THREE ESSAYS IN WAGE DIFFERENTIALS: INEQUALITY GROWTH, EDUCATION STANDARDS, AND IMMIGRATION

by

YUAN GAO

B.A., University of Colorado, Denver, 2003

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Economics
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Manhattan, Kansas

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Abstract

This dissertation consists of three essays focusing on wage inequality and education policy. Essay 1 considers growth in the variance of wages. Prior work has documented that the college premium plays a major role in explaining wage variance growth. This essay examines the extent to which this role can be attributed to an increase in the dispersion of occupation-specific returns to post-secondary education. Using the variance components approach and CPS data between 1979-1981 and 2003-2005, the essay shows that the variation in the college premium across occupations has increased over time, and this variation expansion explains about five percent of the growth in wage variance across the two periods. By dividing the sample workforce into professional and nonprofessional groups, the results suggest that the increased variation in the return to post-secondary education particularly caused the wage gap between the professional and non-professional workers to increase.

Essay 2 applies quantile regression methodology to the study of the determinants of the wage distribution among natives and immigrants in the U.S., using PUMS from 1990 and 2000, and ACS from 2006. Among other findings, the immigrant/native wage gap is concentrated at the lower end to the median of the wage distribution, and the primary source of the wage gap is the relative lack of labor market skills among immigrants. A cross-time comparison shows that the recent immigrant/native wage gap after controlling for skill variables first decreased from 1990 to 2000 and then expanded from 2000 to 2006. The growth is concentrated at the two ends of the wage distribution, and the reason for growth is that the recent immigrants in 2006 are younger and thus have less market experience than their counterparts of 1990.

Essay 3 is coauthored with Dr. Blankenau. We analyze the impact of changes in college admission standards on the skilled labor distribution, skilled firm distribution, and the match of skilled labor with skilled firms. We propose a model of schooling with heterogeneous labor and firms, in which firms' decisions in creating skilled jobs are conditioned on the supply of skilled labor. The model shows that lowering standards without providing incentives to acquire skills does not necessarily motivate accumulation of human capital or expansion of skilled industry. Lower standards tend to create a mismatch of educated labor with unskilled positions. In some specifications, lower standards can lower firms' willingness to create skilled positions, leaving more skilled workers underemployed.

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CHAPTER 1 - Variation in Return to Post-secondary Education and Increasing Wage Inequality

1.1 Introduction

The growth of wage inequality in United States since the 1970s has received considerable attention in various economic studies. The first wave of studies in the early 1990s suggested that the growth of wage inequality could be attributed mainly to the residual inequality, or the wage dispersion within skill groups defined by sex, education, and experience.[1] For example, the widely cited study by Juhn, Murphy, and Pierce (JMP, 1993) shows that, while both observable and unobservable skill premium growth contributed to wage inequality growth, the majority of the growth between 1963 and 1989 is due to a greater return to the unobservable components.[2]

Latter studies criticized the decomposition method in JMP because it did not fully account for the variety of sources generating wage variance. New methods are developed and applied to examine the reasons for wage inequality growth in the context of the full wage distribution. (e.g., DiNardo *et al*., 1996; Chay and Lee, 2000; Melly, 2005; Autor, Katz and Kearney, 2005; Lemieux, 2006a & 2006b). In contrast to the JMP conclusion, these later studies argued that increasing returns to labor market skills and the distributional change of the skills primarily explain the wage inequality growth in U.S. For example, Melly (2005) shows, using quantile regression to estimate the counterfactual distribution for decomposition, that only 20 percent of the wage inequality growth in the U.S. between 1973 and 1989 comes from residuals, while more than 50 percent of the growth is due to the distributional change of labor market skills, or namely the composition effect.

Recent evidence also suggests that rather than being uniform, the growth in wage inequality is disproportionately concentrated at the top of the wage distribution (e.g., Piketty and Saez, 2002; Autor, Katz and Kearney, 2005). In addition, studies on the causal effect of education on earnings show that log wages are an increasingly convex function of years of education, indicating a relative wage growth for more educated workers that enlarges the wage

[1] The residual inequality is so named as it was measured by the distribution of residuals from a Mincerian wage regression, e.g. in Juhn, Murphy, and Pierce (1993).
[2] Katz and Autor (1999) provide a summary of the early wage studies focused on residual inequality.

gap between college graduates and high school graduates (e.g., Mincer, 1997; Murphy and Welch, 2001; Deschênes, 2001). As these two findings are potentially related, Lemieux (2006a) uses a variance components approach and Current Population Survey (CPS) data to measure the effect of the increasing returns of schooling on the "polarized" inequality growth. His results show that the majority of the rise in wage inequality from 1973 to 2005 is explained by the increased returns to post-secondary schooling.

A question then arises from this conclusion as to "why the post secondary education, as opposed to other observed or unobserved measures of skills, plays such a dominant role in wage inequality" (Lemieux, 2006a). A possible answer to this question is contained in the hypothesis that there is unbalanced demand growth in some fields of study of higher education, which causes returns to education to be increasingly unequal among college graduates.[3] Such gaps in the returns to higher education would be more crucial in explaining wage inequality as more of the labor force has higher education. Inspired by the question raised in Lemieux (2006a), this paper empirically examines whether the variance of return to different fields of education has become larger, and, more importantly, how this variation in return to education affects the growth of wage inequality. Such imbalanced demand in different fields of study could potentially explain the dominant role of the return to higher education in explaining the growth of wage inequality.

The intuition of our hypotheses is straightforward: returns to higher education reflect the prices of skills associated with different fields of study of post-secondary education. Post-secondary education is different from earlier education stages because the training is specialized. By choosing major fields of study, students acquire different skills, and thus the wage return to college education can be different for these fields, reflecting the price differences for skills.

Theoretically, a wider distribution of returns to higher education is supported by the theory of the skill-biased technical change (SBTC) (e.g., Acemoglu, 2002), which argues that technology development particularly increases the demand of skilled workers and thus increases their wage return more than for non-skilled workers. The story applies to the different fields of education as well. For example, as personal computers were more widely used during the 1980s and the demand for computer skills increased greatly, college graduates in computer science

[3] Another possible hypothesis is that the relative demand for post-secondary education has increased dramatically over time, which enlarges the wage gap *between* college-educated workers and non-college ones.

could obtain relatively higher returns from college education, than say those in English, whose real returns from a college education were likely to remain stable during the same time. Such unbalanced demand due to the technology development would particularly increase the wage inequality among the workers with college degrees.

As the intuition and theory suggest, when the impact of college premium on wage inequality is assessed, the skills acquired in college should be controlled for in measuring the college premium. However, there is no available data recording workers' college majors. Thus, we use occupations as a proxy to control for the skill differences acquired during the post-secondary education, because the majors are likely to be relevant to occupations.

