046)	0.146** (0.067)
Agric/mining	-0.226 (0.157)	0.185* (0.109)	-0.008 (0.125)	0.259*** (0.042)	0.287** (0.146)	0.210*** (0.057)
Manufacturing	0.133 (0.151)	0.379*** (0.098)	-0.080 (0.125)	0.243*** (0.040)	0.173 (0.142)	0.074 (0.066)
Electr./gas/water	-0.025 (0.160)	0.195 (0.145)	-0.034 (0.132)	0.119* (0.068)	1.623*** (0.315)	1.245** (0.490)
Construction	0.325** (0.152)	0.883*** (0.099)	0.020 (0.125)	0.297*** (0.045)	0.233 (0.147)	0.228*** (0.068)
Sales	0.070 (0.153)	0.222** (0.108)	-0.016 (0.125)	0.223*** (0.040)	0.123 (0.146)	0.162*** (0.061)
Hotels/transpt.	-0.033 (0.154)	0.205* (0.109)	-0.026 (0.127)	0.160*** (0.041)	0.282* (0.155)	0.325*** (0.076)
Finance	0.095 (0.153)	0.395*** (0.097)	-0.022 (0.127)	0.300*** (0.042)	0.146 (0.167)	0.520*** (0.108)
Public admin.	-0.000 (0.153)	0.188* (0.104)	-0.031 (0.127)	0.230*** (0.046)	-1.043*** (0.197)	-0.794*** (0.145)
Social work	0.097 (0.153)	0.225** (0.107)	-0.017 (0.127)	0.266*** (0.043)	-0.245 (0.205)	-0.373*** (0.085)
Central	-0.075*** (0.014)	-0.066*** (0.021)	-0.144*** (0.017)	-0.113*** (0.017)	-0.147** (0.071)	-0.411*** (0.058)
North	-0.279*** (0.026)	-0.308*** (0.037)	-0.350*** (0.020)	-0.250*** (0.020)	-0.206*** (0.078)	-0.490*** (0.065)
Northeast	-0.353*** (0.025)	-0.482*** (0.039)	-0.392*** (0.020)	-0.298*** (0.020)	-0.323*** (0.074)	-0.460*** (0.066)
South	-0.090*** (0.023)	-0.181*** (0.037)	-0.187*** (0.022)	-0.181*** (0.022)	-0.400*** (0.081)	-0.579*** (0.070)
_cons	2.232*** (0.235)	1.168*** (0.264)	2.746*** (0.162)	2.429*** (0.113)	0.930*** (0.353)	0.520 (0.336)

Figure 2.A: Coefficients effects over time

CHAPTER THREE

Discrimination in the Equilibrium Search Model with Wage-Tenure Contracts³²

3.1 Introduction

Race and gender differentials in the labor market are persistent and widespread. The black-white pay gap in the US has remained around 20% since the mid-1970s (Altonji and Blank, 1999). Even after controlling for human capital and other factors, blacks still earn about 10% less than whites on average (Lang and Lehmann, 2010).³³ In addition to wage differentials, blacks have historically higher unemployment rates and longer unemployment duration (Fairlie and Sundstrom, 1999). Similar stylized facts are also found in the gender literature. A series of papers by Blau and Kahn (2000, 2003, 2006) finds that the gender pay gap in the US has stayed roughly constant at 25% since the mid-1990s; they also find that on average, there is a 0.3 log-point differential for 22 countries examined over the 1985-94 period. Gender differences in unemployment are also widely observed. For example, Azmat, Guell and Manning (2006) document a large gender gap in unemployment rates in many OECD countries.³⁴ Du and Dong (2009) find longer unemployment durations for women in post-restructuring urban China while Ollikainen (2003) observes longer duration for men in Finland.

³² This chapter has been presented in 3rd EALE/SOLE joint conference in London and 2010 ESWC in Shanghai. Special thanks go to Professor Audra Bowlus for providing us the data.

³³ Neal and Johnson (1996) find the unexplained wage gap between blacks and whites is significantly narrowed, or even disappears in some subgroups after controlling for AFQT. However, other researchers find wage differentials re-emerge when years of schooling are further controlled with AFQT (Rodgers and Spriggs, 1996).

³⁴ Altonji and Blank (1999), however, find the unemployment among women has been as low as or lower than that among men since the early 1980s. Participation rates, on the other hand, are historically lower among women. Therefore, when it comes to the overall rate of non-employment, it is always higher among women.

One possible explanation for these race and gender differences in labor market outcomes is the presence of differences in endowments of characteristics related to productivity and preferences. The unexplained part, on the other hand, is either due to unobserved productivity skills or discrimination in the labor market. However, distinguishing between the two effects is far from straightforward. Recently, Bowlus and Eckstein (2002) developed an equilibrium search model and separately identified discrimination from unobserved productivity differences because each factor affects the earnings distribution differently. Using a sample of male high school graduates, they find that blacks produce 3.3% less than whites, and 56% of firms in the labor market have a prejudice against blacks, and that the distaste is as high as 31% of the productivity of whites. In a study of gender discrimination, Flabbi (2010) uses maximum likelihood estimation in a search framework with matching and bargaining and concludes that female workers are 6.5% less productive than male workers and that half of employers discriminate against women. This chapter, built on the framework of search model with wage-tenure contracts (see for example, Burdett and Coles, 2003), is able to empirically distinguish discrimination from unobserved productivity differences, and at the same time touches on wage-tenure profiles. Few papers on discrimination theory have attempted to generate predictions in this regard.³⁵

In what follows, we will outline a discrimination search model with wage-tenure contracts and describe equilibrium results. To discuss the effect of discrimination on

³⁵ The positive effect of tenure on wages has been identified in many studies (Altonji and Shakotko, 1987; Topel, 1991; Altonji and Williams, 2005). However, there is competing empirical evidence on gender disparity in wage returns to tenure/experience. Some find that the overall wage return to tenure/experience is lower for women than men (Light and Ureta, 1995; Munasinghe et al., 2008), while others find steeper wage-tenure profiles for women than men (Becker and Lindsay, 1994; Hersch and Reagan, 1997). The difference in returns to tenure between races is found to be insignificant in Bratsberg and Terrell (1998) and the returns to actual experience lower for blacks.

labor market outcomes, we introduce two types of workers and firms: (1) majority workers A and minority workers B ; (2) discriminating firms D and non-discriminating firms N .³⁶ Workers are assumed to be identical except for their appearance. Firms who experience a disutility from hiring minority workers recruit them at a slower rate. So, for type A workers firms are homogenous while for type B workers they are heterogeneous. In this study, discrimination is associated with 3 parameters: the fraction of D -firms, the degree of recruiting discrimination and the disutility taste D -firms have when hiring B -workers, all of which are assumed to be exogenously determined. Our model belongs to a class of random search models. Firms post tenure-based contracts for both types of workers, recruit workers and pay wages specified in the contracts. Workers, both unemployed and employed search for jobs randomly, accept the offers which arrive at an exogenous rate if and only if the expected lifetime value from the new offer is higher than the current one. Firms cannot fire workers or counter-offer workers' outside offers.

In equilibrium, the optimal contract for B workers provided by N -firms is uniformly better than that provided by D -firms. Though by offering a higher tenure-wages profile, the N -firm extracts a lower profit from each B worker, it can hire more B workers who are willing to stay for a longer period so that the total profit B workers have created in the N firm exceeds that in a D firm. In addition, since both firms make the same profit from type A workers, the total profit is also higher for N firms than D firms.

The second finding of the discrimination search model with wage-tenure contracts concerns the relationship between the discrimination associated parameters and wage ranges for minority workers. It proves that, the fewer D firms are in the labor market, the

³⁶One can view majority and minority workers as male and female in the context of gender, or white and black in the context of race.

higher the minimum wage and the lower the maximum wage B workers can expect in D firms. Similarly, the more severe the recruiting discrimination or distaste D firms hold, the higher the lower bound and the lower the upper bound for wages in D firms. The maximum wage in N -firms, is negatively related to all three parameters.

We also find that the lowest wage A workers are willing to accept is smaller than a B worker's lowest acceptable wage and both lowest wages are smaller than the unemployment insurance. This is because A workers can expect a faster wage increase and a larger probability of receiving a new offer than B workers and at the same time, both types of employed workers get a wage promotion that the unemployed do not get. The sign of the mean wage gap between type A and B workers, however, is uncertain. If D firms don't hire any B workers, it is shown that the average A worker earns more than the average B worker while in a general case, the fraction of discriminating firms and their distaste towards minority workers have to be large enough to generate the stylized average wage gap.

Subsequently, we show that in a special case of a CRRA utility function with the coefficient approaching zero, the model degenerates to a simplified version of Bowlus and Eckstein (2002) and has certain similar implications. How the average wage is affected by the discrimination-related parameters is next illustrated in the numerical example, where we also simulate the profile of wage dynamics for both types of workers. It is found that, the wage-tenure effect is positive and it is steeper for A workers than B worker in most cases.

Applying the search discrimination model with wage-tenure contracts using a sample of male high school graduates in 1985-88, we find that the productivity of blacks

is 3% lower than that of whites and that 91% of firms in the labor market possess a distaste against blacks which is as high as 71% of the productivity of whites. In a second application using white high school graduates, we find that the gender difference in productivity is 3% and there are 93% of firms with a strong distaste against female workers which is about 95% of men's productivity. We compare the empirical hourly wage increase over a year with the predicted profiles and observe a certain correspondence between the two.

The contribution of this study is the development of a discrimination search model with wage-tenure contracts that, among other things, generates race/gender differences in unemployment rates, durations of unemployment, and wage dynamics. In the theoretical literature on labor market discrimination, the taste-based theory of discrimination (Becker, 1971) and statistical discrimination (Aigner and Cain, 1977) are often subject to criticism on the grounds that discrimination cannot be sustained in the long run.³⁷ Taste discrimination models within a search framework, on the other hand, are very promising in explaining persistent wage differentials (Altonji and Blank, 1999). An early example is Black (1995) who studied discrimination in an equilibrium search model. In that paper, cost is introduced in job search processes and discriminating firms are assumed to hire only majority workers. He shows in the model that the wage minority workers receive is lower than the wage of their majority counterparts and the wage differential increases with the proportion of minority workers in the labor market. In a similar line of research, Bowlus and Eckstein (2002), by allowing for on-the-job search, construct a discrimination search model that generates wage dispersion among equally

³⁷See Cain (1986) for a good review on the classic theories, Lang and Lehmann (2010) and Charles and Guryan (2011) for a recent review on progresses in both theories and empirics on race discrimination.

productive workers (see also Burdett and Mortensen, 1998). Moreover, they are able to distinguish the skill differences and discrimination in explaining the residual wage differentials between races. This study follows the assumption of on-the-job search, but replaces the constant wage assumption with wage-tenure contracts which was first introduced in Burdett and Coles (2003). It allows for the possibility to predict differences in wage-tenure profiles.

The next section sets up the model and discusses workers' and firms' optimal decisions. Section 3 characterizes the equilibrium solutions and section 4 shows the equilibrium properties. In section 5, we show in a special case, that the optimal wage-tenure contracts degenerate to a constant wage and our discrimination search model with wage-tenure contracts degenerates to a variant of Bowlus and Eckstein (2002). Further, to facilitate comparisons of average wages and their dynamics, we carry out a numerical exercise in section 6. Sections 7 and 8 put the model to data and estimate the race/gender differences in productivity and race/gender discrimination in the labor market. Finally, section 9 concludes and points out promising future research. All proofs are given in the appendix.

3.2 The model

3.2.1 The environment

Consider an economy consisting of two types of workers and firms. The total work force is n , of which the majority workers (type A) are $(1 - \theta)n$ and the minority workers (type B) are θn . Among all the firms in the labor market, a fraction σ has a distaste for minority workers, denoted by D ; and $(1 - \sigma)$ are non-discriminating firms denoted by N .

Workers are assumed to be equally productive (productivity level P), and have utility function $u(w)$, where $u' > 0, u'' < 0$. They are finitely lived, with a death rate δ . To balance the population, it's assumed that birth rate equals death rate and the newly born people enter the labor force immediately as unemployed. Unemployed workers can obtain an insurance compensation b per instant. Workers--both employed and unemployed--search for better opportunities to maximize their expected lifetime utility.

On the other hand, a firm posts a wage-tenure contract and hires workers to maximize its profit. The wage-tenure contract is denoted by $w(t)$, where t denotes tenure—the duration a worker stays in the firm. Suppose the offer arrival rate is λ for A -workers, both employed and unemployed; while for B -workers, it depends on the type of firm the offer originates from. If it is from N firms, the arrival rate is still λ ; if it is from D firms, the offer arrival rate is $(1 - k)\lambda$, where $k \in (0,1)$ reflects the degree of recruiting discrimination.³⁸ The larger k is, the more severe the discrimination. D firms experience a disutility d from hiring B workers, which enters the profit function directly. Therefore, the instantaneous profit from a B worker who has stayed in the D firm for a duration t is: $P - w_B^D(t) - d$. In addition, assume firms cannot fire workers but workers can quit for a better job without suffering any punishment from the previous employer. Time preferences of workers and firms are zero and there are no recalls in the process.

³⁸Parameter k can also be interpreted as indicating the difference in search intensity. Therefore, it only reflects the degree of recruiting discrimination when we assume both types of workers exert the same level of effort in looking for jobs. Indeed, the existence of recruiting discrimination against minority workers such as blacks and women is widely documented (see, for example, Goldin and Rouse, 2000; Bertrand and Mullainathan, 2004; and Pager et al., 2009).

3.2.2 Workers' optimal decision

Let $V_i(t|\widetilde{w}_i^j)$ be the expected lifetime utility of a type i ($i = A, B$) worker who has tenure t under the wage-tenure contract $\widetilde{w}_i^j$ and uses an optimal quit strategy in the future. The term $\widetilde{w}_i^j$ denotes the wage-tenure contract a type i worker has signed with firm j ($j = D, N$). $F_A(V_0)$, $F_B^N(V_0)$ and $F_B^D(V_0)$ are the offer distributions for A and B where superscripts N , D denote non-discriminating and discriminating firms and V_0 is the starting expected lifetime value of the offer. Thus, the offer distribution measures the proportion of firms who provide workers a starting offer value no greater than V_0 . Since all firms treat A the same, there is no difference in the offer distributions for A provided by N or D firms. Let $\underline{V}_A(\overline{V}_A)$ denote the infimum (supremum) of the support of F_A and $\underline{V}_B^j(\overline{V}_B^j)$ the infimum (supremum) of the support of F_B^j where $j = N, D$.

First consider the situation of employed workers. The standard Bellman equations for employed type A and type B workers are:

$$0 = u(w_A(t)) - \delta V_A(t|\widetilde{w}_A) + \lambda \int_{V_A(t|\widetilde{w}_A)}^{\overline{V}_A} [V_0 - V_A(t|\widetilde{w}_A)] dF_A(V_0) + \frac{dV_A(t|\widetilde{w}_A)}{dt} \quad (1a)$$

$$0 = u(w_B(t)) - \delta V_B(t|\widetilde{w}_B^j) + (1 - \sigma)\lambda \int_{V_B(t|\widetilde{w}_B^j)}^{\overline{V}_B^N} \max\{0, [V_0 - V_B(t|\widetilde{w}_B^j)]\} dF_B^N(V_0) + \sigma(1 - k)\lambda \int_{V_B(t|\widetilde{w}_B^j)}^{\overline{V}_B^D} \max\{0, [V_0 - V_B(t|\widetilde{w}_B^j)]\} dF_B^D(V_0) + \frac{dV_B(t|\widetilde{w}_B^j)}{dt} \quad (1b)$$

Note that, an A worker receives an offer at rate λ , whereas a B worker has a probability of $(1 - \sigma)\lambda$ receiving an offer from N firms and a probability of $\sigma(1 - k)\lambda$ receiving an offer from D firms. The optimal quit strategy implies that they will quit and

accept the new offer if and only if its starting value is greater than the current value.³⁹

The last term in both equations calculates the instantaneous change in the expected lifetime value.