Specifically, to empirically test the variance growth in returns to college education, this paper measures how much of the growth of the wage variance is caused by the variation in the college premium, controlled for by occupations. Our objective is to find whether the cross-occupation variation in the return to post-secondary education can explain the major role of the college premium in explaining the growth of wage inequality. The present paper extends Lemieux (2006a) by examining how the variation, in addition to the increase, in wage returns to higher education has contributed to wage inequality growth.

The results of our research suggest that between the two periods being compared (1979-81 and 2003-05), the return to higher education became more diversified across occupations, and this variation expansion accounts for about five percent of total wage variance growth over time. This share is relatively small compared to the wage variance growth due to the increase in the returns to post-secondary education. In addition, after controlling for occupational differences in the return to post-secondary education, the portion of wage variance growth explained by the return to post-secondary education decreased from more than 50 percent to about 36 percent, and the composition effects are actually the dominant factor that boosts wage inequality growth. Finally, when the occupations are grouped into professional and non-professional groups, the five percent variance growth due to the increase of the variation of college premium is shown to stem from a wider return gap in education *between* the two occupation groups. The advantage in the education premium of the professionals has been growing relative to the non-professionals.

The paper is organized as follows. Section two introduces the CPS data for our analysis. Section three uses OLS and quantile regressions to diagnose graphically the occupation effect on the wage gap growth. Section four introduces the variance component approach and uses it to decompose the growth of the wage variance to the determinants of wage inequality. In this section, the variance change in the professional and non-professional occupations is compared to examine the difference in wage variance growth. Section five summarizes and concludes.

1.2 The CPS data

The Merged Outgoing Rotation Group (MORG) from the Current Population Survey (CPS) is used to examine the role of the college education premium in relation to hourly wages and wage inequality. The data are organized and made available by National Bureau of Economic Research (NBER). Two periods are selected to gauge the growth of wage inequality, 1979-81 as the base period and 2003-05 as the end period.[4]

Following existing wage studies using CPS data, our sample in each period includes the white male workers aged 18 to 64 years who have positive potential experience.[5] In addition, to sample only full time workers, we require that all included observations must work 35 hours or more per week. Hourly wage is used for our wage rate measure, because it is more representative than weekly wage as a measure of the price of labor (JMP, 1993). In the CPS data, not all workers report wages based on hourly payment, as they can choose to report either hourly or weekly wages. For those who report only weekly wages, their hourly wages are calculated by dividing their weekly wages by the usual number of working hours per week. To eliminate extreme values, the hourly wages are trimmed to a range from $1 to $100 in 1979 dollar value.[6] Following the standard in wage studies using CPS data, the wage rates labeled as “top-coded” in CPS data are multiplied by 1.4.

CPS data contain different measures for education before and after 1992, making the education codes in the two periods inconsistent. The MORG data by NBER recodes education information after 1992 to make the variable consistent over time. We use this recoded education measure for the 2003-05 period. Similarly, the occupation codes in the CPS changed after 1992, so we regrouped the occupation code in the base period 1979-81 according to the codes in 2003-05. These adjusted occupation codes are presented in Appendix 1.

[4] 1979 yearly data is the earliest MORG available; the end period was chosen to be close to Lemieux (2006a) for comparison purpose.
[5] Potential experience is measured as “age - education - 6”
[6] The inflation rate is calculated using the inflation calculator provided by Bureau of Labor Statistics.

A summary of the data is presented in Table 1.1, which is arranged based on occupations and education. As shown in Table 1.1, pooling three years of CPS data yields large samples in both periods. The base period has 222,661 observations and the end period has 189,655. In terms of education, the end period is better educated than the base period. In the end period, more than 50 percent of observations have at least 12 years of education, and more than 30 percent of them have at least 16 years of education. The two figures for the base period are 43 percent and 23 percent, respectively. This represents an expansion of the college-educated labor force.

The second column for each period summarizes the weight of each occupation in the total sample. For most occupations, its weight in total labor is about the same in the two periods, as the difference is less than one percentage point. Several occupations experienced greater changes proportionally. The construction and production occupation (Occ.=19+21), the largest weighted occupation in both periods, decreased six percentage points over time. Repair and maintenance (Occ.=20) decreased 4.8 percentage points. Architecture and engineering (Occ.= 4) decreased by about 2.4 percentage points. Among the occupations whose weight became larger, sales (Occ.= 16) increased by four percentage points, computer and math science (Occ.=3), food (Occ.=13) and transportation occupation (Occ.=22) each increased more than two percentage points.

When we divide the occupations into two groups: Occ. Codes from 1 to 10, except 6, as professional occupations, and 11 to 22 and 6 as service and production occupations, there was a slight growth in the weight of professional occupations and a slight decrease of services and production occupations. The proportion of the professional workforce in the end period increased 0.69 percentage points.

In Table 1.1, the last two columns under each period summarize the numbers of workers who have received post-secondary education in each occupation and their weight in the total sample.[7] If we divide all labor into two groups, the professional occupations have a higher participation rate for post-secondary education in both periods. The labor share of those having more than 12 years of education in the professional occupations is on average 86.4% in the base period and 89.8% in the end period. The rates for the services and production group are 37.7% and 45.3%. To summarize, the professional occupations in both periods are more likely to have completed at least one year of the post-secondary education than the non-professional group, but

[7] Beyond twelve years of education is picked because this is the start of post-secondary education, and it is where the wage gap starts growing (see Figure 1.1).

the later group experienced a faster growth rate in education. To show this trend more clearly, Table 1.2 presents the average education and experience level for the two groups. Both groups experienced a growth in the average level of education and experience, but the growth is larger in the production and services group.

1.3 Diagnostic evidence by OLS and quantile regressions

In this section, we use basic regression techniques to show that our data features the characteristics highlighted in prior wage inequality studies. We first show that the return to higher education has increased over time and the increasing return or convex-shaped return to education only exists in the later period. This increasing return to education is then shown to be primarily accountable for the growth of wage inequality. Finally, we show the return to education across occupations has been more diversified in the end period, and illustrate the effect of this diversified return to wage inequality using graphs.

To see the cross-time change of returns to skill characteristics, OLS regressions are applied to each period. Following the literature, we include quadratic terms for education and quartic terms for experience in the OLS regressions, to account for the nonlinear returns to education and experience.[8] The first regression equation considers:

$$w = \alpha + \beta_1 * edu + \beta_2 * edu^2 + \gamma_1 * ex + \gamma_2 * ex^2 + \gamma_3 * ex^3 + \gamma_4 * ex^4 + \varepsilon \quad (1)$$

where w is log hourly wage, α is a constant, edu is years of education, ex is years of experience, and ε is the residual. The estimates from the base period for equation (1) are presented in Table 1.3. In the base period, β_2= 0.0015, so there is a small increase in the return to an additional year of education. According to the estimates, during the base period a college graduate (edu =16) earns an hourly wage that is 25% higher than a high school graduate (edu =12), when other things equal.[9]

To make of the difference in returns between the post-secondary and pre-college education more apparent, a linear spline model as shown in equation (2) is estimated:

$$w = \alpha + \beta_1 * edu + \beta_2 * hi + \gamma_1 * ex + \gamma_2 * ex^2 + \gamma_3 * ex^3 + \gamma_4 * ex^4 + \varepsilon \quad (2)$$

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8 Lemiux (2006a) used the same equation for quantile regressions. The same setting fits well to my data to account for the nonlinear functional form of log wage on the skill characteristics.