Similarly, we can get the Bellman equations for unemployed workers of both types:

$$0 = u(b) - \delta V_{AU} + \lambda \int_{V_{AU}}^{\bar{V}_A} [V_0 - V_{AU}] dF_A(V_0) \quad (2a)$$

$$\begin{aligned} 0 = & u(b) - \delta V_{BU} + (1 - \sigma) \lambda \int_{V_{BU}}^{\bar{V}_B^N} [V_0 - V_{BU}] dF_B^N(V_0) \\ & + \sigma(1 - k) \lambda \int_{V_{BU}}^{\bar{V}_B^D} [V_0 - V_{BU}] dF_B^D(V_0) \end{aligned} \quad (2b)$$

The expected lifetime value of an offer from firms should be no less than the unemployed lifetime value V_U ; otherwise, no worker would be hired. Therefore, $\underline{V}_A \geq V_{AU}$ and $\underline{V}_B^j \geq V_{BU}$ ($j = D, N$).

3.2.3 Firms' optimal decision

The optimization problem faced by a firm is to choose two wage-tenure contracts, one for A workers and the other for B workers, to maximize the total expected profit at the steady state. To begin with, we need to derive the expressions of total expected profit for each firm.

Since the quit rate of a type A worker who has stayed t periods under the wage-tenure contract $w_A(t)$ is $\lambda(1 - F_A(V_A(t|\widetilde{w}_A)))$, the survival probability of such a worker is:

$$\psi_A(t|\widetilde{w}_A) \triangleq \exp \left\{ - \int_0^t \left[\delta + \lambda \left(1 - F_A(V_A(s|\widetilde{w}_A)) \right) \right] ds \right\}. \quad (3a)$$

Similarly, the survival probability of worker B is:

³⁹Since the relationship between the current expected lifetime value and the supremum of offers from $N(D)$ -firm is not clear yet, the maximum of zero and instantaneous change that occurs when the worker accepts the offer ensures the non-negativity and economic meaning. Intuitively, the current value should always be smaller than $\bar{V}_B^N$, which means the first *max* is trivial; however, it may or may not be smaller than $\bar{V}_B^D$ which makes the second *max* indispensable.

$$\psi_B(t|\widetilde{w}_B^J) \triangleq \exp\left\{-\int_0^t \left\{\delta + (1-\sigma)\lambda \left[1 - F_B^N\left(V_B(s|\widetilde{w}_B^J)\right)\right] + \sigma(1-k)\lambda \left[1 - F_B^D\left(V_B(s|\widetilde{w}_B^J)\right)\right]\right\} ds\right\} \quad (3b)$$

Let $G_A(V)$ denote the steady state proportion of A workers who have an expected lifetime utility less than or equal to V (including the unemployed); and correspondingly, $G_B(V)$ for worker B . Thus, at the steady state, a firm posting an offer V can recruit $[\lambda G_A(V)(1-\theta)n]$ A workers and $\lambda G_B(V)\theta n$ (if N -firm) or $\lambda(1-k)G_B(V)\theta n$ (if D firm) B workers. The steady state profits of N and D firms are then functions of the wage-tenure contracts:

$$\begin{aligned} \Omega^N(V_0^A, V_0^B) &= \lambda G_A(V_0^A)(1-\theta)n \int_0^\infty \psi_A(t|\widetilde{w}_A)[P - w_A(t)] dt \\ &\quad + \lambda G_B(V_0^B)\theta n \int_0^\infty \psi_B(t|\widetilde{w}_B^N)[P - w_B^N(t)] dt \end{aligned} \quad (4a)$$

$$\begin{aligned} \Omega^D(V_0^A, V_0^B) &= \lambda G_A(V_0^A)(1-\theta)n \int_0^\infty \psi_A(t|\widetilde{w}_A)[P - w_A(t)] dt \\ &\quad + \lambda(1-k)G_B(V_0^B)\theta n \int_0^\infty \psi_B(t|\widetilde{w}_B^D)[P - w_B^D(t) - d] dt \end{aligned} \quad (4b)$$

In each equation, the first part is the profit from A and the second part is the profit from B . The integration calculates the expected profit that each worker brings to the firm; the part before the integration measures the steady state number of workers hired at given offers. So, the multiplication reflects the firms' expected profit from each type of worker. As both firms treat A equally, profit earned from A is the same between firms in equilibrium.

To derive the optimal decisions of firms, we need to solve the profit maximization problems. Due to additivity, we can solve separately for A ; B in N firms and B in D firms. Each sub-problem can be solved in two steps:

- (i) Conditional on the offer chosen, the optimal wage-tenure contract solves:

$$\begin{aligned}
& \text{Max}_{w_i^j(t)} \int_0^\infty \psi_i(t|\widetilde{w}_i^j) [P - w_i^j(t)] dt \\
& \text{s.t } \psi_i(t|\widetilde{w}_i^j) \text{ satisfies (3)} \\
& \quad V_i(t|\widetilde{w}_i^j) \text{ satisfies (1)} \\
& \text{and, } \psi_i(0|\widetilde{w}_i^j) = 1; V_i(0|\widetilde{w}_i^j) = V_0^{ij}.
\end{aligned}$$

(ii) The optimal offer solves:

$$\begin{aligned}
& \text{Max}_{V_0^{ij}} G_i(V_0^{ij}) \int_0^\infty \psi_i(t|\widetilde{w}_i^j) [P - w_i^j(t)] dt \\
& \text{s.t } w_i^j(t) \text{ solves (i)}
\end{aligned}$$

where $i = A, B; j = N, D$.

When it comes to type B workers in D firms, the disutility taste d should be further subtracted from $P - w_i(t)$.

3.3 Equilibrium

Since worker A faces homogenous firms in the labor market, the market equilibrium outcomes for this sub-problem are exactly the same as specified in Burdett and Coles (2003). To solve for the steady state equilibrium for worker B , we first show in proposition 1 that the optimal offer for B provided by D firms is uniformly smaller than that provided by N -firms.

Proposition 1: Let V_{0N}^B denote the optimal offer for B given by N -firms and V_{0D}^B the optimal offer provided by D firms; then we have $V_{0N}^B \geq V_{0D}^B$.

Proposition 1 simplifies the subsequent analysis substantially.⁴⁰ As $V_{0N}^B \geq V_{0D}^B$, equations (1b) and (3b) can be rewritten for B in N and D firms separately. Specifically, the Bellman equation for B workers working in N firms is reduced to:

$$0 = u(w_B^N(t)) - \delta V_B^N(t|\widetilde{w}_B^N) + (1 - \sigma)\lambda \int_{V_B^N(t|\widetilde{w}_B^N)}^{\overline{V}_B^N} [V_0 - V_B^N(t|\widetilde{w}_B^N)] dF_B^N(V_0) + \frac{dV_B^N(t|\widetilde{w}_B^N)}{dt} \quad (5)$$

For those working in D firms the Bellman equation becomes:

$$0 = u(w_B^D(t)) - \delta V_B^D(t|\widetilde{w}_B^D) + (1 - \sigma)\lambda [EV_B^N - V_B^D(t|\widetilde{w}_B^D)] + \sigma(1 - k)\lambda \int_{V_B^D(t|\widetilde{w}_B^D)}^{\overline{V}_B^D} [V_0 - V_B^D(t|\widetilde{w}_B^D)] dF_B^D(V_0) + \frac{dV_B^D(t|\widetilde{w}_B^D)}{dt} \quad (6)$$

Similarly, survival probabilities of B workers who are employed by N firms and D firms change from 3(b) to:

$$\psi_B(t|\widetilde{w}_B^N) = \exp\left\{-\int_0^t [\delta + (1 - \sigma)\lambda(1 - F_B^N(V_B(s|\widetilde{w}_B^N)))] ds\right\} \quad (7)$$

$$\psi_B(t|\widetilde{w}_B^D) = \exp\left\{-\int_0^t [\delta + (1 - \sigma)\lambda + \sigma(1 - k)\lambda(1 - F_B^D(V_B(s|\widetilde{w}_B^D)))] ds\right\} \quad (8)$$

This makes disentanglement of the sub-problems for B workers in N and D firms possible. The following proposition describes the equilibrium outcomes in the labor market. The crucial step in the proof is to define $G_B^D(V_0)$ and $G_B^N(V_0)$ to replace $G_B(V_0)$. Let $G_B^D(V_0), V_0 \in [\underline{V}_B^D, \overline{V}_B^D)$ be the proportion of B workers who have an expected lifetime value no greater than V_0 in all B workers excluding those working in N firms and $G_B^N(V_0), V_0 \in [\underline{V}_B^N, \overline{V}_B^N)$ be the proportion of B workers with expected lifetime value no greater than V_0 in all B -workers. Then, the proof of the equilibrium outcomes could fit nicely in that of Burdett and Coles (2003). Moreover, through constructing the overall

⁴⁰ Burdett and Coles (2010) prove that offer values can be ranked according to the productivity level of firms. Consider the market of B workers only, if we think the marginal productivity of D firms as $P - d$ and N firms as P , proposition 1 here is implied by their result.

$G_B(V_0)$ from $G_B^D(V_0)$ and $G_B^N(V_0)$, we show that the lower bound of the starting wage in N -firms is the upper limit of starting wages offered by D firms. The assumption of differentiable $F_B^j(\cdot)$ is necessary to derive the equilibrium. Otherwise, a mass point exists in $F_B^j(\cdot)$ at the extreme offer value and wages in N -firms can be smaller than wages in D -firms when the rank of offer values remains (Burdett and Coles, 2010). For the detailed proof, please refer to the appendix.

Proposition 2: (1) Given $\underline{w}_A, \underline{w}_B > 0$ and $F_A(V), F_B^N(V), F_B^D(V)$ are increasing and continuously differentiable, there exists a unique market equilibrium. At the steady state equilibrium, the baseline salary scale for worker A satisfies:

$$\frac{P - \overline{w}_A}{P - \underline{w}_A} = \left(\frac{\delta}{\delta + \lambda} \right)^2 \quad (9)$$

$$u(\underline{w}_A) = u(b) - \frac{\sqrt{P - \underline{w}_A}}{2} \int_{\underline{w}_A}^{\overline{w}_A} \frac{u'(x) dx}{\sqrt{P - x}} \quad (10)$$

The optimal wage-tenure contract for worker A follows the dynamic path:

$$\frac{dw_A}{dt} = \frac{\delta(P - w_A)}{u'(w_A)} \int_{w_A}^{\overline{w}_A} \frac{u'(x) dx}{\sqrt{(P - \overline{w}_A)(P - x)}} \quad (11)$$

For worker B , the baseline salary scale satisfies:

$$\frac{P - \overline{w}_B^D - d}{P - \underline{w}_B^D - d} = \left(\frac{\delta + (1 - \sigma)\lambda}{\delta + (1 - \sigma k)\lambda} \right)^2 \quad (12)$$

$$u(\underline{w}_B^D) = u(b) - \frac{\sqrt{P - \underline{w}_B^D - d}}{2} \int_{\underline{w}_B^D}^{\overline{w}_B^D} \frac{u'(x) dx}{\sqrt{P - x - d}} \quad (13)$$

$$\underline{w}_B^N = \overline{w}_B^D \quad (14)$$

$$\frac{P - \overline{w}_B^N}{P - \underline{w}_B^N} = \left(\frac{\delta}{\delta + (1 - \sigma)\lambda} \right)^2 \quad (15)$$

And the dynamics of baseline salaries are:

$$\frac{dw_B^D}{dt} = \frac{(\delta + (1-\sigma)\lambda)(P - w_B^D - d)}{u'(w_B^D)} \int_{w_B^D}^{\overline{w_B^D}} \frac{u'(x)dx}{\sqrt{(P - \overline{w_B^D} - d)(P - x - d)}} \quad (16)$$

$$\frac{dw_B^N}{dt} = \frac{\delta(P - w_B^N)}{u'(w_B^N)} \int_{w_B^N}^{\overline{w_B^N}} \frac{u'(x)dx}{\sqrt{(P - \overline{w_B^N})(P - x)}} \quad (17)$$

(2) At equilibrium, the earnings distributions are given by:

$$K_w^A(w) = \frac{\delta}{\lambda} \left[\sqrt{\frac{P - w_A}{P - w}} - 1 \right] \quad (18)$$

$$K_w^B(w) = \begin{cases} \frac{\delta}{(1-\sigma k)\lambda} \left[\sqrt{\frac{P - w_B^D - d}{P - w - d}} - 1 \right], & \text{if } w \in [\underline{w_B^D}, \overline{w_B^D}] \\ \frac{\delta + (1-\sigma k)\lambda}{(1-\sigma k)\lambda} \sqrt{\frac{P - \overline{w_B^N}}{P - w}} - \frac{\delta}{(1-\sigma k)\lambda}, & \text{if } w \in [\underline{w_B^N}, \overline{w_B^N}] \end{cases} \quad (19)$$

And the unemployment rates of each type of workers are:

$$u_A = \frac{\delta}{\lambda + \delta} \quad (20)$$

$$u_B = \frac{\delta}{\delta + (1-\sigma k)\lambda} \quad (21)$$

The maximized total profits earned by a D firm and a N firm are:

$$\Omega^D = \lambda(1 - \theta)n \frac{P - \overline{w_A}}{\delta} + \lambda(1 - k)\theta n \delta \frac{P - \overline{w_B^D} - d}{[\delta + (1-\sigma)\lambda]^2} \quad (22)$$

$$\Omega^N = \lambda(1 - \theta)n \frac{P - \overline{w_A}}{\delta} + \lambda\theta n \frac{P - \overline{w_B^N}}{\delta} \quad (23)$$

Baseline salary scale is a succinct way to describe all the equilibrium solutions. For any starting value V_0 from the support of offer distribution F_A , there exists a point t_0 such that $V_0 = V_s(t_0)$ where the subscript s denotes baseline. So the wage-tenure contract with a starting value V_0 can be expressed as $w(t|V_0) = w_s(t + t_0)$; that is, any equilibrium wage-tenure contract can be found on the baseline salary scale starting with a specific point t_0 . In this study, we suppress the s -subscript for simplicity of presentation. The optimal decision implied in the proposition 2(1) is: for worker A , a firm can set any wage

between $[\underline{w}_A, \overline{w}_A)$ as the starting wage offer and backload it as described in the optimal wage-tenure dynamic (11); the total profit from A will be the same across firms no matter which wage-tenure contract they choose. Since $\frac{dw_A}{dt}$ is positive, the optimal wage increases with tenure and the upper limit of the increment is $\overline{w}_A$. Obviously, the wage support for type A workers can be solved by combining (9) and (10), from which the earnings distribution (18) can be derived.

Similarly, for worker B , D firms can set any starting wage between $[\underline{w}_B^D, \overline{w}_B^D)$ and then backload the wage using the rule described in (16). Profit from type B workers is the same across the discriminating firms. N -firms can determine any starting wage between $[\underline{w}_B^N, \overline{w}_B^N)$, increase the wage with tenure as described in (17) and make the same profit as any other N firms. One point to note is that although $\underline{w}_B^N = \overline{w}_B^D$, $\underline{V}_B^N \neq \overline{V}_B^D$. Rather, employees hired in N firms with a payment $\underline{w}_B^N$ have a higher expected lifetime value than the high wage earners in D firms, i.e., $\underline{V}_B^N > \overline{V}_B^D$; because workers with $\underline{w}_B^N$ can expect an immediate increase in the payment while those approaching $\overline{w}_B^D$ cannot.