9 The 25% wage difference is calculated by plugging in 16 and 12 years education into equation (1), while other things are equal.

where hi is the years of post-secondary education.[10] According to the spline model, the return to pre-college education is measured by β_1, and the return to the post-secondary education is measured by β_1+β_2, because β_2 measures additional return to post-secondary education relative to pre-college education. The estimates for 1979-81 are presented in the third column of Table 1.3.

In the base period, the return to one year of post-secondary education is only 0.04% (as β_2=0.0004) higher than one year of education before college, and β_2 is not statistically different from zero. While the estimates based on equation (2) still indicate a 25% increase in hourly wage for college graduates compared to high school graduates, the result by equation (2) indicates that this wage increase is due to an increase in the number years of education, rather than a higher payoff for post-secondary education relative to earlier education.

Equations (1) and (2) are estimated for the end period to examine the changes in wage composition over time, particularly the growth of returns to post-secondary education. The results are shown in the third and fourth column of Table 1.3. In the end period, a worker with college education (edu=16) earned an hourly wage 41% higher than a high school graduate (edu=12), a larger change compared to the 25% premium in the base period.

Based on the estimates from equation (2), in the end period, one year of college education returns 0.045 log wage points (β_2=.045) higher than one year of pre-college education, and, in contrast to the base period, this payoff difference is statistically significant. The marginal return to one year of pre-college education is 0.063 log wage points, so the return to post-secondary education is about 70% higher than the return to pre-college.[11]

Because our interest is to examine the variation in returns to post-secondary education by occupation, interactive variables between college education and occupation are added to equation (2) to get equation (3):

$$w = \alpha + \beta_1 * edu + \beta_2 * hi + \sum \lambda_j Occ_j + \sum \delta_j Occ_j * hi + \gamma_1 * ex + \gamma_2 * ex^2 + \gamma_3 * ex^3 + \gamma_4 * ex^4 + \varepsilon \quad (3)$$

where Occ_j is an occupation dummy of occupation j, and the coefficients for the occupation dummies, λ_j, control for the wage differences by occupations. The estimators of interest are the

[10] For the individuals whose education is less than or equal to 12, this term is zero. For the ones that have more than 12 years of education, it is in a range of 0 to 6, depending on the years of post-secondary education.
[11] "A 70% increase" is the additional return to college divided by return to earlier education, or 4.5%/6.2%.

coefficients δ_j, which measures the occupation-specific return to one year of post-secondary education. The estimates of δ_j and the absolute return of post-secondary education for each occupation are presented in Table 1.4.

By adding occupation related variables, the adjusted R^2 is larger compared to using equation (2), especially in the later time period. In addition, both the Wald test and LR test reject the hypotheses that all δ_j's or λ_j's are equal to zero. Because the δ_j's are measured relative to the occupation dropped to avoid dummy trap, the absolute returns to post-secondary education are computed and presented in columns 3 and 4 of Table 1.4, so the comparison could be demonstrated more vividly. For example, the return to post-secondary education in occupation j is computed by adding up the common return of education and the relative return by occupation, or $\beta_1 + \beta_2 + \delta_j$.[12]

As shown at the bottom of Table 1.4, the average and the standard deviation of the occupation-specific returns to post-secondary education are both larger in the end period. The occupation average return to post-secondary education increased from 0.048 to 0.071 over time, a 46% increase. The standard deviation increased by 35%. If weighted by each occupation's share in the sample, the average return increased by 38%, and the standard deviation increased by 15%. The larger variation in the college premium, the growth of the standard deviation, suggests that the variation can enlarge the wage inequality among college-educated workers.

Evidence of occupation effect based on quantile regressions

To examine the role of the returns to education in explaining the growth of wage inequality along the wage distribution, quantile regressions are applied to measure the returns to education at different wage levels of the wage distribution. Equations (1), (2) and (3) are estimated for the 10th, 50th and 90th wage percentiles, and the estimates are used to graph wage functions against education. The occupation effect on wage inequality is graphed by comparing the estimated wage gaps with occupations controlled to the gaps without occupations controlled. Note that though the same equations estimated by OLS also applied to quantile regressions, quantile regression estimates need to be interpreted differently. The coefficients by quantile regressions are the returns to the skill characteristics at different percentiles of the wage

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[12] β_1 plusβ_2 is the return to post-secondary education of the dropped occupation, which is food operation (occ.=13) in our sample.

distribution (i.e., Buchinsky, 1994). For example, for each equation of (1) to (3), β_1 and β_2 are estimated from the quantile regressions at the 90th percentile of the wage distribution, measuring the return to education at the top 10 percent wage distribution.

The estimates of the quantile regressions with equation (1) and (2) are presented in Table 1.5. Consistent with the results from OLS, in the base period, higher returns to post-secondary education relative to earlier education exist at the 90th percentile of the wage distribution. In contrast, all three wage percentiles in the end period show positive additional returns to post-secondary education.

Based on the estimates shown in Table 1.5, the graphs in Figures 1.1a and 1.1b show the fitted log wage as a function of education at each wage quantile. All wage functions are computed assuming a fixed 20 years of experience. The resulting log wages are normalized relative to the median wage with 12 years of education and 20 years of experience. In other words, the fitted log wages are the relative values to the same period's median wage of average workers with 12 years of education and 20 years of experience, whose wage rate is normalized to zero.

Figure 1.1a shows that the wage functions of education in all three wage percentiles become more convex in the end period, compared to the more linear shape of the base period.[13] The convexity is especially obvious when education exceeds 12 years for the 90th wage percentile, so the return difference between post-secondary and pre-college education is particularly pronounced for the top wage quantile.

Because of this more convex function of education in the end period, the wage gap between the 90th and 10th wage percentiles (referred as 90-10 gap from here on) in the end period grows as the number of years of education increases, particularly after 12 years of education. In contrast, the 90-10 wage gap was stable in the base period. As the wage functions are computed with a fixed number of years of experience, the graphed wage gap is due to the differences in the returns to education. It means that the differences in the return to post-secondary education are capable of replicating the growing wage gap concentrated at the top end of the wage distribution.

Figure 1.1b is graphed based on equation (2). Figure 1.1b has a convex shape of wage functions that is less smooth then Figure 1.1a, because the linear spline model restricts the

[13] Similar findings and graphs can be found in Mincer (1998), Deschenes (2002), and Lemieux (2006a).

education return to be different than only after 12 years of education. The purpose of Figure 1.1b is to make a comparison to Figure 1.1c, in which case occupation effect is controlled for.