Second, from the expression for the unemployment rate (21), we can see that disutility d has no effect on u_B ; it is always higher than A 's unemployment rate given in (20) as long as there is discrimination in the labor market ($\sigma k \neq 0$). If any of the two indicators equals zero, there would be no discriminating firms in the labor market.

Third, from (22) and (23), it is easy to get the difference in profits in N and D firms:

$$\Omega^N - \Omega^D = \lambda \theta n \frac{\delta[k(P - \overline{w}_B^D) + (1-k)d]}{[\delta + (1-\sigma)\lambda]^2} > 0 \quad (24)$$

This is a general finding in the discrimination literature. Though D firms earn higher profit from a single B worker by paying a lower wage, the total profit is less than that in N firms; because the negative effect of lower employment and higher quit rate in a D firm outweighs the positive effect of a lower wage. Besides, the disutility taste D firms have towards B workers widens the profit gap further. The larger θ, n, k or d is, the larger the gap.⁴¹ This indicates that having more minority workers in the labor market places the discriminating firms in a worse situation; and, the more prejudiced the discriminating firms are, the higher loss they will bear.

3.4 Equilibrium Properties

To facilitate the comparisons of average wages between two types of workers, we calculate the mean wages from (9), (12), (14), (15), (18) and (19), which gives

$$\begin{aligned} Ew_A &= \int_{\underline{w}_A}^{\overline{w}_A} w dK_w^A(w) \\ &= \overline{w}_A + \frac{\delta}{\lambda} (\overline{w}_A - \underline{w}_A) - \frac{2\delta}{\delta + \lambda} (P - \underline{w}_A) \end{aligned} \quad (25)$$

$$\begin{aligned} Ew_B &= \int_{\underline{w}_B^D}^{\overline{w}_B^N} w dK_w^B(w) \\ &= \overline{w}_B^N + \frac{\delta}{(1-\sigma k)\lambda} (\overline{w}_B^N - \underline{w}_B^D) - \frac{2}{1-\sigma k} \left[\frac{\delta \sigma (1-k)}{\delta + (1-\sigma k)\lambda} (P - \underline{w}_B^D - d) + \frac{(1-\sigma)[\delta + (1-\sigma k)\lambda]}{\delta} (P - \overline{w}_B^N) \right] \end{aligned} \quad (26)$$

Note that the unemployed workers are not included in the calculation.

Under some general conditions, we discuss the equilibrium properties in the following proposition:

⁴¹ Though values of k and d also influence $\overline{w}_B^D$ in the expression of profit difference, the negative correlation between k, d and $\overline{w}_B^D$ (which to be shown in section 4) will enhance the positive relationship between k, d and the profit gap.

Proposition 3 If $b \leq \frac{3}{4}(P - d)$, $\frac{u'(\overline{w_B^D})}{u'(w_B^D)} > \frac{\eta}{\eta+2}$ and $\frac{\partial \overline{w_B^D}}{\partial \sigma} < \frac{2\lambda(P - \overline{w_B^D})}{\delta + (1-\sigma)\lambda}$ where $\eta = \frac{\delta + (1-\sigma)\lambda}{\delta + (1-\sigma)\lambda}$

is the relative hazard rate, then the equilibrium has the following properties:

$$(1) \quad \frac{\partial w_B^D}{\partial \sigma} < 0 \quad \frac{\partial \overline{w_B^D}}{\partial \sigma} > 0 \quad \frac{\partial \overline{w_B^N}}{\partial \sigma} < 0$$

$$(2) \quad \frac{\partial w_B^D}{\partial k} > 0 \quad \frac{\partial \overline{w_B^D}}{\partial k} < 0 \quad \frac{\partial \overline{w_B^N}}{\partial k} < 0$$

$$(3) \quad \frac{\partial w_B^D}{\partial d} > 0 \quad \frac{\partial \overline{w_B^D}}{\partial d} < 0 \quad \frac{\partial \overline{w_B^N}}{\partial d} < 0$$

$$(4) \quad \underline{w_A} < \underline{w_B^D} \leq b < \overline{w_B^D} < \overline{w_A}$$

$$(5) \quad Ew_A > Ew_B \text{ when discriminating firms only hire } A \text{ workers (i.e., } k = 1 \text{ and } \sigma \neq 0 \text{)}$$

The discriminating wage bounds solved from equations (12) and (13) and non-discriminating wage bounds solved from equations (14) and (15) are functions of productivity P , unemployment insurance b , birth-death rate δ , normal offer arrival rate λ and three discrimination indicators (σ, k, d) . Under conditions specified in proposition 3, the comparative statics of wage bounds with respect to the three discrimination associated parameters, described in properties (1)-(3), can be easily obtained.

Property (1) shows that the higher the proportion of D -firms in the market, the wider the range of discriminating wages will be; and the range extends in both directions. On the contrary, the degree of recruiting discrimination has an opposite effect: severe discrimination in the hiring process will lead to a narrowing of the discriminating wage range which converges to the unemployment insurance (which is implied by property (4)). Disutility has the same effect on discriminating wage bounds. Finally, the highest non-discriminating wage decreases as any of the three parameters increases.

The next two properties compare the equilibrium wages between two types of workers. Several points are noteworthy. First, the lowest acceptable wage is lower than the unemployment insurance, which is a unique result within the search model with wage-tenure contracts. In Burdett and Mortensen (1998), firms set a constant wage rather than a wage-tenure contract; hence the lowest acceptable wage is the unemployment insurance b (when the offer arrival rate is the same for both the employed and the unemployed). Under the wage-tenure framework, however, workers are willing to work at a wage lower than the unemployment insurance only because they can expect an immediate increase in the payment. In fact, the expected lifetime value at the lowest wage is virtually equal to that at the status of unemployment.

Second, A 's lowest acceptable starting wage is less than the lowest starting wage for B . This is because on the one hand, worker A 's wage increases with tenure more quickly than B 's; on the other hand, compared to B , A is more likely to get a new and better job offer in the labor market.

Third, the upper bound of A 's wages being higher than their counterpart's is within expectation, since discriminating firms are unlikely to set too high a wage due to their disutility tastes.

In a special case where discriminating firms hire only type A , property (5) shows that "minority workers receive lower wages than workers not facing discrimination" (Black, 1995). However, this finding cannot be generalized. In the numerical example, we will show that if D -firms can hire B ($0 \leq k < 1$), the average worker B might be able to earn a slightly higher wage than worker A .

3.5 A special case

In this section, a special case of the CRRA utility function: $u(w) = \frac{w^{1-\gamma}}{1-\gamma}$ ($\gamma \rightarrow \infty$) is considered. Tractable equilibrium solutions that are derived from proposition 2 can shed more light on the labor market with discrimination. Proposition 4 below summarizes the equilibrium results in this special case.

Proposition 4: Given that both types of workers have the same CRRA utility function:

$u(w) = \frac{w^{1-\gamma}}{1-\gamma}$ with $\gamma \rightarrow \infty$, the following statements hold:

(1) The optimal strategy of a firm is to set fixed wages instead of the wage-tenure contracts, i.e., $\frac{dw_i^j}{dt} = 0$.

(2) The wage bounds are:

$$\underline{w}_A = b \quad \overline{w}_A = P - \left(\frac{\delta}{\lambda + \delta} \right)^2 (P - b)$$

$$\underline{w}_B^D = b \quad \overline{w}_B^D = \underline{w}_B^N = P - d - \left(\frac{\delta + (1-\sigma)\lambda}{\delta + (1-\sigma k)\lambda} \right)^2 (P - b - d)$$

$$\overline{w}_B^N = P - \left(\frac{\delta}{\delta + (1-\sigma)\lambda} \right)^2 d - \left(\frac{\delta}{\delta + (1-\sigma k)\lambda} \right)^2 (P - b - d)$$

$$\text{And, } \underline{w}_A = \underline{w}_B^D = b < \overline{w}_B^D < \overline{w}_B^N < \overline{w}_A.$$

(3) A 's earnings distribution first order dominates B 's earnings distribution, i.e., $K_w^A < K_w^B$ for all w .

(4) $Ew_A > Ew_B$ and the mean wage gap increases with (σ, k, d) .

As $\gamma \rightarrow \infty$, workers are infinitely risk averse; thus the optimal wage contract is constant wages. The equilibrium search model with wage-tenure contracts then degenerates to Burdett and Mortensen (1998) and the discriminating wage-tenure equilibrium search model degenerates to a simplified version of Bowlus and Eckstein

(2002).⁴² Figure 3.1 describes the earnings distributions for both types of workers and apparently A 's cumulative earnings distribution first order dominates B 's distribution. From first order dominance, property (4) is directly obtained. In addition, the same reservation wages between A and B results from the assumption that the offer arrival rate is invariant between the employed and unemployed workers. The upper wage limit of B is less than that of A because of the existence of the three non-zero discrimination parameters (σ, k, d) .

Moreover, the larger (σ, k, d) is, the smaller B 's average wage is. Since (σ, k, d) does not enter type A worker's wage, the average wage gap increases as (σ, k, d) increases. This conclusion is in line with the empirical findings. For example, Charles

⁴²Bowlus and Eckstein (2002) extend Burdett and Mortensen (1998)'s model to discuss the contributions of discrimination and skill differences to the wage gaps. In their paper, the offer arrival rate is assumed to be different between the employed and the unemployed and therefore unlike what we get in this special case, the reservation wage is larger than the unemployment compensation

and Guryan (2008) plot the black-white wage gap against prejudicial attitude and find a wider gap at regions where many people will not vote for the black candidate for presidency or are against interracial marriages.

3.6 A Numerical Example

As mentioned in section 4, it is interesting to examine the effect of the three discrimination-relevant parameters on the difference in the mean wages between type A and B workers. We assume in the section that all workers have the same CRRA utility function. Let $P = 300, b = 100, \lambda = 0.03$ and $\delta = 0.003$ so that the average wage is close to that in the real data. If the coefficients of relative risk aversion are 0.9, 1.4 and 1.9, equation (25) gives that A 's average wages are 273.3307, 275.3025 and 276.8115 respectively. It seems that the more risk averse workers are, the higher the average wage they would earn.

For worker B , we vary the values of (σ, k, d) to see how the mean wage changes accordingly. Results are presented in Table 3.1 in which the first panel fixes d and k , and changes the measure of discriminating firms σ ; the second panel changes the recruiting discrimination k and keeps the other two measures unchanged; and the third one modifies disutility taste d given certain values of σ and k . The findings are as follows: First, the mean wage of type B worker decreases in σ and d , but increases in γ while the relationship with k is uncertain. Second, the fraction of D -firms plays a key role in the average wage; the other three parameters, though mattering to some extent, have only limited influence on the wage outcomes. Third, if only D -firms exist in the labor market (see the case $\sigma = 1$ in Panel 1), the wage gap is very large; however, the gap will drop

dramatically when N -firms begin to appear. In addition, Panel (2) indicates that the wage gap does not change much even when D -firms are forbidden to discriminate in hiring (see $k = 0$); on the other hand, what appears to be against expectation is that severe discrimination in recruitment leads to a higher average wage for B and hence a smaller wage gap (see $k = 0.9$). However, one should realize that this does not mean type B workers are better off because only a few will be hired in this situation and the overall welfare of type B workers is in fact jeopardized. Finally, compared to A 's average wage, the numbers in Table 3.1 are almost consistently smaller, which accords with the common sense that discriminated workers have a lower average wage.⁴³

Table 3.1: The mean wage of type B workers

(1) $d = 80$ $k = 0.2$

	$\gamma = 0.9$	$\gamma = 1.4$	$\gamma = 1.9$
$\sigma = 0.2$	276.6618	276.7661	276.8648
$\sigma = 0.4$	269.3880	269.9290	270.3657
$\sigma = 0.6$	258.4842	259.7430	260.6239
$\sigma = 0.8$	238.7852	240.6891	241.9693
$\sigma = 1.0$	196.9306	199.2000	200.7968

(2) $d = 80$ $\sigma = 0.5$

	$\gamma = 0.9$	$\gamma = 1.4$	$\gamma = 1.9$
$k = 0.0$	264.9373	265.9374	266.6517
$k = 0.3$	264.4216	265.2213	265.8328
$k = 0.6$	264.4312	264.8563	265.2231
$k = 0.9$	265.7274	265.7662	265.8044

(3) $\sigma = 0.5$ $k = 0.5$

	$\gamma = 0.9$	$\gamma = 1.4$	$\gamma = 1.9$
$d = 10$	269.3757	270.4330	271.2300
$d = 80$	264.3334	264.9009	265.3683
$d = 150$	259.9760	260.1040	260.2230

⁴³ One exception is when $\sigma = 0.2$ in Panel 1, B 's average wage is slightly larger than A 's. These rare cases seem to imply that the fraction of discriminating firms has to be large enough to generate the result of minority workers earning less than majority workers on average. Becker (1971) gives the exact condition σ should satisfy to derive the wage differential in the framework of competitive labor market. Aigner and Cain (1977) find a similar result in a group of low skilled workers, that discriminated-against workers have a higher average wage than their counterparts under the assumption of same mean productivity and different variances.

Next, we discuss the difference in wage dynamics between the two types of workers. To be representative, we choose a most realistic case where $\gamma = 0.9$, $k = 0.8$, $\sigma = 0.8$ and $d = 80$ and an extreme case in which B 's mean wage exceeds that of type A worker (See Figure 3.2).⁴⁴

There are several points worth noting. First, the slope of the wage-tenure contract is positive, meaning that the wage always increases with tenure. Second, for type A workers, the increase accelerates at the beginning, and slows down gradually; on the other hand, for type B workers the increasing rate drops from the very beginning. Besides, the slope of A 's wage-tenure contract is, in general, larger than B 's, especially in D -firms. N -firms, though owning no prejudice towards worker B , have less incentive to backload their wages as quickly as they do to worker A because there are fewer outside opportunities to worker B . If, however, only a small number of firms discriminate against worker B so that they can still seek many job offers from non-discriminating firms, then the slope of wage-tenure contracts designed for B workers by N -firms can be very close to, or even exceed the wage increase rate of worker A (Figure 3.2(b)).

3.7 Application one: Racial wage discrimination

One empirical difficulty in the discrimination literature is how to distinguish the unobserved productivity differences and discrimination in the residual wage gaps. Bowlus and Eckstein (2002) build a structural model they are able to identify due to the different impacts productivity differences and discrimination have on the earnings

⁴⁴Given those values, the simulated average wages for A and B are 273.3307 and 229.4995 respectively, very close to 273.9 and 230.96 derived from real data (Bowlus and Eckstein, 2002).

Figure 3.2: Wage Dynamics

distribution. In this exercise, using the same data as Bowlus and Eckstein (2002) and similar identification strategy, we estimate the structural parameters of the wage-tenure discrimination model, and compare how the inferences on the extent of productivity differences versus discrimination in explaining racial wage gaps differ between the two

models. Table 3.2 is a summary of the data that is useful in the estimation; detailed data description refers to Bowlus and Eckstein (2002).

Table 3.2 Summary of NLSY data for male high school graduates, 1985-1988

	Whites	Blacks	Pooled
Unemployment rate	0.077	0.157	0.089
Unemployment duration in weeks	22.15	29.05	23.65
Minimum weekly wage	118.18	120.39	118.18
Maximum weekly wage	605.97	428.16	605.97
Mean weekly wage	273.90	230.96	268.03

3.7.1 Identification

In the model section, we assume no differences between the two types of workers except the observable characteristic which in this exercise refers to race. Now, to match the empirical observations in the data, we allow for racial differences in productivity P and the death rate δ . The wage and unemployment data is used for identification. The following illustrates the identification in the most general case where both productivity difference and discrimination exist. Identification of the structural parameters in other cases is just straightforward.

First, using the unemployment duration, rate of unemployment rate and wage bound of whites, λ , δ_A and P_A are identified, as duration of unemployment_A = $\frac{1}{\lambda}$,

$$u_A = \frac{\delta_A}{\delta_A + \lambda} \text{ and the equilibrium condition } \frac{P_A - \bar{w}_A}{P_A - \underline{w}_A} = u_A^2.$$

Next, σk and δ_B are identifiable using blacks' unemployment rate and duration of unemployment data as duration of unemployment_B = $\frac{1}{(1-\sigma k)\lambda}$ and $u_B = \frac{\delta_B}{\delta_B + (1-\sigma k)\lambda}$.

Note that hiring discrimination is key to matching the racial difference in unemployment duration and varying death rate is crucial in determining the different unemployment rates.

Third, parameters associated with discrimination, d, σ, k and $\overline{w_B^D}$, and blacks productivity P_B are simultaneously identified from the system of equations: the estimated σk , two equilibrium conditions $\frac{P_B - \overline{w_B^D} - d}{P_B - \underline{w_B} - d} = \left(\frac{\delta_B + (1-\sigma)\lambda}{\delta_B + (1-\sigma k)\lambda} \right)^2$, $\frac{P_B - \overline{w_B}}{P_B - \overline{w_B^D}} = \left(\frac{\delta_B}{\delta_B + (1-\sigma)\lambda} \right)^2$, the mean wage $Ew_B = \overline{w_B} + \frac{\delta_B}{(1-\sigma k)\lambda} (\overline{w_B} - \underline{w_B}) - \frac{2}{1-\sigma k} \left[\frac{\delta_B \sigma (1-k)}{\delta_B + (1-\sigma k)\lambda} (P_B - \underline{w_B} - d) + \frac{(1-\sigma)[\delta_B + (1-\sigma k)\lambda]}{\delta_B} (P_B - \overline{w_B}) \right]$ and the median wage:

$$w_B^5 = \begin{cases} P_B - d - (P_B - \underline{w_B} - d) \left(\frac{\delta_B}{\delta_B + (1-\sigma k)\lambda} \right)^2 & \text{if } \frac{\delta_B (1-k)\sigma}{(1-\sigma k)[\delta_B + (1-\sigma)\lambda]} > 0.5 \\ P_B - (P_B - \overline{w_B}) \left(\frac{\delta_B + (1-\sigma k)\lambda}{\delta_B + (1-\sigma k)\lambda} \right)^2 & \text{if } \frac{\delta_B (1-k)\sigma}{(1-\sigma k)[\delta_B + (1-\sigma)\lambda]} \leq 0.5 \end{cases}.$$

The estimation procedure is as follows: first, try the value of P_A as the estimate of P_B and get all other parameters through the system of equations but the median one; then, predict the median wage according to the median wage equation, if it approximates the empirical median wage, keep all the parameter estimates, if not, modify the estimate of P_B accordingly and redo all the above until the predicted median wage tallies with the empirical one. One can also compare the predicted and empirical value at any other quantile to determine the appropriate estimates of parameters.

3.7.2 Estimation

We estimate the parameters in six versions from a simple case where there are no differences between whites and blacks towards a complete model with both productivity difference and discrimination. In the simplest scenario where $P_A = P_B = P$; $\delta_A = \delta_B = \delta$ and no discrimination present ($d = k = 0, \sigma = 1$), parameters λ and δ are solved from the pooled unemployment duration and rate of unemployment. Productivity level P is then identified from the equilibrium condition $\frac{P - \overline{w}}{P - \underline{w}} = \left(\frac{\delta}{\delta + \lambda} \right)^2$ where $\underline{w}$ and $\overline{w}$ are replaced

with 118.18 and 605.97 respectively. The assumptions and estimation results are presented in column (1) of Table 3.3. In scenarios (2) and (3), we calculate δ_i and P_i using the separate unemployment rate and equilibrium condition by race instead. The productivity levels differ significantly between whites and blacks and P_B/P_A ratios are indeed smaller than the mean wage ratio as predicted in Bowlus and Eckstein (2002).

Varying δ is important in explaining the unemployment rate differential in the data.

Table 3.3 Parameter Estimates

Parameter	(1) $P_A = P_B$; no discrimination; $\delta_A = \delta_B$	(2) $P_A \neq P_B$; no discrimination; $\delta_A = \delta_B$	(3) $P_A \neq P_B$; no discrimination; $\delta_A \neq \delta_B$	(4) $P_A \neq P_B$; discrimination present ($k = 0$); $\delta_A \neq \delta_B$	(5) $P_A \neq P_B$; discrimination present; $\delta_A \neq \delta_B$	(6) $P_A = P_B$; discrimination present; $\delta_A \neq \delta_B$
λ	0.0423	0.0423	0.0423	0.0423	0.0451	0.0451
δ_A	0.0041	0.0041	0.0035	0.0035	0.0038	0.0038
δ_B	0.0041	0.0041	0.0079	0.0079	0.0064	0.0064
P_A	609.86	609.86	608.88	608.88	608.88	608.88
P_B	609.86	430.62	435.94	537.21	591.02	608.88
d	0	0	0	441	429.67	436.34
k	0	0	0	0	0.2608	0.2580
σ	1	1	1	0.8122	0.9106	0.9206
$\overline{w_B^D}$	-	-	-	99	158.65	169.41

Scenario (4) begins to incorporate the assumption of discrimination by allowing for the disutility experienced by prejudiced firms from hiring blacks. P_B , d , σ and $\overline{w_B^D}$ are calculated simultaneously using two equilibrium conditions and the equations of mean and median wages for blacks. The disutility level is found to be 72.4% of the white productivity, and 81.2% of the firms are prejudiced against blacks. When the restriction on equal hiring rate is relaxed in scenario (5), 91.1% of firms in the labor market have a distaste of 70.6% of the white productivity and offer to hire blacks at a rate 26.1% lower

than the offer rate to whites.⁴⁵ The productivity of blacks is only 3% lower than their counterpart. In this estimation, the model can not only match the racial differences in unemployment rates but unemployment durations as well. Finally, we get the parameter estimates in the scenario of pure discrimination in column (6). The last row of Table 3.3 presents the estimate of $\overline{w_B^D}$ when there is discrimination present in the labor market.

The earnings distributions predicted in the pure productivity difference (scenario (3)), pure discrimination (scenario (6)) and mixed cases (scenario (5)) are shown in Figure 3.3, which clearly demonstrates the distinguishing effects productivity difference versus discrimination have on the earnings distribution. Besides, the wage-tenure discrimination model also allows for the depiction of wage dynamics. Figure 3.4 shows how the wage increase varies between blacks and whites at each wage level. In the case of pure productivity difference, the two lines have a similar shape and the blue line lies above the red one, suggesting a higher wage increasing rate in whites compared to blacks at any wage level. In the case of pure discrimination, there is a striking gap between the blue line and the red line; moreover, the red line is discontinuous at the jump point. It indicates that discrimination is an influential factor in wage-tenure contracts, and the presence of discrimination leads to a sharp decrease in the wage increasing rate for blacks in both discriminating and non-discriminating firms. Intuitively, although non-discriminating firms do not discriminate against blacks, they have incentives to offer a less attractive contract to blacks than otherwise as there is now less competition among firms to hire blacks and black workers will be willing to stay and accept the less attractive

⁴⁵ These estimates are obtained to match the wage of blacks at the 10% percentile. When the median is matched in the estimation, the result implies blacks are more productive than whites and 96.5% of firms are prejudiced with a distaste as high as 97.5% of the white productivity and an offer rate 24.6% lower to blacks ($P_B = 812.41$; $d = 593.59$; $k = 0.2462$; $\sigma = 0.9649$; $\overline{w_B^D} = 215.04$).

contract because of no better options outside. When there are both productivity difference and discrimination in the labor market, the line indicating the wage dynamic of blacks is a combination of the two effects.

[Figure 3.3 & Figure 3.4 about here]

3.7.3 Comparison

The estimation results of our model imply that for the high school male graduates in 1985-1988, the productivity of black workers is 3% less than that of whites; and 91.1% of firms in the labor market have a distaste against blacks that is as high as 70.6% of whites productivity. Besides, these firms offer to hire blacks at a rate 26.1% lower than the offer rate they send to whites. Compared with the results in Bowlus and Eckstein (2002), we come to the same conclusion regarding the productivity differential between races. However, in our model, the fraction of discriminating firms in the labor market is higher, the disutility discriminating firms feel in hiring black workers is stronger, while the recruiting discrimination is not as severe as that predicted in Bowlus and Eckstein (2002). We speculate, the reason may be that there are so many firms that have a strong prejudice towards blacks that it turns out to be costly to have such a distaste and profitable to relax the discrimination a little during recruitment.

One should notice a few differences between the wage-tenure discrimination model and Bowlus and Eckstein (2002) (BE henceforth). First and foremost, a constant wage is assumed in BE while our model assumes wage changes with tenure. Therefore, except for using mean wages in estimation, we also utilize wage ranges. Second, productivity is different in interpretation. BE interpret P as the average productivity level in a market with firm heterogeneity while P in our model is the marginal productivity a

worker brings to the firm that does not vary across firms. It implies that P must be greater than the maximum wage observed in the data. The estimated P in our model is thus much greater than those in BE. Third, offer arrival rates are different among employed and unemployed workers in BE but they are the same in our model and δ is the destruction rate in BE but birth/death rate in our model.

These simplifications help us focus on the different effects productivity differential and discrimination have on the wage gap and their respective wage dynamics. Figure 3.5 depicts how wage increases with tenure when there are both productivity differential and discrimination in the labor market. The blue line represents the wage dynamic for whites, the red line for blacks hired in discriminating firms and the yellow line for blacks hired in non-discriminating firms. Obviously, the slope of the blue line is greater than the slope of the yellow line, which is greater than that of the red line. It implies that white workers will experience a steeper wage increase with tenure, followed by the black workers in non-discriminating firms. Black workers employed in discriminating firms have to search for opportunities in non-discriminating firms after around 50 weeks otherwise the wage will stagger and remain almost unchanged.

3.8 Application two: Gender wage discrimination

The second exercise is to estimate gender wage discrimination in the labor market. Besides, we will see how the predicted pattern of wage dynamics matches the empirical one.

3.8.1 Data

The sample used is extracted from the NLSY79 for the period 1985-1987. To be included in our sample, an individual must be a white, either employed or unemployed in 1985, graduated from high school and not enrolled in further education in the period 1985-1987. For the unemployed worker, we calculate the unemployment duration. There are two versions of unemployment duration. *DurU1* is the period that dated back from the week the unemployed worker became unemployed (no earlier than year 1984) till the week he/she was either employed or out of labor force (no later than year 1987). *DurU2* is the period that dated back from the week the unemployed worker became not employed (either unemployed or out of labor force, but no earlier than year 1984) till the week he/she was employed (no later than year 1987). Since *DurU2* takes out-of-labor-force into the calculation of unemployment duration, it is greater than *DurU1* which only counts the period unemployed.⁴⁶ For the employed worker, we keep workers who have been employed all the time in 1985-1986, and calculate the increase in hourly wages. Table 3.4 summarizes the statistics that are useful in the estimation. Figure 3.6 plots the cdf and pdf of hourly wage for both genders.

⁴⁶ Bowlus (1997) built a three stage model (employment, unemployment and nonparticipation) to study the role of gender differences in behavior patterns on wage differentials. Our model, however, only allows for two stages, i.e., employment and unemployment. Therefore, when applying it to labor market differences on the basis of gender, “unemployment” refers to the status of unemployment or nonparticipation. *Dur1*(real unemployment duration) and *Dur2*(nonemployment duration) generate two groups of estimates that help us to compare the implications.

Table 3.4 Summary of NLSY data for high school white graduates, 1985-1987

	Male	Female	Pooled
Unemployment rate	4.314%	5.257%	4.749%
<i>DurU1</i> (weeks)	29.237	19.668	24.237
<i>DurU2</i> (weeks)	34.661	36.771	35.664
Wage range (hourly pay in cents)	[41, 1923]	[45, 1511]	[41,1923]
Average wage (hourly pay in cents)	823.3616	634.6458	743.4436
Median wage (hourly pay in cents)	769	591	682

[Figure 3.6 about here]

Next, we explore the difference in patterns of wage increase between men and women. Figure 3.7 draws two scatter plots to show a rough relationship between wage increase and 1985 hourly wage, one is not weighted and the other weighted. It is found that points cluster in the lower middle part where the hourly wage is between \$2.50 and \$12.00 and wage increase is below \$5.00; and, substantially more “male” points lie at higher wages. The predicted lines describe the trends of wage increase over levels. To compare the wage profiles of men and women more clearly, Figure 3.8 plots the magnitude of average wage increase over twenty or forty wage categories for male and female workers. Numbers on X-axis represent the middle point of each wage category. It is observed that women’s wage increase is almost consistently smaller than men’s wage increase. In addition, for both men and women, the magnitude of wage increase is much higher at low wages than at high wages. At very high wages (above \$16.00), only male workers are observed. In the next subsection, we will see whether our model is able to explain the regularities found in data, i.e., gender wage gap, differences in unemployment rate and unemployment duration and the patterns of wage increase. Since identification strategy is the same as specified in last exercise, we present the estimation results directly.

[Figure 3.7 & Figure 3.8 about here]

3.8.2 Estimation

Table 3.5 reports the estimation results in three scenarios under two measures of unemployment duration. Assuming no discrimination present in the labor market, the productivity of women is estimated to be 21% lower than men's.⁴⁷ If discrimination is taken into account, the productivity gap shrinks to 3% of men's productivity, smaller than the 6.5% reported in Flabbi (2010) who uses the sample of white, college graduates from CPS 1995. Looking at the estimates of discrimination parameters, one can find k is negative under *DurU1*, suggesting that a job offer goes to women more frequently. This is completely opposite to our expectation and problematic. As a matter of fact, compared to men, women are more often ending the status of unemployment by not participating in the labor market rather than finding a job. Therefore, it results in a seemingly lower unemployment duration among unemployed females than unemployed males, when it is measured by *DurU1*. *DurU2*, on the other hand, avoids this problem and is more appropriate in the situation of male-female discrimination. As indicated in column (5), when there is no productivity difference between men and women and all the gender wage gap is attributable to discrimination, about 94.3% of the firms are prejudiced against women, with a distaste as high as 94% of the productivity, and search for female workers is 6% less intensive than for male workers. If there are both productivity differential and discrimination, it is estimated that fewer firms (93.2%) have a slightly stronger distaste (96%) and stronger recruiting discrimination (6.1%) against women. Our estimate of fraction of discriminating firms is higher than 52% in Flabbi (2010) and 56% in Bowlus and Eckstein (2002).

⁴⁷ Using a search model that does not allow for discrimination, Bowlus (1997) finds the average productivity differential between male and female college graduates is 17.1% and 25.3% for high school graduates.