The growing 90-10 wage gap due to returns to education shown in Figures 1.1a and 1.1b indicates that the returns to higher education is more widely distributed in the end period than in the based period. It can be evidence of unbalanced demand growth for the skills acquired through higher education. Thus, we will focus on the variation in the return to education beyond twelve years and its impact on wage inequality growth.

To see the change in wage functions when occupations are controlled for, equation (3) is estimated with the same quantile regressions. Equation (3) controls for cross-occupation wage differences, so quantile regression estimates by equation (3) account for the variation by occupations as well as by different wage levels. The results are presented in Table 1.6 and the corresponding Figure 1.1c.

To compare the two cases with and without occupation effects, we compute fitted log wages in Figure 1.1c by assuming all workers at the same level of the wage distribution earn the same average return to post-secondary education regardless of occupation by leaving out the term $\sum \delta_j Occ_j * hi$ in equation (3). In this way, the occupations' diversification effect on the college premium is left out, but the general trend with the mean of returns is retained. In other words, Figure 1.1c shows the wage function as if there were no difference in the college premium across occupations. Similarly, only the average of occupation-specific constants is used when wage functions are computed, and the variation by occupation dummies is left out. Thus, Figure 1.1c is actually computed using the same formula of equation (1), but the coefficients estimated from equation (3). Because the occupation effect is not excluded in Figure 1.1b, a comparison of Figure 1.1b to Figure 1.1c illustrates the effect of occupation on the wage distribution.

The difference between Figure 1.1b and 1.1c is not easy to read, because both show larger wage gaps at the high value of education in the end period. To show the occupation effect precisely, the wage gap growth at each education level from Figure 1.1b and 1.1c is compared, and the result is graphed in Figure 1.2. According to Figure 1.2, up to 16 years of education, the wage gap becomes smaller after controlling for occupation effect. Accordingly, the variation by occupation in the returns to the post-secondary education is a positive factor for the growth of the wage gap up to 16 years of education, but it becomes negative for more than 16 years of education.

In summary, the results by OLS and quantile regressions show that an increasing return to post-secondary education relative to earlier education is responsible for the growth of wage inequality on the top end of the wage distribution. Meanwhile, the returns to the post-secondary education were distributed wider across occupations in the end period. These two findings suggest that the increased variation by occupation could, at least partially, explain the growing gap in the college premium. As shown in Figure 1.2, the variation by occupations affected the size of the wage gap. These results serve as descriptive evidence suggesting a positive effect of variation in college premium on the growth of wage inequality. To quantitatively measure its contribution to the wage gap growth, variance decomposition with a variance components model is applied.

1.4 Variance decomposition model

The three-step wage variance decomposition approach introduced by Lemieux (2006a) is applied to decompose the growth of the wage inequality to the wage distribution determinants, including the returns to skills, the heterogeneous return components, and the composition effect. The variance components (VC) model consists of three estimation steps. First, the means and the variance of the wage distribution are measured by an OLS regression of wages. Second, the marginal effects of the skill variables on the means and the variances of wage are estimated by nonlinear least squares (NLS). The estimates from NLS are then used to compute the variance decomposition. The advantage of the VC model is that it simultaneously estimates the conditional mean and the conditional variance of log wages, so the distribution of returns across heterogeneous individuals is modeled at the same time as the means of the returns.

As explained in Lemieux (2006a), the commonly used Mincer wage equation implies strong restrictions on the sources of wage variances. For example, consider the following Mincer regression:

$$w_i = \alpha * a_i + \beta * edu_i + \gamma * ex_i + \varepsilon_i \quad (4)$$

where a_i represents unobserved ability, α is its return, β and γ are the mean of returns to education and experiences.[14] This simple model restricts the returns to education and experience

[14] The return to unobservable skill in equation (4) is the payoff of basic skill to a worker without education and

to be the same for all workers at a given time. As individuals are actually heterogeneously rewarded with the same education or experience, this simple model ignores a possible source for wage variance. Therefore, it cannot be consistent with our earlier findings shown in Figure 1.1 that wage dispersion increases at higher values of education. To incorporate the heterogeneous returns to education and experience, the following random coefficient model is introduced:

$$w_i = \alpha * a_i + \beta * b_i * edu_i + \gamma * c_i * ex_i + \varepsilon_i. \quad (5)$$

In equation 5, β, γ and α account for the means of returns, thus they are the same for everyone at a given time. They capture the common trend in wage returns to skills. The individual specific parameters a_i, b_i and c_i measure the individual returns for person i. They are so-called "heterogeneous return components," as they address the person-to-person difference in returns to the same level of skills. Based on this formula, for example, one more year of education would pay differently for two workers if they have different b_i.

If we normalize the means of these heterogeneous return components (a_i, b_i and c_i) to be one, then the conditional mean of equation (5) would be:

$$E(w_i|edu_i, ex_i) = \alpha + \beta * edu_i + \gamma * ex_i + \varepsilon_i. \quad (6)$$

In addition, if we assume the three skill characteristics are not correlated with each other, and treat the means of α, β and γ and the variables of education and experience as non-random variables, the conditional wage variance of equation (6) would be:

$$Var(w_i|edu_i, ex_i) = \sigma_a^2 * \alpha^2 + \sigma_b^2 * (\beta * edu_i)^2 + \sigma_c^2 * (\gamma * ex_i)^2 + \sigma_\varepsilon^2 \quad (7)$$

where $\sigma_a^2 = var(a_i)$, $\sigma_b^2 = var(b_i)$ and $\sigma_c^2 = var(c_i)$. The latter two are the variances of the heterogeneous return components for education and experience, respectively. Because we have no quantitative measure of unobservable skill, $\sigma_a^2 = var(a_i)$ can be viewed as the variance of the unobservable ability. According to equation (7), the wage variance can be attributed to different wage determinants. For example, the measure of wage variance relevant to education in equation (7) is denoted by $\sigma_b^2 * (\beta * edu_i)^2$. According to this measure, an increase in the wage variance by education could either be caused by an increase of average education return (β), a growth of the variance of the heterogeneous return to education (σ_b^2), a boost in the level of education (edu_i), or a mix of these. Therefore, it is possible to incorporate the observed feature in Figures 1.1 so that the wage variance could be larger for more educated workers.

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experience. This measure of unobservable ability is defined differently from the residual measure of unobservable ability as in JMP (1993), and thus the conclusion of its effect on wage inequality is different.

Equations (6) and (7) can be estimated simultaneously by nonlinear least squares (NLS). Before estimating the NLS model, we need to have the measures of the conditional means and conditional variances of the log wages, which are dependent variables in equation (6) and (7), respectively. The means and variances are estimated by an OLS regression:

$$w_i = \sum_l D_l e_l + \sum_j D_j x_j + \sum_l \sum_j D_{lj} e_l x_j + r_i = \bar{w}_i + r_i \ . \quad (8)$$

Equation 8 is a log wage regression on an unrestricted set of dummies that controls for years of schooling, potential experience, and interactive effects between schooling and experience. In equation (8), e_l is a dummy for one education level, and x_j is a dummy for one experience level.[15] These dummies divide the workforce into school-experience groups in which workers have a similar education and experience background. The fitted value of equation (8) assigns an average wage to each school-experience group, so $\bar{w}_i$ stands for the average wage of one group that a person i belongs to, based on person i's schooling and experience. The residual r_i, as $r_i = w_i - \bar{w}_i$, stands for the difference between person i's real wage and the group average wage.