Table 3.5 Parameter estimates

Parameter	<i>DurU1</i>			<i>DurU2</i>		
	(1) $P_A \neq P_B$; no discrimination; $\delta_A \neq \delta_B$	(2) $P_A = P_B$; discrimination on present; $\delta_A \neq \delta_B$	(3) $P_A \neq P_B$; discrimination on present; $\delta_A \neq \delta_B$	(4) $P_A \neq P_B$; no discrimination; $\delta_A \neq \delta_B$	(5) $P_A = P_B$; discrimination on present; $\delta_A \neq \delta_B$	(6) $P_A \neq P_B$; discrimination on present; $\delta_A \neq \delta_B$
λ	0.0413	0.0342	0.0342	0.0280	0.0289	0.0289
δ_A	0.0019	0.0015	0.0015	0.0013	0.0013	0.0013
δ_B	0.0023	0.0028	0.0028	0.0016	0.0015	0.0015
P_A	1926.5	1926.50	1926.5	1926.5	1926.5	1926.5
P_B	1515.1	1926.50	1863.4	1515.1	1926.5	1863.4
d	0	1801.6	1851.2	0	1801.6	1851.2
k	0	-0.5342	-0.5445	0	0.0608	0.0615
σ	1	0.9107	0.8935	1	0.9434	0.9324
$\overline{w_B^D}$	-	123.91	12.638	-	123.91	12.638

How well does our model match the empirical wage dynamics? Using the estimates in column (6) of Table 3.5, we plot the theoretical pattern of wage increases for both men and women in Figure 3.9, which also shows a greater wage increase among male workers than female workers and a steeper increase in the lower wages as in Figure 3.7 and Figure 3.8, although the magnitude of wage increase differs.

3.9 Conclusion

This chapter develops a discrimination search model with wage-tenure contracts and predicts: 1) minority workers have a higher unemployment rate and a longer duration of unemployment; 2) non-discriminating firms make higher profits than discriminating firms; 3) the lowest acceptable wage for a minority worker is greater than that for a majority worker while the highest expected wage of a minority worker is lower; 4) generally, minority workers earn less than majority workers on average, and their wage increases more slowly than their counterpart. Moreover, we also show how the fraction of discriminating firms, distaste and recruiting discrimination affect the wage ranges and mean wages for both types of workers.

Applying the model to data in 1985-1988 from NLSY79, we investigate race/gender discrimination in the labor market. Productivity differences between blacks and whites are estimated to be 3% of whites productivity; productivity differences between men and women are estimated to be 3% of male productivity. 91% of firms possess prejudice towards black workers and 93% towards female workers. The distaste they hold towards blacks is about 70% of whites productivity and that towards women is 95% of male productivity. Compared to estimates in Bowlus and Eckstein (2002) and Flabbi (2010), we got similar results on productivity differences, but much higher estimation on discrimination. In addition, the predicted patterns of wage increase and that from data seem to exhibit some common characteristics. First, the wage increases faster for men than women; second, the wage increases faster at low wages than high wages.

There are some limitations in the discrimination search model with wage-tenure contracts. First, it does not consider the status of nonparticipation and other

characteristics of jobs but wages in the labor market. This is crucial in comparing gender differences in labor market outcomes. Bowlus (1997) shows women have a greater tendency to exit jobs to nonparticipation due to family, pregnancy or health issues. Flabbi and Moro (2010) measure women's preference for work flexibility and find an impact on wage distributions. The second limitation of the model exists in the empirical application. We follow the identification strategy in Bowlus and Eckstein (2002) but it would be better if we can generate an econometric approach from the model and do some robustness check. Finally, we suggest some future researches along this line. One can study taste discrimination in the directed search model with wage-tenure contract (Shi, 2009) and see what different predictions can be obtained.⁴⁸ Or, it may be modified to some extent to explain glass ceiling/sticky floor effects found in empirical work.

⁴⁸ In a random search model, workers receive offers randomly and exogeneously while in a directed search model, employees direct their search to the most attractive contracts. Shi (2009) has proved that a worker's optimal decision and a firm's optimal contract are independent of the distribution of workers (block recursivity) in a directed search model with wage-tenure contracts, which may significantly simplify the equilibrium analysis in the discrimination search model.

Figure 3.3 Predicted earnings distributions

Figure 3.4 Predicted wage dynamics

Figure 3.6 Hourly wage distributions

Figure 3.7 Scatter plots of wage increase and hourly pay

Figure 3.8 Hourly wage increase using 1986-1985

3.10 Appendix

A1. Proof of proposition 1

Since V_{0N}^B and V_{0D}^B are offers chosen by N - and D -firms to maximize their respective profit flow at the steady state, it implies

$$\begin{aligned} \lambda G_B(V_{0N}^B) \theta n \int_0^\infty \psi_B(t | \widetilde{w}_B^N) [P - w_B^N(t)] dt \\ \geq \lambda G_B(V_{0D}^B) \theta n \int_0^\infty \psi_B(t | \widetilde{w}_B^D) [P - w_B^D(t)] dt \end{aligned}$$

and

$$\begin{aligned} (1-k) \lambda G_B(V_{0D}^B) \theta n \int_0^\infty \psi_B(t | \widetilde{w}_B^D) [P - w_B^D(t) - d] dt \\ \geq (1-k) \lambda G_B(V_{0N}^B) \theta n \int_0^\infty \psi_B(t | \widetilde{w}_B^N) [P - w_B^N(t) - d] dt. \end{aligned}$$

Note that $\widetilde{w}_B^j$ ($j = N, D$) is the wage-tenure contract designed to deliver the offer,

so it's a function of V_{0j}^B . The two inequalities then imply:

$$\begin{aligned} G_B(V_{0N}^B) \theta n \int_0^\infty \psi_B(t | \widetilde{w}_B^N) [P - w_B^N(t)] dt \\ - G_B(V_{0N}^B) \theta n \int_0^\infty \psi_B(t | \widetilde{w}_B^N) [P - w_B^N(t) - d] dt \\ \geq G_B(V_{0D}^B) \theta n \int_0^\infty \psi_B(t | \widetilde{w}_B^D) [P - w_B^D(t)] dt \\ - G_B(V_{0D}^B) \theta n \int_0^\infty \psi_B(t | \widetilde{w}_B^D) [P - w_B^D(t) - d] dt. \end{aligned}$$

If we define:

$$\Psi(V_0^B) \triangleq d G_B(V_0^B) \int_0^\infty \psi_B(t | \widetilde{w}_B) dt,$$

Then the above inequality is:

$$\Psi(V_{0N}^B) \geq \Psi(V_{0D}^B).$$

Because,

$$\Psi'(V_0^B) = d \frac{\partial G_B(V_0^B)}{\partial V_0^B} \int_0^\infty \psi_B(t|\widetilde{w}_B) dt + d G_B(V_0^B) \int_0^\infty \frac{\partial(\psi_B(t|\widetilde{w}_B))}{\partial V_0^B} dt > 0;$$

due to the increasing property of $G_B(V_0^B)$ and $\psi_B(t|\widetilde{w}_B)$ with respect to V_0^B , we have

$$V_{0N}^B \geq V_{0D}^B.$$

A2. Proof of proposition 2

For the derivation of equilibrium results for worker A , refer to Burdett and Coles (2003).

Below is a similar derivation of equilibrium results for worker B .

(1) First consider the optimal wage-tenure contract designed for B -workers by discriminating firms.

Given the starting offer V_0 , the wage-tenure function solves:

$$\max_{w(t)>0} \int_0^\infty \psi_B(t|\widetilde{w}_B^D) [P - w_B^D(t) - d] dt$$

$$\text{where } \dot{\psi}_B = -[\delta + (1 - \sigma)\lambda + \sigma(1 - k)\lambda(1 - F_B^D(V_B^D))] \psi_B \quad (\text{A1})$$

$$\dot{V}_B^D = \delta V_B^D - u(w_B^D(t)) - (1 - \sigma)\lambda[EV_B^N - V_B^D] - \sigma(1 - k)\lambda \int_{V_B^D}^{\overline{V}_B^D} [x - V_B^D] dF_B^D(x) \quad (\text{A2})$$

$$\text{with starting values } \psi_B(0) = 1; V_B^D(0) = V_0$$

To solve the dynamic optimization problem, define the Hamiltonian:

$$H = \psi_B [P - w_B^D(t) - d] - \Lambda_\psi [\delta + (1 - \sigma)\lambda + \sigma(1 - k)\lambda(1 - F_B^D(V_B^D))] \psi_B \\ + \Lambda_V \left[\delta V_B^D - u(w_B^D(t)) - (1 - \sigma)\lambda[EV_B^N - V_B^D] - \sigma(1 - k)\lambda \int_{V_B^D}^{\overline{V}_B^D} [x - V_B^D] dF_B^D(x) \right],$$

where Λ_ψ, Λ_V are costate variables with respect to ψ_B and V_B^D .

The necessary conditions are:

$$H_w = -\psi_B - \Lambda_V u'(w_B^D(t)) = 0 \quad (\text{A3})$$

$$\dot{\Lambda}_\psi = -H_\psi = -[P - w_B^D(t) - d] + \Lambda_\psi [\delta + (1 - \sigma)\lambda + \sigma(1 - k)\lambda(1 - F_B^D(V_B^D))] \quad (\text{A4})$$

$$\dot{\Lambda}_V = -H_V = -\Lambda_V [\delta + (1 - \sigma)\lambda + \sigma(1 - k)\lambda(1 - F(V_B^D))] - \Lambda_\psi \sigma(1 - k)\lambda F_B^{D'}(V_B^D) \psi_B \quad (\text{A5})$$

And the two differential equations ψ_B and V_B^D should satisfy (A1), (A2).

Integrate (A4) with the integrating factor ψ_B yields:

$$\Lambda_\psi \psi_B = \int_t^\infty \psi_B(s | \widetilde{w}_B^D) [P - w_B^D(s) - d] ds + C_1$$

Define the expected future profit flow from tenure period t onwards as:

$$\Pi_B^D(t | \widetilde{w}_B^D) = \int_t^\infty \frac{\psi_B(s | \widetilde{w}_B^D)}{\psi_B(t | \widetilde{w}_B^D)} [P - w_B^D(s) - d] ds$$

Then,

$$\Lambda_\psi = \Pi_B^D(t | \widetilde{w}_B^D) + \frac{C_1}{\psi_B(t | \widetilde{w}_B^D)}$$

Since it's an autonomous control problem, the optimized Hamiltonian is zero, i.e.,

$H = 0$. Substituting Λ_ψ, Λ_V in H out yields:

$$\begin{aligned} 0 = & [P - w_B^D(t) - d] - \left\{ \Pi_B^D(t | \widetilde{w}_B^D) + \frac{C_1}{\psi_B(t | \widetilde{w}_B^D)} \right\} \left[\delta + (1 - \sigma)\lambda + \sigma(1 - k)\lambda (1 - F_B^D(V_B^D)) \right] \\ & - \frac{1}{u'(w_B^D(t))} \left[\delta V_B^D - u(w_B^D(t)) - (1 - \sigma)\lambda [EV_B^N - V_B^D] - \sigma(1 - k)\lambda \int_{V_B^D}^{\overline{V}_B^D} [x - V_B^D] dF_B^D(x) \right] \end{aligned}$$

Therefore, C_1 has to be zero to make Π_B^D bounded. Thus $\Lambda_\psi = \Pi_B^D(t | \widetilde{w}_B^D)$ and

(A4) turns to be

$$\frac{d\Pi_B^D(t | \widetilde{w}_B^D)}{dt} = -[P - w_B^D(t) - d] + \Pi_B^D(t | \widetilde{w}_B^D) [\delta + (1 - \sigma)\lambda + \sigma(1 - k)\lambda (1 - F_B^D(V_B^D))] \quad (A6)$$

And (A2), (A6) and $H = 0$ give:

$$\frac{dV_B^D(t | \widetilde{w}_B^D)}{dt} = -u'(w_B^D(t)) \frac{d\Pi_B^D(t | \widetilde{w}_B^D)}{dt} \quad (A7)$$

Integrating (A5) with the integrating factor $\frac{1}{\psi_B}$ and substituting Λ_ψ with Π_B^D yields:

$$\frac{\Lambda_V}{\psi_B} = - \int_0^t \Pi_B^D \sigma(1 - k)\lambda F_B^{D'}(V_B^D) ds + C_2$$

To Substitute Λ_V in (A3) using the above expression and differentiate with respect to t , we get:

$$-\frac{u''(w_B^D)}{u'(w_B^D)^2} \frac{dw_B^D(t)}{dt} = \sigma(1-k)\lambda F_B^{D'}(V_B^D)\Pi_B^D \quad (\text{A8})$$

In addition, the transversality condition implies $\lim_{t \rightarrow \infty} V_B^D(t|\widetilde{w}_B^D) = \overline{V}_B^D$.

(2) Next, we present the equilibrium results in terms of baseline wage.

If the solution to the above optimization problem with $V_0 = \underline{V}_B^D$ is taken as the baseline, then for any starting offer $V_0 \in [\underline{V}_B^D, \overline{V}_B^D)$, there exists t_0 such that $V_s^{BD}(t_0) = V_0$. So, the optimal wage contract of any firm and all the equilibrium solutions could be expressed in terms of the baseline. For example, $w_B^D(t|V_0) = w_s^{BD}(t_0 + t)$, $V_B^D(t|\widetilde{w}_B^D) = V_s^{BD}(t_0 + t)$ and $\Pi_B^D(t|\widetilde{w}_B^D) = \Pi_s^{BD}(t_0 + t)$. Then, it's easy to derive $w_s^{BD} \uparrow \overline{w}_B^D$ and $\Pi_s^{BD} \uparrow \overline{\Pi}_B^D$. Further, from (A2) we can obtain $\overline{V}_B^D = \frac{u(\overline{w}_B^D) + (1-\sigma)\lambda EV_B^N}{\delta + (1-\sigma)\lambda}$; and from (A6), we get $\overline{\Pi}_B^D = \frac{P - \overline{w}_B^D - d}{\delta + (1-\sigma)\lambda}$.

Let u_B denote the unemployment rate, d_B denote the share of B workers employed in D -firms and n_B the share employed in N -firms. The flow conditions imply

$$\delta = u_B(\delta + (1-\sigma)\lambda + \sigma(1-k)\lambda);$$

$$u_B\sigma(1-k)\lambda = d_B(\delta + (1-\sigma)\lambda);$$

$$(1 - n_B)(1 - \sigma)\lambda = n_B\delta$$

So, the unemployment rate is $u_B = \frac{\delta}{\delta + (1-\sigma k)\lambda}$.

And the employment rate of type B workers in D -firms and N -firms are:

$$d_B = \frac{\delta\lambda\sigma(1-k)}{[\delta + (1-\sigma k)\lambda][\delta + (1-\sigma)\lambda]}; \quad n_B = \frac{(1-\sigma)\lambda}{\delta + (1-\sigma)\lambda}$$

Let $G_B^D(V_0), V_0 \in [\underline{V}_B^D, \overline{V}_B^D]$ be the proportion of B workers who have an expected lifetime value no greater than V_0 in all the B workers excluding those working in N -firms. Then $G_s^{BD}(t)$ is the corresponding baseline expression which satisfies:

$$G_s^{BD}(0) = \frac{u_B}{u_B + d_B} = \frac{\delta + (1-\sigma)\lambda}{\delta + (1-\sigma k)\lambda} \quad (\text{A9})$$

and the flow condition for B workers employed in D firms with salary point greater than t :

$$[\delta + (1-\sigma)\lambda](1 - G_s^{BD}(t)) = \frac{dG_s^{BD}(t)}{dt} + G_s^{BD}(t)\sigma(1-k)\lambda(1 - F_s^{BD}(t)) \quad (\text{A10})$$

As every D -firm makes the same profit from B -workers at the equilibrium, and $G_s^{BD} \rightarrow 1, \Pi_s^{BD} \rightarrow \overline{\Pi}_B^D$, from the profit function:

$$\Omega_B^D = \lambda(1-k)G_s^{BD}(t)\theta n(1-n_B)\Pi_s^{BD}(t)$$

we can get $G_s^{BD}(t)\Pi_s^{BD}(t) = \frac{P - \overline{w}_B^D - d}{\delta + (1-\sigma)\lambda}$. So,

$$\frac{dG_s^{BD}}{dt}\Pi_s^{BD} + \frac{d\Pi_s^{BD}}{dt}G_s^{BD} = 0$$

Then substituting out $\frac{dG_s^{BD}}{dt}$ and $\frac{d\Pi_s^{BD}}{dt}$ using (A6) and (A10) and combining it with (A10) yields:

$$G_w^{BD} = \sqrt{\frac{P - \overline{w}_B^D - d}{P - w_B^D - d}}$$

$$\Pi_w^{BD} = \frac{1}{\delta + (1-\sigma)\lambda} \sqrt{(P - \overline{w}_B^D - d)(P - w_B^D - d)}$$

Putting the expression of G_w^{BD} into (A9) thus gets,

$$\frac{P - \overline{w}_B^D - d}{P - w_B^D - d} = \left(\frac{\delta + (1-\sigma)\lambda}{\delta + (1-\sigma k)\lambda} \right)^2.$$

The offer distribution could be derived from (A6), (A7), (A8) and the expression of Π_w^{BD} :

$$1 - F_w^{BD} = \frac{\delta + (1-\sigma)\lambda}{\sigma(1-k)\lambda} \left[\sqrt{\frac{P - \underline{w}_B^D - d}{P - \overline{w}_B^D - d}} - 1 - \frac{1}{2u'(\underline{w}_B^D)} \int_{\underline{w}_B^D}^{\overline{w}_B^D} \frac{u'(x)dx}{\sqrt{(P - \overline{w}_B^D - d)(P - x - d)}} \right] \quad (A11)$$

Further, $V_s^{BD}(0) = V_{BU}$ at the equilibrium.

Since,

$$\frac{dV_s^{BD}(0)}{dt} = u(b) - u(\underline{w}_B^D)$$

which is derived from the baseline expression of (A2) at $V_B^D = V_s^{BD}(0)$ and the Bellman equation for unemployed B workers; and,

$$\frac{dV_s^{BD}(0)}{dt} = \frac{\sqrt{P - \underline{w}_B^D - d}}{2} \int_{\underline{w}_B^D}^{\overline{w}_B^D} \frac{u'(x)dx}{\sqrt{P - x - d}}$$

which could be derived from substitutions using (A6), (A7), (A11) and the expression of Π_w^{BD} ; we can derive another relationship between the bounds of the support of

discriminating wages, i.e., $u(\underline{w}_B^D) = u(b) - \frac{\sqrt{P - \underline{w}_B^D - d}}{2}$.

Besides, the dynamics of baseline tenure-wages (equation (16)) could be easily derived from (A8), (A11) and Π_w^{BD} expression.

(3) By the same token, we can get the equilibrium outcomes for B workers in the non-discriminating firms. Following the same procedures, we can prove that (17) holds. However, the support of the non-discriminating wages is somewhat different in the derivation.

Let $G_B^N(V_0), V_0 \in [\underline{w}_B^N, \overline{w}_B^N]$ be the proportion of B workers (including the unemployed) who have an expected lifetime value no greater than V_0 . Then, for the baseline expression, we have :

$$G_w^{BN} = \sqrt{\frac{P - \overline{w}_B^N}{P - \underline{w}_B^N}}.$$

So, the overall proportion of type B workers (including the unemployed) who earn less than or equal to w at the steady state is:

$$G_w^B(w) = \begin{cases} \frac{\delta}{\delta + (1-\sigma)\lambda} G_w^{BD}, & \text{if } w \in [\underline{w}_B^D, \overline{w}_B^D] \\ G_w^{BN}, & \text{if } w \in [\underline{w}_B^N, \overline{w}_B^N] \end{cases}$$

Since $G_w^B(\overline{w}_B^D) = G_w^B(\underline{w}_B^N)$ and $G_w^B(w)$ is monotonically increasing, $\overline{w}_B^D = \underline{w}_B^N$.

Further, as $G_s^{BN}(0) = \frac{\delta}{\delta + (1-\sigma)\lambda}$, we can get:

$$\frac{P - \overline{w}_B^N}{P - \underline{w}_B^N} = \left(\frac{\delta}{\delta + (1-\sigma)\lambda} \right)^2$$

Thus, (14) (15) are proved.

(4) Finally, we derive the earnings distribution of type B workers.

Given G_w^{BD} and G_w^{BN} , the earning distributions of B workers in the D - and N - firms at the steady state are:

$$K_w^{BD} = \frac{u_B + d_B}{d_B} [G_w^{BD}(w) - \frac{u_B}{u_B + d_B}]$$

And:

$$K_w^{BN} = \frac{1}{n_B} [G_w^{BN}(w) - (u_B + d_B)]$$

So, the overall earning distribution is:

$$K_w^B(w) = \begin{cases} \frac{d_B}{d_B + n_B} K_w^{BD}, & \text{if } w \in [\underline{w_B^D}, \overline{w_B^D}] \\ \frac{d_B}{d_B + n_B} + \frac{n_B}{d_B + n_B} K_w^{BN} & \text{if } w \in [\underline{w_B^N}, \overline{w_B^N}] \end{cases}$$

Substituting the expressions of G_w^{BD} , G_w^{BN} , u_B , d_B and n_B inside, gives equation (19).

A3. Proof of Equations (22), (23)

As shown above:

$$\Omega_B^D = \lambda(1 - k)G_s^{BD}(t)\theta n(1 - n_B)\Pi_s^{BD}(t) = \frac{\lambda(1-k)\theta n\delta}{[\delta + (1-\sigma)\lambda]^2} \left(P - \overline{w_B^D} - d \right)$$

Similarly,

$$\Omega_B^N = \lambda G_s^{BN}(t)\theta n\Pi_s^{BN}(t) = \lambda\theta n \frac{P - \overline{w_B^N}}{\delta}$$

Profits from A are:

$$\Omega_A = \lambda G_s^A(t)(1 - \theta)n\Pi_s^A(t) = \lambda(1 - \theta)n \frac{P - \overline{w_A}}{\delta}$$

So, $\Omega^D = \Omega_A + \Omega_B^D$ and $\Omega^N = \Omega_A + \Omega_B^N$.

A4. Proof of proposition 3

First, let's consider properties (1)-(3).

Taking partial derivatives of equation (13) with respect to (σ, k, d) yields:

$$A \frac{\partial w_B^D}{\partial \sigma} + B \frac{\partial \overline{w_B^D}}{\partial \sigma} = 0; \quad A \frac{\partial w_B^D}{\partial k} + B \frac{\partial \overline{w_B^D}}{\partial k} = 0; \quad A \frac{\partial w_B^D}{\partial d} + B \frac{\partial \overline{w_B^D}}{\partial d} = \frac{1}{4}C;$$

where

$$A = \frac{u'(\underline{w_B^D})}{2} - \frac{1}{4\sqrt{\overline{P - w_B^D} - d}} \int_{\underline{w_B^D}}^{\overline{w_B^D}} \frac{u'(x)dx}{\sqrt{P - x - d}} > 0;$$

$$B = \frac{u'(\overline{w_B^D})}{2} \sqrt{\frac{P - \overline{w_B^D} - d}{\overline{P - w_B^D} - d}} > 0;$$

$$C = \frac{1}{\sqrt{P - \underline{w}_B^D - d}} \int_{\underline{w}_B^D}^{\overline{w}_B^D} \frac{u'(x)dx}{\sqrt{P-x-d}} - \sqrt{P - \underline{w}_B^D - d} \int_{\underline{w}_B^D}^{\overline{w}_B^D} \frac{u'(x)dx}{(P-x-d)^{3/2}} < 0.$$

Similarly, partial differentiation of equation (12) gives:

$$\begin{aligned} \frac{\partial \underline{w}_B^D}{\partial \sigma} &= \eta_1^2 \frac{\partial \overline{w}_B^D}{\partial \sigma} - \eta_2 (P - \underline{w}_B^D - d); \quad \frac{\partial \underline{w}_B^D}{\partial k} = \eta_1^2 \frac{\partial \overline{w}_B^D}{\partial k} + \eta_3 (P - \overline{w}_B^D - d); \\ \frac{\partial \underline{w}_B^D}{\partial d} &= \eta_1^2 \frac{\partial \overline{w}_B^D}{\partial d} + \eta_1^2 - 1; \end{aligned}$$

where:

$$\eta_1 = \frac{\delta + (1-\sigma)k\lambda}{\delta + (1-\sigma)\lambda}; \quad \eta_2 = \frac{2\lambda(\delta + \lambda)(1-k)}{[\delta + (1-\sigma)\lambda][\delta + (1-\sigma)k\lambda]}; \quad \eta_3 = \frac{2\sigma\lambda}{\delta + (1-\sigma)k\lambda}.$$

Substituting them into the first group of equations thus proves:

$$\frac{\partial \underline{w}_B^D}{\partial \sigma} < 0; \quad \frac{\partial \overline{w}_B^D}{\partial \sigma} > 0; \quad \frac{\partial \underline{w}_B^D}{\partial k} > 0; \quad \frac{\partial \overline{w}_B^D}{\partial k} < 0; \quad \frac{\partial \overline{w}_B^D}{\partial d} < 0.$$

$$\text{In addition, as } (A\eta_1^2 + B) \frac{\partial \underline{w}_B^D}{\partial d} = \frac{\eta_1(\eta_1 - 1)}{2} \left[u'(\overline{w}_B^D) (\eta_1 + 2) - u'(\underline{w}_B^D) \eta_1 \right],$$

when $\frac{u'(\overline{w}_B^D)}{u'(\underline{w}_B^D)} > \frac{\eta_1}{\eta_1 + 2}$, we have $\frac{\partial \underline{w}_B^D}{\partial d} > 0$.

Since $\underline{w}_B^N = \overline{w}_B^D$, the partial derivative with respect to (σ, k, d) in (15) yields:

$$\begin{aligned} \frac{\partial \underline{w}_B^N}{\partial k} &= \left(\frac{\delta}{\delta + (1-\sigma)\lambda} \right)^2 \frac{\partial \overline{w}_B^D}{\partial k}; \\ \frac{\partial \underline{w}_B^N}{\partial d} &= \left(\frac{\delta}{\delta + (1-\sigma)\lambda} \right)^2 \frac{\partial \overline{w}_B^D}{\partial d}; \\ \frac{\partial \underline{w}_B^N}{\partial \sigma} &= \left(\frac{\delta}{\delta + (1-\sigma)\lambda} \right)^2 \frac{\partial \overline{w}_B^D}{\partial \sigma} - \frac{2\delta^2\lambda}{[\delta + (1-\sigma)\lambda]^3} (P - \overline{w}_B^D). \end{aligned}$$

So, $\frac{\partial \underline{w}_B^N}{\partial k}$ and $\frac{\partial \underline{w}_B^N}{\partial d}$ have the same sign as $\frac{\partial \overline{w}_B^D}{\partial k}$ and $\frac{\partial \overline{w}_B^D}{\partial d}$; and, $\frac{\partial \underline{w}_B^N}{\partial \sigma} < 0$ if $\frac{\partial \overline{w}_B^D}{\partial \sigma} < \frac{2\lambda(P - \overline{w}_B^D)}{\delta + (1-\sigma)\lambda}$.

$$\frac{2\lambda(P - \overline{w}_B^D)}{\delta + (1-\sigma)\lambda}.$$

Next, prove property (4).

From (13) we get : $u(\underline{w}_B^D) \leq u(b)$. Thus, $\underline{w}_B^D \leq b$ because of the increasing property of $u(w)$.

To prove the other side, let's assume $\overline{w}_B^D \leq b$. The integrated variable hence satisfies $\underline{w}_B^D \leq x \leq \overline{w}_B^D \leq b$. So we have:

$$\frac{\sqrt{P-\underline{w}_B^D-d}}{2} \int_{\underline{w}_B^D}^{\overline{w}_B^D} \frac{u'(x)dx}{\sqrt{P-x-d}} \leq \frac{\sqrt{P-\underline{w}_B^D-d}}{2} \int_{\underline{w}_B^D}^b \frac{u'(x)dx}{\sqrt{P-b-d}} = \frac{\sqrt{P-\underline{w}_B^D-d}}{2\sqrt{P-b-d}} [u(b) - u(\underline{w}_B^D)].$$

If $b \leq \frac{3}{4}(P-d)$, then $\underline{w}_B^D > 4b - 3(P-d)$. Thus, $\frac{\sqrt{P-\underline{w}_B^D-d}}{2\sqrt{P-b-d}} < 1$ and

$$\frac{\sqrt{P-\underline{w}_B^D-d}}{2} \int_{\underline{w}_B^D}^{\overline{w}_B^D} \frac{u'(x)dx}{\sqrt{P-x-d}} < u(b) - u(\underline{w}_B^D) \text{ which violates equation (13). Therefore, the}$$

assumption is false and we have proved $\overline{w}_B^D > b$ if $b \leq \frac{3}{4}(P-d)$.

Besides, the wage bounds of worker A can be seen as a special case of worker B 's where $d = 0, k = 0$ and $\sigma = 1$. From properties (1)-(3), property (4) is easily derived, i.e., $\underline{w}_A < \underline{w}_B^D$ and $\overline{w}_A > \overline{w}_B^D$.

As for property (5), if $k = 1$, equation (26) is reduced to

$$Ew_B = \overline{w}_B^N + \frac{\delta}{(1-\sigma)\lambda} (\overline{w}_B^N - \underline{w}_B^N) - \frac{2\delta}{\delta + (1-\sigma)\lambda} (P - \underline{w}_B^N)$$

where $\underline{w}_B^N$ and $\overline{w}_B^N$ satisfy:

$$u(\underline{w}_B^N) = u(b) - \frac{\sqrt{P-\underline{w}_B^N}}{2} \int_{\underline{w}_B^N}^{\overline{w}_B^N} \frac{u'(x)dx}{\sqrt{P-x}} \quad \text{and} \quad \frac{P-\overline{w}_B^N}{P-\underline{w}_B^N} = \left(\frac{\delta}{\delta + (1-\sigma)\lambda} \right)^2.$$

The only difference in the system of equations compared with those for type A workers is the offer arrival rate, i.e., $\sigma = 0$ for type A while $\sigma > 0$ for type B .

Let $k \triangleq \frac{\delta}{\delta + (1-\sigma)\lambda}$, after some algebra the mean wage could be rewritten as:

$$Ew = P - (k^3 + k^2 + k)(P - \underline{w})$$

From the system of equations about $\underline{w}$ and $\overline{w}$, we can get:

$$\frac{\partial \underline{w}}{\partial k} = \frac{u'(\overline{w})(P - \underline{w})}{A + \frac{u'(\overline{w})k}{2}}$$

where $A = \frac{u'(\underline{w})}{2} - \frac{1}{4\sqrt{P-\underline{w}}} \int_{\underline{w}}^{\overline{w}} \frac{u'(x)dx}{\sqrt{P-x}} > 0$.

$$\begin{aligned} \text{So, } \frac{\partial Ew}{\partial k} &= -(3k^2 + 2k + 1)(P - \underline{w}) + (k^3 + k^2 + k) \frac{\partial \underline{w}}{\partial k} \\ &= \frac{(P - \underline{w})}{A + \frac{u'(\overline{w})k}{2}} \left[\frac{u'(\overline{w})(k - k^3)}{2} - A(3k^2 + 2k + 1) \right] < 0 \end{aligned}$$

where the last inequality holds due to:

$$\frac{u'(\overline{w})(k - k^3)}{2} - A(3k^2 + 2k + 1) < \frac{u'(\overline{w})(k - k^3)}{2} - \frac{u'(\underline{w})(3k^3 + 2k^2 + k)}{2} < 0$$

In addition, as k is increasing in σ , we get $\frac{\partial Ew}{\partial \sigma} < 0$. So the proposition is proved.