The residual r_i represents the wage difference within the school-experience groups, which is parallel to the 90-10 wage gap in the figures by quantile regressions. The estimated $\bar{w}_i$'s are used as the dependent variable of equation (6) because they are the expected wages conditional on education and experience. The residual squares, r_i^2's, are used as the dependent variable for equation (7), as the average of r_i^2's represent the within-group wage variance. After replacing with the $\bar{w}_i$ and r_i^2, equations (6) and (7) become:

$$\bar{w}_i = \alpha + \beta * edu_i + \gamma * ex_i + \varepsilon_i \quad (6a)$$

$$r_i^2 = \sigma_a^2 * \alpha^2 + \sigma_b^2 * (\beta * edu_i)^2 + \sigma_c^2 * (\gamma * ex_i)^2 + \sigma_\varepsilon^2 \ . \ (7a)$$

The residual ε_i in equation (6a) is the wage difference that exists *between* the school-experience groups, because this wage difference is not explained by the skill characteristics, so $Var(\bar{w}_i)$, or equally $E(\varepsilon_i^2)$, is referred to as the between-group variance in the following discussion. The conditional mean of equation (7a),$E(r_i^2)$, represents the wage variance within the school-experience groups, so it is referred as within-group variance in the following discussion.

[15] The 7 schooling dummies are for years of education of 0-6, 7-9, 10-11, 12, 12-15, 16 and more than 16, and the 9 experiences dummies are from 0 to more than 40 years, with 5 years interval. The overall dummy groups are 79, but some of them are dropped in estimation due to being empty or too small group size. Later, as occupation dummies included, the total number of dummies in equation (8) is over 1000.

Finally, to allow nonlinear functional forms on the returns to education and experience, the education terms in equation (6a) and (7a) are extended to the linear spline model, and the experience terms are extended to be quartic:

$$\bar{w}_i = \alpha + \beta_1 * edu_i + \beta_2 * hi_i + \gamma_1 * ex_i + \gamma_2 * ex_i^2 + \gamma_3 * ex_i^3 + \gamma_4 * ex_i^4 + \varepsilon_i \quad (9)$$

$$r_i^2 = \sigma_a^2 * \alpha^2 + \sigma_b^2 * (\beta_1 * edu_i + \beta_2 * hi_i)^2 +$$
$$\sigma_c^2 * (\gamma_1 * ex_i + \gamma_2 * ex_i^2 + \gamma_3 * ex_i^3 + \gamma_4 * ex_i^4)^2 + \sigma_\varepsilon^2 \quad (10)$$

where hi_i measures years of post-secondary education. As there is only a small fraction of the workforce in each period that did not finish six years of primary education, education is normalized to be zero for six years of education.[16] This normalization fits the model to the data of Figure 1 by letting component $\sigma_a^2 * \alpha^2$ capture the stable wage dispersion at low values of education. Equations (9) and (10) are separately estimated for the base period and end period, so the variances of heterogeneous components are allowed to be different over time. Equations (9) and (10) are similar to the ones in Lemieux (2006a). To make a comparison of our results to Lemieux (2006a), this formula is estimated and the estimates are presented in Table 1.7.[17] The variance decomposition result based on these estimates is shown in Table 1.8.

The variance decomposition is computed as following: with the estimates of equations (9) and (10) in the base period, we can calculate the within- and between- group variances of the base period. Then, we can replace the coefficients of one wage determinant in the base period by the end period counterparts, and then calculate counterfactual wage variance after the replacement. The variance change between the counterfactual variance and the originally estimated variance is then attributed to the replaced coefficients. Specifically, for the base period t = 1979-81, the observed within-group variance is $E(r_{i,t}^2)$ and the between-group variance is $Var(\bar{w}_{i,t})$. The sum of the within- and between-group variance is the overall wage variance in the base period. To calculate the counterfactual variance, we first plug in particular coefficients of one skill factor from the end period back into equations (9) and (10) while other elements are the same as in base period. We then re-compute the within- and between-group variance using

[16] This normalization is following Lemieux (2006a). As the normalization applied, the interpretation of the constant becomes the return to the first six years of education and the unobservable ability that is *common* to everyone. So it is a measure a basic skill without experience and beyond 6 years of education.

[17] With equation (10), the implicit assumption is that the distribution of unobservable ability is the same for all the education-experiences groups. This could lead to an overestimation of effects by education and experiences to wage variances. Lemieux (2006a) paper dealing this problem by assuming the variance component for return to unobservable ability to be a linear function of education and experience, so people with high education or long experience could have higher unobservable ability.

the base period observations. For example, the change of the variance due to the price effect of experience is computed by plugging the relevant coefficients (which are $\gamma_1, \gamma_2, \gamma_3, \gamma_4$) estimated from the end period into the base period equations. To translate it into equations:

$$\bar{w}_i = \alpha + \beta_1 * edu_i + \beta_2 * hi_i + \gamma_{1,t2} * ex_i + \gamma_{2,t2} * ex_i^2 + \gamma_{3,t2} * ex_i^3 + \gamma_{4,t2} * ex_i^4 + \varepsilon_i \quad (9b)$$

$$r_i^2 = \sigma_a^2 * \alpha^2 + \sigma_b^2 * (\beta_1 * edu_i + \beta_2 * hi_i)^2 + \sigma_c^2 *$$

$$\left(\gamma_{1,t2} * ex_i + \gamma_{2,t2} * ex_i^2 + \gamma_{3,t2} * ex_i^3 + \gamma_{4,t2} * ex_i^4\right)^2 + \sigma_\varepsilon^2 \quad (10b)$$

where the subscript $t2$ = 2003-2005. The variables and coefficients not subscripted with $t2$ are from the base period. Based on equations (9b) and (10b), the counterfactual between- and within-group variance is recomputed. Other things equal, if only the returns to experience are changed, the change in wage variance, calculated using the counterfactual variance minus the estimated variance, would be attributed to the change of the experience price.

Note that the variance change attributed to unobservable ability is computed differently, because unlike education and experience, we have no quantitative measure of workers' unobservable skill, but only a measure of its variance. Thus, we cannot completely separate the effect of the price change and the distribution of the unobservable skill. Instead, we compute the total variance change due to the unobservable skill by replacing the return to unobservable skill and the variance of its heterogeneous component at the same time. Finally, the composition effect is measured by the difference between the total variance change of the two periods minus all estimated variance change due to the price effects and the heterogeneous return effects.

Table 1.8 shows a large increase in wage variance over time. As a benchmark, the total wage variance in 1979-81 was about 0.213. The 0.082 change represents an increase of 38 percent. While both between- and within-group variance increased over time, the between group growth is more severe as the size doubled. From column one in Table 1.8, about 66 percent of the between-group variance growth is due to the increase of the return to post-secondary education. As a result, more than half of the total variance growth comes from the increase in the return to post-secondary education. This result is similar to the one presented in Lemieux (2006a), which suggested that 54 percent of the wage variance growth between the periods1973-75 and 2003-05 was due to the increase in the return to post-secondary education. As shown later, once the occupation effect is controlled for, the proportion of the variance change explained by the return to post-secondary education would be smaller.

Our interest in this work is to measure the impact of the variation in the college premium across occupations on the wage inequality growth. To measure this effect, we add the interactive variables of higher education and occupation dummies to account for the effect of occupations on wage inequality. The empirical model is extended from equations (9) and (10) to equations (11) and (12):

$$\overline{w}_i = \alpha + \beta_1 * edu_i + \beta_2 * hi_i + \sum \lambda_j Occ_j + \sum \delta_j Occ_j * hi_i + \gamma_1 * ex_i + \gamma_2 * ex_i^2 + \gamma_3 * ex_i^3 + \gamma_4 * ex_i^4 + \varepsilon_i \quad (11)$$

$$r_i^2 = \sigma_a^2 * \left(\alpha + \sum \lambda_j Occ_j\right)^2 + \sigma_b^2 * \left(\beta_1 * edu_i + \beta_2 * hi_i + \sum \delta_j Occ_j * hi_i\right)^2 + \sigma_c^2 * (\gamma_1 * ex_i + \gamma_2 * ex_i^2 + \gamma_3 * ex_i^3 + \gamma_4 * ex_i^4)^2 + \sigma_\varepsilon^2 \quad (12)$$

where Occ_j are the occupation dummies. The interactive variables $\sum \delta_j Occ_j * hi$ measure the returns to a year of post-secondary education for different occupations. The coefficient of our interest, δ_j, is the occupation-specific return to the post-secondary education relative to the dropped occupation. After including occupation dummies, α measures the return to unobservable skill common to the workers in one occupation, depending on which occupation is dropped. Similarly, β_2 can be viewed as an occupation-specific return to post-secondary education, depending on which occupation's interactive variable is dropped. Therefore, $\beta_2 + \delta_j$ measures the additional return to the higher education relative to pre-college education for occupation j. Equations (11) and (12) are estimated for the base period and end period separately. Note that equation (8) is also re-estimated with equations (11) and (12), because the "school-experience groups" need to be re-defined as "school-experience-occupation groups" to be consistent with the added occupation dummies.[18]

Table 1.9 shows that returns to education and experience both increased in the second period. The estimated return to post-secondary education is the additional return to education, and it is the return particularly for the dropped occupation. Therefore, to compute the total return to one year of post-secondary education for one occupation, we need to add the return to education, the return to post-secondary education and the additional return to post-secondary education in one occupation. For example, for occ.=3, the return to one more year of post-secondary education in the end period would be the sum of 0.0667+(-0.0282)+0.0310 =0.0695 log wage points. The computed returns to post-secondary education for occupations are listed in

[18] As it can be helpful to estimate the variance precisely, we clustered occupations, assuming the wage variances within each occupation are not independent. The result does not change including this cluster or not.

the second and fourth columns of Table 1.9. The standard deviation of the occupation-specific returns increased from 0.019 to 0.026, and the increased variation is expected to be a positive contributor to the wage variance growth.

The variances of the heterogeneous return component of unobservable ability and education both slightly decreased over time. In contrast, the variance of the heterogeneous return to experience has dramatically increased in the end period, indicating a more diversified return to the same experience level. The average return to unobservable ability, which is the average of the constant and the occupation dummies, is lowered. Because the constant and occupation dummies address the returns to the unobservable skill with six or less years of education in each occupation, the lower return indicates a less important role for the basic skills in determining the wage rate.

The variance decomposition is presented in Table 1.10. As the education variables become complex, the computation of the counterfactual variance is adjusted. To compute the counterfactual variance due to a price change of post secondary education, the coefficients for higher education as well as the coefficients for the interactive terms of higher education and occupations are all replaced in the base period equation, which can be seen in the following equations:

$$\overline{w}_i = \alpha + \beta_1 * pre\_edu_i + (\beta_{1,t2} + \beta_{1,t2}) * hi_i + \sum \lambda_j Occ_j + \sum \delta_{j,t2} Occ_j * hi_i + \gamma_1 * ex_i + \gamma_2 * ex_i^2 + \gamma_3 * ex_i^3 + \gamma_4 * ex_i^4 + \varepsilon_i \quad (11b)$$

$$r_i^2 = \sigma_a^2 * \left(\alpha + \sum \lambda_j Occ_j\right)^2 + \sigma_b^2 * \left(\beta_1 * pre_{edu_i} + (\beta_{1,t2} + \beta_{1,t2}) * hi_i + \sum \delta_{j,t2} Occ_j * hi_i\right)^2 + \sigma_c^2 * (\gamma_1 * ex_i + \gamma_2 * ex_i^2 + \gamma_3 * ex_i^3 + \gamma_4 * ex_i^4)^2 + \sigma_\varepsilon^2 \quad (12b)$$

where $pre_edu_i$is the years of pre-college education. Again, the variables without subscript $t2$ are from the base period. Thus, the variance change calculated from the price change of post-secondary education includes the increase in the average price and the price change in every occupation. Based on (11b) and (12b), the variance change by the price effect of post-secondary education is 0.0263, about 32 percent of the total change (see Table 1.10).

To separate the effect of cross-occupation variation in the college premium from the mean, the deviations of the occupation’s college premium from the same period’s average return are computed, and the deviations of the base period are replaced with those from the end period. This is shown in the following equations:

$$\bar{w}_i = \alpha + \beta_1 * pre\_edu_i + ave * hi_i + \sum \lambda_j Occ_j + \sum d_{j,t2} * Occ_j * hi_i + \gamma_1 * ex_i + \gamma_2 * ex_i^2 + \gamma_3 * ex_i^3 + \gamma_4 * ex_i^4 + \varepsilon_i \quad (11c)$$

$$r_i^2 = \sigma_a^2 * \left(\alpha + \sum \lambda_j Occ_j\right)^2 + \sigma_b^2 * (\beta_1 * pre_{edu_i} + ave * hi_i + \sum d_{j,t2} * Occ_j * hi_i)^2 + \sigma_c^2 * (\gamma_1 * ex_i + \gamma_2 * ex_i^2 + \gamma_3 * ex_i^3 + \gamma_4 * ex_i^4)^2 + \sigma_\varepsilon^2 \quad (12c)$$

where ave is the estimated average return to post-secondary education, and $d_{j,t2}$ is the deviation of the return to post-secondary occupation for occupation j in the end period. The estimated average return is presented in the second and fourth columns of Table 1.9. The deviation for each occupation's college return is the occupation-specific college return minus the average. In this way, if we only replace the estimated deviations, a general increase in the mean of return to post-secondary education is controlled for, while the greater variation in the later period is accounted for when the counterfactual variances with the end period's deviation is calculated. The counterfactual variance computed by equations (11c) and (12c) minus the observed variance would be attributed to the increasing variation in the return to post-secondary education. If this variation accounts for a big proportion of the wage variance growth due to the increase of college premium, it would explain the major role of the post-secondary education in wage variance growth. In Table 1.10, the variance change due to this cross-occupation variation of the college premium is about 0.0042, or 5.1 percent of the total change.