A5. Proof of proposition 4

(1) and (2) can be directly derived from proposition 1 and proposition 2. $\overline{w}_B^N < \overline{w}_A$

because

$$\begin{aligned} \overline{w}_A - \overline{w}_B^N &= \\ (P - b) \left[\left(\frac{\delta}{\delta + (1 - \sigma k)\lambda} \right)^2 - \left(\frac{\delta}{\lambda + \delta} \right)^2 \right] + d \left[1 - \left(\frac{\delta + (1 - \sigma)\lambda}{\delta + (1 - \sigma k)\lambda} \right)^2 \right] \left(\frac{\delta}{\delta + (1 - \sigma)\lambda} \right)^2 &> 0. \end{aligned}$$

Next, consider the comparison of earning distributions.

Since

$$K_w^A = \frac{\delta}{\lambda} \left[\sqrt{\frac{P-b}{P-w}} - 1 \right],$$

$$K_w^B = \begin{cases} \frac{\delta}{(1-\sigma k)\lambda} \left[\sqrt{\frac{P-b-d}{P-w-d}} - 1 \right], & \text{if } w \in [\underline{w}_B^D, \overline{w}_B^D] \\ \frac{\delta}{(1-\sigma k)\lambda} \left[\frac{\delta + (1-\sigma k)\lambda}{\delta + (1-\sigma)\lambda} \sqrt{\frac{P-\underline{w}_B^N}{P-w}} - 1 \right], & \text{if } w \in [\underline{w}_B^N, \overline{w}_B^N] \end{cases}$$

and

$$\frac{\delta}{\lambda} < \frac{\delta}{(1-\sigma k)\lambda}, \quad \sqrt{\frac{P-b}{P-w}} < \sqrt{\frac{P-b-d}{P-w-d}}, \quad \sqrt{\frac{P-b}{P-w}} < \frac{\delta + (1-\sigma k)\lambda}{\delta + (1-\sigma)\lambda} \sqrt{\frac{P-\underline{w}_B^N}{P-w}},$$

we can get $K_w^A < K_w^B$ for all w , i.e., A 's earnings distribution first-order stochastically dominates B 's earnings distribution. Therefore, $EW_A > EW_B$ and $w_A^q > w_B^q$.

Through tedious calibration, we can get the comparative statics of $EW_A - EW_B$:

$$\frac{\partial [EW_A - EW_B]}{\partial (\sigma, k, d)} > \vec{0}.$$

CHAPTER FOUR

Conclusion

Using counterfactual decomposition combined with quantile regression, Chapter 1 investigates the pattern of gender wage differentials in Asian and Latin American countries and finds glass ceiling effects in Argentina, Brazil and Chile, sticky floor effects in Bolivia, Guatemala, Mexico, Indonesia and Singapore, and mixed patterns for Vietnam, Cambodia and the Philippines. The findings are robust with as well as without occupation controls. In addition, analysis by sector points to glass ceilings in the public sector in most countries, while in the private sector the patterns vary. Combining the new evidence from this study with existing evidence for European countries and elsewhere (more than 50 countries), a comprehensive global picture of gender wage differentials is displayed. This study could help policy-makers to identify the target for the implementation of anti-discrimination policies.

The methodology used in Chapter 1 does not allow identification of the contribution of individual covariates. To understand how much gender wage gaps are attributable to differences in education, experience, and industry etc., one has to implement detailed decompositions. Chapter 2 utilizes a quantile decomposition that combines recently developed unconditional quantile regression with Oaxaca-Blinder decomposition to study the distributional pattern of gender wage gaps in Thailand 1991-2007. In addition, we propose a double decomposition method to explore the evolution of gender wage gaps. Through the analysis, we find that gender wage gaps in Thailand are mainly attributable to differences in the return to experience, mostly at the middle of the distribution, as well as differences in returns to education at both ends of the wage distribution. Although wage gaps have been declining over time in Thailand, especially in

the 1990s, little is explained by relative changes in characteristics. The policy implications are straightforward: more focus should be placed on gender inequality among low-income groups and improving the return to education and experience for female workers.

We recognize that unobserved productivity-related characteristics may influence our empirical studies, as is the case in most empirical studies. To the extent that this is so, part of the gaps that should be assigned to productivity differences is inaccurately assigned to potential “discrimination”. Chapter 3 is an attempt to explore issues underlying the discriminating behavior. In a random search framework, we assume two types of workers: majority and minority workers, and two types of firms: discriminating and non-discriminating firms. Discrimination is in the sense that firms possess disutility taste against minority workers and send offers to them at a slower rate. On the one hand, workers, both employed and unemployed, search for jobs randomly, and accept the offers which arrive at an exogenously given rate if and only if the expected lifetime value from the new offer is higher than his/her current one. On the other hand, firms post tenure-based contracts for each type of workers, recruit workers, and pay wages specified in the contracts to maximize their own profit. We assume firms cannot fire workers, or counter-offer workers’ outside offers.

In this discrimination search model with wage-tenure contracts, it is shown that minority workers have a higher unemployment rate and a longer duration of unemployment, while discriminating firms earn lower profits. Furthermore, minority workers are associated with a higher reservation wage but a lower wage upper limit, and a slower wage increase compared to majority workers. We finally put the model to data

and are able to distinguish the effect of productivity differences and discrimination on wage gaps.

To conclude, the contribution of the thesis in the literature of gender wage differentials is to first provide new evidence on glass ceilings/sticky floors and display a global picture of the distributional pattern of wage gaps. After showing more evidence, this thesis tries to address two research challenges. The first challenge is to get detailed (unconditional) quantile decomposition in a similar way as the traditional Oaxaca-Blinder methodology, and to explain the over-time changes in wage gaps at different points of the wage distribution. The second challenge is to identify the contributions of discrimination and unobserved characteristics differences to the residual wage gap. The thesis proposes some promising solutions, but there are also limitations. For example, the detailed quantile decomposition may be problematic if changes in the distribution of X are substantial, as the estimate of unconditional quantile regression is based on first order linear approximation. Besides, sample selection and endogeneity are not dealt with in our empirical studies. In the discrimination search model with wage-tenure contracts, the offer arrival rate may depend on the effort an individual worker has put into seeking jobs. In other words, λ may be endogenous. Furthermore, there are other dimensions besides the wage to consider when workers, especially female workers, are choosing a job. For example, they may take into consideration benefits such as flexible working hours, generous maternity benefits and parental leave when they are making a job decision. If these extra benefits are controlled in the analysis, the degree of pay gap may be reduced to a certain extent. Finally, the status “not in labor force” is not considered in our model.

Another extension of the discrimination search model could consider using a directed search framework rather than random search as we have done in the thesis.

Except for addressing these limitations and extensions, there are other interesting research questions to answer in the future. First, the definitions of glass ceilings and sticky floors are ad hoc and somehow arbitrary. They may be better defined in a more quantitative and explicit way.⁴⁹ Second, theoretical models that aim to explain the empirical findings regarding glass ceilings/sticky floors are rare. It would, therefore, be of interest to establish a model that is able to systematically generate these two effects. We speculate that taste based discrimination within a search framework is promising in this direction. Third, a comparative study across countries which are at different stages of economic development can be done to examine whether the trend of gender pay gap patterns is related to the economic progress and labor market maturity and explore further the policy implications.

⁴⁹ For example, a glass ceiling may be defined as monotonically increasing gap from the 75th percentile to the top. Correspondingly, a monotonically decreasing gap from the bottom to the 25th percentile is a sticky floor. The null hypothesis is to be tested before a conclusion can be made. However, how to test the hypothesis is yet to be solved.

Bibliography

Ahmed, S., and P. Maitra. 2011. "A distribution analysis of gender wage gap in Bangladesh." Working Paper, Department of Economics, Monash University, Australia.

Aigner, D. J., and G. G. Cain. 1977. "Statistical theories of discrimination in labor markets." *Industrial and Labor Relations Review*, Vol. 30, No. 2, pp. 175-87.

Akerlof, G. A., and R. E. Kranton. 2000. "Economics and identity." *The Quarterly Journal of Economics*, Vol. 115, No. 3, pp. 715-53.

Albrecht, J., A. van Vuuren, and S. Vroman. 2009. "Counterfactual distributions with sample selection adjustments: Econometric theory and an application to the Netherlands." *Labour Economics*, Vol. 16, No. 4, pp. 383-396.

Albrecht, J., A. Björklund, and S. Vroman. 2003. "Is there a glass ceiling in Sweden?" *Journal of Labor Economics*, Vol. 21, No. 1, pp. 145-77.

Altonji, J. G., and N. Williams. 2005. "Do wages rise with job seniority? A reassessment." *Industrial and Labor Relations Review* 58(3): pp. 370-397.

Altonji, J. G., and R. A. Shakotko. 1987. "Do wages rise with job seniority?" *Review of Economic Studies* 54(3): pp. 437-459.

Altonji, J. G., and R. M. Blank. 1999. "Race and gender in the labor market." In Orley Ashenfelter and David E. Card, ed., *Handbook of Labor Economics*, Vol. 3, pp. 3143-259. Amsterdam: North Holland.

Arulampalam, W., A. L. Booth, and M. L. Bryan. 2007. "Is there a glass ceiling over Europe? Exploring the gender pay gap across the wage distribution." *Industrial and Labor Relations Review*, Vol. 60, No. 2, pp. 163-86.

Atkinson, S. M., S. B. Baird, and M. B. Frye. 2003. "Do female mutual fund managers manage differently?" *Journal of Financial Research*, Vol. 26, No. 1, pp. 1-18.

Azmat, G., M. Guell, and A. Manning. 2006. "Gender gaps in unemployment rates in OECD countries." *Journal of Labor Economics* 24(1): 1-38.

Becker, G. 1971. *The Economics of Discrimination*. University of Chicago Press.

Becker, E., and C. M. Lindsay. 1994. "Sex differences in tenure profiles: Effects of shared firm-specific investment." *Journal of Labor Economics* 12(1): 98-118.

Bertrand, M., and K. F. Hallock. 2001. "The gender gap in top corporate jobs." *Industrial and Labor Relations Review*, Vol. 55, No. 1, pp. 3-21.

Bertrand, M., and S. Mullainathan. 2004. "Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination." *American Economic Review*, Vol. 94, No. 4, pp. 991-1013.

Black, Dan A. 1995. "Discrimination in an equilibrium search model." *Journal of Labor Economics*, Vol. 13, No. 2, pp. 309-34.

Blau, F. D., and L. M. Kahn. 1996. "Wage structure and gender earnings differentials: An international comparison." *Economica*, Vol. 63 (Suppl.), pp. S29-62.

Blau, F. D., and L. M. Kahn. 2000. "Gender differences in pay." *Journal of Economic Perspectives* 14(4): 75-99.

Blau, F. D., and L. M. Kahn. 2003. "Understanding international differences in the gender pay gap." *Journal of Labor Economics*, Vol. 21, No. 1, pp. 106-44.

Blau, F. D. and L. M. Kahn. 2006. "The U.S. gender pay gap in the 1990s: slowing convergence." *Industrial and Labor Relations Review* 60(1): 45-66.

Blinder, A. S. 1973. "Wage discrimination: Reduced form and structural estimates." *Journal of Human Resources*, 8(4): 436-455.

Bonjour, D., and M. Gerfin. 2001. "The unequal distribution of unequal pay--An empirical analysis of the gender wage gap in Switzerland." *Empirical Economics*, Vol. 26, No. 2, pp. 407-27.

Booth, A. L. 2009. "Gender and competition." *Labour Economics*, Vol. 16, No. 6, pp. 599-606.

Booth, A. L., and A. K. Leigh. 2010. "Do employers discriminate by gender? A field experiment in female-dominated occupations." *Economics Letters*, Vol. 107, No. 2 (May), pp. 236-38.

Booth, A. L., and P. J. Nolen. 2009. "Gender differences in risk behaviour: Does nurture matter?" IZA Discussion Paper No. 4026, Institute for the Study of Labour, Bonn, Germany.

Bowles, S., H. Gintis, and M. Osborne. 2001. "Incentive-enhancing preferences: Personality, behavior, and earnings." *American Economic Review*, Vol. 91, No. 2, pp. 155-58.

Bowlus, A. J. 1997. "A search interpretation of male-female wage differentials." *Journal of Labor Economics* 15(4): pp. 625-657.

Bowlus, A. J., and Z. Eckstein. 2002. "Discrimination and skill differences in an equilibrium search model." *International Economic Review*, Vol. 43, No. 4, pp. 1309-45.

Bratsberg, B., and D. Terrell. 1998. "Experience, tenure, and wage growth of young Black and White men." *Journal of Human Resources* 33(3): 658-682.

Buchinsky, M. 1994. "Changes in the U.S. wage structure 1963-1987: Application of quantile regression." *Econometrica*, Vol. 62, No. 2, pp. 405-58.

Buchinsky, M. 1998. "Recent advances in quantile regression models: A practical guideline for empirical research." *Journal of Human Resources*, Vol. 33, No. 1, pp. 88-126.

Buchinsky, M. 1998. "The dynamics of changes in the female wage distribution in the USA: a quantile regression approach." *Journal of Applied Econometrics*, 13(1): 1-30.

Buchinsky, Moshe. 2001. "Quantile regression with sample selection: Estimating women's return to education in the U.S." *Empirical Economics*, Vol. 26, No. 1, pp. 87-113.

Burdett, K., and D. T. Mortensen. 1998. "Wage differentials, employer size, and unemployment." *International Economic Review*, Vol. 39, No. 2, pp. 257-73.

Burdett, K. and M. Coles. 2003. "Equilibrium wage-tenure contracts." *Econometrica* 71(5): 1377-1404.

Burdett, K. and M. Coles. 2010. "Wage/tenure contracts with heterogeneous firms." *Journal of Economic Theory* 145(4): 1408-1435.

Cain, G. G. 1986. "The economic analysis of labor market discrimination: A survey." *Handbook of Labor Economics* 1: 693-785.

Cardoso, A. R., and R. Winter-Ebmer. 2007. "Mentoring and segregation: Female-led firms and gender wage policies." IZA Discussion Paper No. 3210, Institute for the Study of Labor, Bonn, Germany.

Chamberlain, G. 1994. "Quantile regression, censoring and the structure of wages." In Christopher A. Sims, ed., *Advances in Econometrics*, pp. 171-209. New York: Elsevier.

Charles, K. K., and J. Guryan. 2008. "Prejudice and wages: an empirical assessment of Becker's *The economics of discrimination*." *Journal of Political Economy*, Vol. 116, No. 5, pp. 773-809.

Charles, K. K. and J. Guryan. 2011. "Studying discrimination: Fundamental challenges and recent progress." *National Bureau of Economic Research*.

Chay, K. Y., and B. E. Honore. 1998. "Estimation of semiparametric censored regression models: An application to changes in Black-White earnings inequality during the 1960s." *The Journal of Human Resources*, Vol. 33, No. 1, pp. 4-38.

Chernozhukov, V., I. Fernandez-Val, and B. Melly. 2009. "Inference on counterfactual distributions." Institute for Fiscal Studies, Working Paper CWP09/09, London.

Chi, W., and B. Li. 2008. "Glass ceiling or sticky floor? Examining the gender earnings differentials across the earnings distribution in urban China, 1987-2004." *Journal of Comparative Economics*, Vol. 36, No. 2, pp. 243-63.

Chzhen, Y., and K. A. Mumford. 2009. "Gender gaps across the earnings distribution in Britain: Are women bossy enough?" IZA Discussion Paper No. 4331, Institute for the Study of Labour, Bonn, Germany.