As shown in Table 1.10, the total change of wage variance between the two periods is 0.082, which is a 38.5 percentage increase from the base period. As the workforce is regrouped with occupations in addition to education and experience, the within- and between-group variance is re-defined and different from the decomposition result shown in Table 1.8. A greater portion of the total variance growth is sorted into the between-group component, because the groups are defined with the added dimension of occupation.

The increase in the return to pre-college education accounts for 11 percent of total variance growth. This weight is about the same as the corresponding weight in Table 1.8. In contrast, the proportion of variance growth explained by the college premium is quite different. The increase in the return to post-secondary education accounts for 35 percent of the within-group variance increase, and it accounts for 32 percent of the total change. Recall from Table 1.8 that more than half of the total variance change was due to the increase of the return to post-secondary education. This difference suggests that without controlling for the occupation effect in wage inequality analysis, some wage variance change caused by occupation differences was mistakenly accounted by the return to the post-secondary education. This can be due to the correlation between the occupation and college background in determining the wage rate.

In Table 1.10, the variance change due to the college premium is still much larger than the change due to the return to pre-college education. We hypothesize that because post-secondary education facilitates different skills, the returns to the post-secondary education are diversified to reflect the prices for different skills. Using occupation to control for this skill difference [see equation (11c) and (12c)], the variation explains about five percent of the total variance increase. It is only about one-sixth of the variance increase explained by the return to post-secondary education. If there were no cross-occupation variation in the return to post-secondary education, the return to the post-secondary education would still account for more than 25 percent of the overall wage variance increase, which remains a much larger variance change than the one for pre-college education. Therefore, the cross-occupation variation of the college premium, although an important factor that increases wage variance, is not the major factor that explains why the college premium change accounts for a major variance growth. In conclusion, this college premium variation, at least when we use the 23 occupation codes to verify skill characteristics, fails to explain the major role of the post-secondary education in wage variance growth.

Though not large, the positive variance change due to the variation of the college premium still implies an interesting economic story: an unbalanced demand among different skills through post-secondary education exists, and it has promoted wage variance growth. The SBTC theory would suggest that technology development enlarges the demand gap among the workers who acquired different skills in college. Our result supports this hypothesis by confirming that the SBTC effect is observable throughout the returns to higher education.

Among the other elements affecting the wage variances, the slightly higher return to experience accounts for about nine percent of the wage variance increase. Unobservable ability contributes negative 21 percent of the variance change. The negative effect comes from a lower return to the unobservable skill as well as the smaller variance of the unobservable skill distribution (see Table 1.9). It indicates that the unobservable skill becomes a less important factor to explain the wage rate, probably because the workforce generally has more education and experience.

The variances of the heterogeneous return components of education and experience account for 19 percent of the total variance increase. The variance of the heterogeneous return to education was smaller in the end period, so the variance increase must be due to the wider distributed returns to the same number of years of experience.

The composition effect, which refers to the change of the distributions of the skill characteristics, is computed by subtracting the variance changes by the skill prices and variance components from the overall variance change. The composition effect accounts for about 50 percent of the overall wage variance increases, the largest among all factors. The data in Table 1.1 show that the composition change can be linked to labor force's better education and more experience in the end period. The average education has increased by more than .6 years, and average experience has increased by two years. Meanwhile, the variance of education also increased.

Professional vs. Nonprofessional wage inequality growth

To determine whether the professional and non-professional occupations exhibit the same pattern of variance change, we regroup the occupations into professional occupation (Occ. 1-10, except 6) and non-professional occupation group, including the production and services occupations (Occ. 11-22, plus 6). Equations (11) and (12) are estimated for the two occupation groups. Table 1.11 shows estimates for the professional occupation group and Table 1.12 shows the resulting variance decomposition.

Table 1.12 shows that the wage variance in the professional group increased by 0.051, a 25 percent increase compared to the base period. This variance growth over time is much smaller for the professional occupations than for the whole sample. According to the second column, the variance growth in the professional occupations is focused on the within-group component.

The increase in the return to post-secondary education explains more than half of the total growth of wage variance. This growth due to the college premium is mainly located in the between-group variance component. The increase of the return to pre-college education accounted for 41 percent of the growth, but the variance increase is mainly found in the within-group component. In summary, the increased return to education is the dominant force driving the growth of wage variance among the professional workforce, but the channels by which post- and pre-college education raise the variance are different. The former enlarges the wage gap by raising the relative return to college-educated workers and the latter by widening the wage distribution of workers having similar education.

Because the standard deviation of the returns to post-secondary education across occupations has doubled over time (see Table 1.11), it is surprising to find that this growth of variation in the college premium is a negative factor on the overall wage variance growth.[19] It reduced the total wage variance change by 6 percent. According to equations (11c) and (12c), this negative change means that if the deviation of each occupation's college premium from the average in the base period were the same as in the end period, and other things were equal, this end period college premium distribution across occupations would offset 6 percent of wage variance in the base period. If the result is not due to a measurement error, the explanation must be that the growth in education returns is greater among the workers in the base period whose returns from other skills are lower than the average. For example, the workers in the base period who were paid less for experience or unobservable skills received a greater-than-average increase in the return from post-secondary education in the end period. It remains to be understood, however, why the returns to higher education work in this way.

Among other wage determinants shown in Table 1.12, the increasing return to experience increases the wage variance by 2 percent. The change in the return to the unobservable ability, which is also controlled for by occupation, is again negative in wage variance growth. This results from two elements oppositely affecting the wage variance. On the one hand, the smaller average of the occupation dummies means the unobservable skill required in professional occupations was generally paid less over time. On the other hand, the higher heterogeneous return component variance indicates that the variation of unobservable skill was increasing in professional occupations. The net outcome is that the unobservable skill becomes less important for explaining the change of the wage variance of professional workers.

In contrast to the result observed for the whole sample, the variances of the heterogeneous return component of education and experience together made a small negative contribution to variance growth. The composition effect in the professional group is compressed to 20 percent of the total change. As shown in Table 1.2, the average level of education and experience in the professional group both increased, but both with smaller variances, so the composition effect is less important in professional occupations than in the whole sample.

[19] Taking account of the weight of the occupations, the standard deviation still increases from 0.011 to 0.017.