Cobb-Clark, D. A. 2001. "Getting ahead: The determinants of and payoffs to internal promotion for young U.S. men and women." IZA Discussion Paper No. 288, Institute for the Study of Labour, Bonn, Germany.

Croson, R., and U. Gneezy. 2009. "Gender differences in preferences." *Journal of Economic Literature*, Vol. 47, No. 2, pp. 448-74.

De la Rica, S., J. J. Dolado, and V. Llorens. 2008. "Ceilings or floors? Gender wage gaps by education in Spain." *Journal of Population Economics*, Vol. 21, No. 3, pp. 751-76.

Dénurget, S., M. Fournier, and Y. Chen. 2007. "The evolution of gender earnings gaps and discrimination in urban China, 1988-95." *Developing Economies*, 45(1): 97-121.

DiNardo, J., N. M. Fortin, and T. Lemieux. 1996. "Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach." *Econometrica*, 64(5): 1001-1044.

Dohmen, T., H. Lehmann, and A. Zaiceva. 2008. "The gender earnings gap inside a Russian firm: First evidence from personnel data-1997 to 2002". ESCIRRU Working Paper No. 06, Berlin, Germany.

Dolado, J., F. Kramarz, et al. 1996. "The economic impact of minimum wages in Europe." *Economic Policy*, Vol. 11, No. 23, pp. 319-72.

Du, F. and X. Y. Dong. 2009. "Why do women have longer durations of unemployment than men in post-restructuring urban China." *Cambridge Journal of Economics* 33(2): 233-252.

Eckel, C. C., and P. J. Grossman. 2003. "Rebate versus matching: does how we subsidize charitable contributions matter?" *Journal of Public Economics*, Vol. 87, No. 3-4 (March), pp. 681-701.

Fairlie, R. W. and W. A. Sundstrom. 1999. "The emergence, persistence, and recent widening of the racial unemployment gap." *Industrial and Labor Relations Review* 52(2): 252-270.

Fang, Z., and C. Sakellariou. 2011. "A case of sticky floors: Gender wage differentials in Thailand." *Asian Economic Journal*, Vol. 25, No. 1, pp. 35-54.

Firpo, S., N. M. Fortin, and T. Lemieux. 2007. "Decomposing wage distributions using recentered influence function regressions." Working paper, University of British Columbia (June).

Firpo, S., N. M. Fortin, and T. Lemieux. 2009. "Unconditional quantile regressions." *Econometrica*, Vol. 77, No. 3, pp. 953-73.

Fitzenberger, B., R. Koenker, and J. A.F Machado. 2002. "Economic applications of quantile regression." Heidelberg: Physica-Verlag.

Flabbi, L. 2010. "Gender discrimination estimation in a search model with matching and bargaining." *International Economic Review* 51(3): 745-783.

Flabbi, L. and A. Moro. 2010. "The effect of job flexibility on female labor market outcomes: Estimates from a search and bargaining Model." IZA Discussion Paper No. 4829, Institute for the Study of Labour, Bonn, Germany.

Fortin, N. M., and T. Lemieux. 1998. "Rank regressions, wage distribution, and the gender gap." *The Journal of Human Resources*, Vol. 33, No. 3, pp. 610-43.

Ganguli, I., and K. Terrell. 2005. "Wage ceilings and floors: The gender gap in Ukraine's transition". IZA Discussion Paper No. 1776, Institute for the Study of Labour, Bonn, Germany.

García, J., P. J. Hernández, and A. López-Nicolás. 2001. "How wide is the gap? An investigation of gender wage differences using quantile regression." *Empirical Economics*, Vol. 26, No. 1, pp.149-67.

Gardeazabal, J., and A. Ugidos. 2005. "Gender wage discrimination at quantiles." *Journal of Population Economics*, Vol. 18, No. 1, pp. 165-79.

Gneezy, U., K. L. Leonard, and J. A. List. 2009. "Gender differences in competition: Evidence from a matrilineal and a patriarchal society". *Econometrica*, Vol. 77, No. 5 (Sep.), pp. 1637-64.

Gneezy, U., M. Niederle, and A. Rustichini. 2003. "Performance in competitive environments: gender differences." *Quarterly Journal of Economics*, Vol. 118, No. 3 (August), pp. 1049-74.

Goldberg, M. S. 1982. "Discrimination, nepotism, and long-run wage differentials." *The Quarterly Journal of Economics*, Vol. 97, No. 2 (May), pp. 307-19.

Goldin, C., and C. Rouse. 2000. "Orchestrating impartiality: The impact of "blind" auditions on female musicians." *American Economic Review*, Vol. 90, No. 4, pp. 715-41.

Goldsmith, A. H., J. R. Veum, and W. Darity. 1997. "The impact of psychological and human capital on wages." *Economic Inquiry*, Vol. 35, No. 4, pp. 815-29.

Gunewardena, D., D. Abeyrathna, et al. 2008. "Glass ceilings, sticky floors or sticky doors? A quantile regression approach to exploring gender wage gaps in Sri Lanka". Poverty and Economic Policy Research Network Working Paper No. 2008-04.

Gysler, M., J. Kruse, and R. Schubert. 2002. "Ambiguity and gender differences in financial decision making: An experimental examination of competence and confidence effects." CER-ETH Economics Working Paper No. 02/23.

Hao, L., and D. Q. Naiman. 2007. Quantile regression: Quantitative applications in the social sciences. Sage Publications.

Hersch, J. and P. B. Reagan. 1997. "Worker effort decisions and efficient gender-specific wage-tenure profiles." *Economic Inquiry* 35(1): 193-207.

Huber, M., and B. Melly. 2011. "Quantile regression in the presence of sample selection". Discussion Paper No. 2011-09, School of Economics and Political Science, University of St. Gallen.

Hyder, A., and B. Reilly. 2005. "The public sector pay gap in Pakistan: a quantile regression analysis." PRUS Working Paper No. 33. Department of Economics, University of Sussex.

Jellal, M., and C. J. Nordman. 2009. "A theory of gender wage gap." MPRA Paper No. 17409, University Library of Munich, Germany.

Juhn, C., K. M. Murphy, and B. Pierce. 1993. "Wage inequality and the rise in returns to skill." *The Journal of Political Economy*, 101(3): 410-442.

Kandil, L. E. 2009. "Gender wage discrimination in Egypt: A quantile regression analysis." Université Paris I Panthéon-Sorbonne Working Paper, Paris, France.

Kassenböhrer, S. and M. Sinning. 2010. "Distributional change in gender wage gap." IZA Discussion Paper No. 5303, Institute for the Study of Labour, Bonn, Germany.

Kee, H. J. 2006. "Glass ceiling or sticky floor? Exploring the Australian gender pay gap." *Economic Record*, Vol. 82, No. 259, pp. 408-27.

Knodel, J. 1997. "The closing of the gender gap in schooling: The case of Thailand." *Comparative Education*, 33(1): 61-86.

Koenker, R., and G. Bassett. 1978. "Regression quantiles." *Econometrica*, Vol. 46, No. 1 (Jan.), pp. 33-50.

Lang, K. and J. Lehmann. 2010. "Racial discrimination in the labor market: Theory and empirics." Boston University Working Paper.

Laptiev, A. 2010. "Examining the gender pay gap in the US in 1979-2009: The unconditional quantile regression approach". Master's. Dissertation, Department of Economics, Central European University, Budapest.

Light, A. and M. Ureta. 1995. "Early-career work experience and gender wage differentials." *Journal of Labor Economics* 13(1): 121-154.

Lipman-Blumen, J. 1976. "Toward a homosocial theory of sex roles: An explanation of the sex segregation of social institutions." *Signs*, Vol. 1, No. 3, pp. 15-31.

Machado, J. A. F., and J. Mata. 2005. "Counterfactual decomposition of changes in wage distributions using quantile regression." *Journal of Applied Econometrics*, Vol. 20, No. 4, pp. 445-65.

Mammen, K. and C. Paxson. 2000. "Women's work and economic development." *The Journal of Economic Perspectives*, 14(4): 141-164.

Manning, A., and J. Swaffield. 2008. "The gender gap in early-career wage growth." *The Economic Journal*, Vol. 118, No. 530, pp. 983-1024.

Martins, P. S., and P. T. Pereira. 2004. "Does education reduce wage inequality? Quantile regression evidence from 16 countries." *Labour Economics*, Vol. 11, No. 3, pp. 355-71.

Melly, B. 2005. "Public-private sector wage differentials in Germany: Evidence from quantile regressions." *Empirical Economics*, Vol. 30, No. 2 (Sep.), pp. 505-20.

Melly, B. 2006. "Estimation of counterfactual distributions using quantile regression." Swiss Institute for International Economics and Applied Economic Research (SIAW), University of St. Gallen.

Mendes, R. 2010. "Glass ceilings in Portugal?: An analysis of the gender wage gap using a quantile regression approach." *International Journal of Human Capital and Information Technology Professionals*, Vol. 1, No. 2, pp. 1-18.

Miller, P. W. 2005. "The role of gender among low-paid and high-paid workers." *Australian Economics Review*, Vol. 38 (4):405-417.

Miller, P. W. 2009. "The gender pay gap in the US: Does sector make a difference?" *Journal of Labor Research*, Vol. 30, No. 1 (March), pp. 52-74.

Millimet, D. L., and L. Wang. 2006. "A distributional analysis of the gender earnings gap in urban China." *The B.E. Journal of Economic Analysis & Policy*, Vol. 5, No. 1, pp. 5.

Montenegro, C. 2001. "Wage distribution in Chile: Does gender matter? A quantile regression approach". Policy Research Report on Gender and Development No. 20, World Bank, Washington, D.C.

Motonishi, T. 2006. "Why has income inequality in Thailand increased? An analysis using surveys from 1975 to 1998." *Japan and the World Economy*, 18: 464-487.

Mueller, G., and E. Plug. 2006. "Estimating the effect of personality on male and female earnings." *Industrial and Labor Relations Review*, Vol. 60, No. 1, pp. 3-22.

Munasinghe, L., T. Reif, and A. Henriques. 2008. "Gender gap in wage returns to job tenure and experience." *Labour economics* 15(6): 1296-1316.

- Nakavachara, V. 2010. "Superior female education: Explaining the gender earnings gap trend in Thailand." *Journal of Asian Economics*, 21(2): 198-218.
- Neal, D. A. and W. R. Johnson. 1996. "The role of premarket factors in Black-White wage differences." *Journal of Political Economy* 104(5): 869-895.
- Nestic, D. 2010. "The gender wage gap in Croatia--Estimating the impact of differing rewards by means of counterfactual distributions." *Croatian Economic Survey*, Vol. 12, No. 1 (April), pp. 83-119.
- Newell, A., and B. Reilly. 2001. "The gender pay gap in the transition from communism: some empirical evidence." *Economic Systems*, Vol. 25, No. 4, pp. 287-304.
- Ng, Y. 2007. "Gender earnings differentials and regional economic development in urban China, 1988-97." *Review of Income and Wealth*, 53(1): 148-166.
- Nicodemo, C. 2009. "Gender pay gap and quantile regression in European families". IZA Discussion Paper No. 3978, Institute for the Study of Labor, Bonn, Germany.
- Niederle, M., and L. Vesterlund. 2007. "Do women shy away from competition? Do men compete too much?" *The Quarterly Journal of Economics*, Vol. 122, No. 3 (Aug.), pp. 1067-1101.
- Nielsen, H. S. 2000. "Wage discrimination in Zambia: An extension of the Oaxaca-Blinder decomposition." *Applied Economics Letters*, 7(6): 405-408.
- Nordman, C. J., and F-C, Wolff. 2009. "Islands through the glass ceiling? Evidence of gender wage gaps in Madagascar and Mauritius." in Ravi Kanbur and Jan Svejnar, ed., *Labor Markets and Economic Development*, pp. 521-44. Routledge Studies in Development Economics, Routledge.
- Nordman, C. J., and F-C. Wolff. 2009. "Is there a glass ceiling in Morocco? Evidence from matched worker-firm Data." *Journal of African Economies*, Vol. 18, No. 4, pp. 592-633.

Ntuli, M. 2007. "Exploring gender wage "discrimination" in South Africa, 1995-2004: A quantile regression approach." IPC Working Paper No. 56, International Policy Center, University of Michigan.

Ollikainen, V. 2003. "The determinants of unemployment duration by gender in Finland." VATT Discussion Papers.

Oaxaca, R. L. 1973. "Male-female wage differentials in urban labor markets." *International Economic Review*, 14(3): 693-709.

Oaxaca, R. L. and M. R. Ransom. 1999. "Identification in detailed wage decompositions." *Review of Economics and Statistics*, 81(1): 154-157.

Pager, D., B. Western and B. Bonikowski. 2009. "Discrimination in a low-wage labor market: A field experiment." *American Sociological Review*, Vol. 74, No. 5 (Oct.), pp. 777-799.

Papapetrou, E. 2004. "Gender wage differentials in Greece." *Economic Bulletin*, No. 23 (July), pp. 47-64.

Pastore, F., and A. Verashchagina. 2011. "When does transition increase the gender wage gap?" *Economics of Transition*, Vol. 19, No. 2, pp. 333-69.

Patrinos, H., C. Ridao-Cano, and C. Sakellariou. 2009. "A note on schooling and wage inequality in the public and private sector." *Empirical Economics*, Vol. 37, No. 2, pp. 383-92.

Pham, H. T., and B. Reilly. 2007. "The gender pay gap in Vietnam, 1993-2002: A quantile regression approach." *Journal of Asian Economics*, Vol. 18, No. 5, pp. 775-808.

Riach, P. A., and J. Rich. 2002. "Field experiments of discrimination in the market place." *Economic Journal*, Vol. 112, No. 483 (Nov.), pp. 480-518.

Rodgers, W. M. and W. E. Spriggs. 1996. "What does the AFQT really measure: race, wages, schooling and the AFQT score." *The Review of Black Political Economy* 24(4): 13-46.

Rothe, C. 2010. "Partial distributional policy effects." Working Paper, Toulouse School of Economics (GREMAQ), Toulouse, France.

Sakellariou, C. 2004a. "Gender-earnings differentials using quantile regressions." *Journal of Labor Research*, Vol. 25, No. 3, pp. 457-68.

Sakellariou, C. 2004b. "The use of quantile regressions in estimating gender wage differentials: A case study of the Philippines." *Applied Economics*, Vol. 36, No. 9. 1001-7.

Sakellariou, C. 2010. "Returns to education and skills in Lesotho". The World Bank. Washington D.C. (mimeo).

Shi, S. 2009. "Directed search for equilibrium wage-tenure contracts." *Econometrica* 77(2): 561-584.

Siphambe, H. K. 2000. "Rates of return to education in Botswana." *Economics of Education Review*, Vol. 19: 291-300.

Smith, J. P., and F. R. Welch. 1989. "Black Economic Progress After Myrdal." *Journal of Economic Literature*, Vol. 27: 519-564.

Sutter, M., and D. Rutzler. 2010. "Gender differences in competition emerge early in life". IZA Discussion Paper No. 5015, Institute for the Study of Labour, Bonn, Germany.

Topel, R. H. 1991. "Specific capital, mobility, and wages: Wages rise with job seniority." *Journal of Political Economy* 99(1): 145-176.

Wei, Y., A. Pere, R. Koenker and X. He. 2006. "Quantile regression methods for referenced growth charts." *Statistics in Medicine*, Vol. 25, No. 8, pp. 1369-82.

Wellington, A. J. 1993. "Changes in the Male/Female Wage Gap, 1976-85." *Journal of Human Resources*, Vol. 28: 383-411.

Yun, M.-S. 2005. "A simple solution to the identification problem in detailed wage decompositions." *Economic Inquiry*, 43(4): 766-772.