In summary, in the professional occupations the college premium is the major source for the wage inequality growth. This is consistent with existing evidence that the college premium is more relevant to wage inequality growth at the top end of the wage distribution (Autor, Katz and Kearney, 2005). Another interesting finding is that although the cross occupation variation in college premium was enlarged, it did not enlarge the wage inequality among professional workers, because the increase in returns to higher education is larger among the workers who were paid less in other skills.

Referring to the nonprofessional (production and services) group, Tables 1.13 and 1.14 present the estimates and variance decomposition results. As shown in Table 1.13, the standard deviation of the returns to the post-secondary education is smaller in the end period, which is quite different from the cases of the professional occupations and the whole workforce.

As shown in Table 1.14, the overall wage variance increased by 0.041, a 22.7% increase over the base period wage variance. This variance growth again is much smaller than it was for the whole sample. A striking difference in the production and services occupations is that the increase in the return to pre-college education explains more wage variance than the return to post-secondary education. This is the opposite of our findings for the total sample and the professional occupations. A possible explanation can be found in Table 1.2: the average education growth for this group is from 11 to 12 years of education, which does not yet represent general progress into post-secondary education. Thus, the increasing return to high school is more influential than the returns to college premium on the wage distribution change. For the same reason, although the returns to post-secondary education are less diversified across occupations in this group, the effect on wage variance change is so small that it is almost zero.

Interestingly, within both the professional and non-professional groups, the variation in returns to the post-secondary education creates negative and zero changes in wage variance. Thus, the 5 percent positive change found in the whole sample must be *between* the two professional groups. Therefore, the positive change of total variance by the variation in the returns to the higher education actually enlarged the wage inequality between the professional and non-professional workforce.

The increase in return to experience contributes 21.6 percent of the wage variance increase in the non-professional group. This portion is much larger than it is for either the professional group or the whole sample, making the return to experience an important source for wage variance growth within production and services occupations. The change in the unobservable ability return largely offsets the growth of wage inequality in the services and production occupations. This is because that both of the average return to the unobservable ability by occupations and the variance of the heterogeneous unobservable ability became smaller over time (see Table 1.13). In summary, as the production and services occupation group generally gains more education and experience, the return to the unobservable ability becomes less important in determining the wage difference. This is generally true for the whole workforce and the professional group, but is particularly obvious and influential in the production and services group.

The variance components of education and experience were larger in the end period (See Table 1.13), which explains 18 percent of the wage variance increase within the production and services occupations. The composition effect of education and experience explains 80 percent of the variance growth, which makes it the primary source of variance growth in the production and services group. This is consistent with the distribution change shown in Table 1.2, which shows that the average levels of education and experience of non-professional workers, as well as the variance of education of the workers have increased.

1.5 Conclusion

Recent studies suggest that the increasing wage gap that is concentrated at the top end of the wage distribution can be explained primarily by the increase in the return to post-secondary education. This work examines to what extent this major role of the college premium in explaining wage variance growth can be related to the variation in college return by skill differences, which are controlled for by occupations in our analysis.

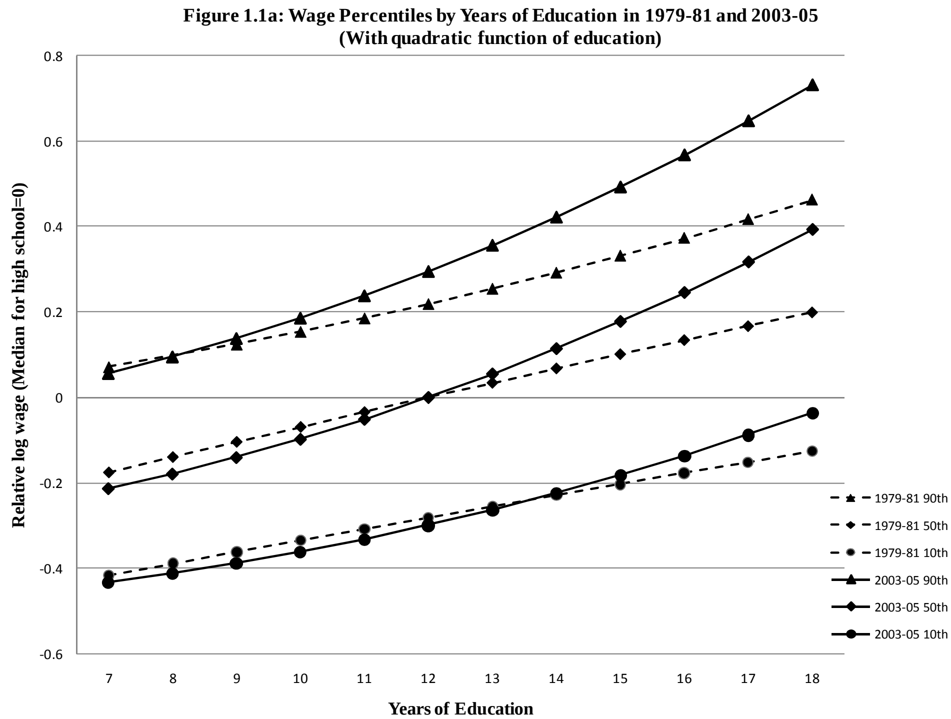
Using CPS data from 1979-81 and 2003-05 and the variance decomposition approach of variance components model, our empirical analysis shows that the distribution of the returns to the post-secondary education has been more diversified by occupations over time. Such variation expansion adds about five percent of the wage variance growth across the two periods. Five percent is relatively small compared to the overall wage variance growth due to the increasing return to post-secondary education. Therefore, the education-return variation by occupations does not explain why post-secondary education is so important to the growth of the wage inequality, at least when the variation is controlled for by the 22 occupation classification in CPS.

After controlling for the occupation variation, the wage variance change due to the increase in the return to post-secondary education is reduced from more than half to about one-third of the total. It suggests that the variance change attributed to the college premium is overstated, if we do not account for the occupation effect. Our results show that the composition effect was the dominant source in rising wage inequality between 1979-81 and 2003-05.

The patterns of the wage variance growth in the professional and nonprofessional occupations are shown to be quite different. The increasing return to education is the dominant driver of the wage variance growth in the professional group. In contrast, in the service and production group, wage variance growth is mainly due to the composition effect. This finding is consistent with the findings presented in Autor, Katz and Kearney (2005), which suggests that the growth in the 90-50 wage gap is mostly due to the price effect of education while the 50-10 wage gap growth is mainly due to the composition effect. More importantly, within the professional and nonprofessional groups, the variation in college premium made no positive change on the wage inequality growth. Therefore, the positive effect of the variation found from total workforce must particularly enlarge the wage gap between the professional and non-professional workers.

For future study, to see how supply of education has responded to the relative demand in different fields of education, it would be interesting to examine the change of the wage variance at several periods between the two periods compared in our analysis. Then we can see if the college premium gaps first get larger than get smaller or if the gaps has grown continuously. In addition, the same methodology can be easily applied to study the impact of other interactively related skill characteristics on wage distribution, i.e. experience and occupations.

Figure 1.1 Wage Percentiles by Years of Education



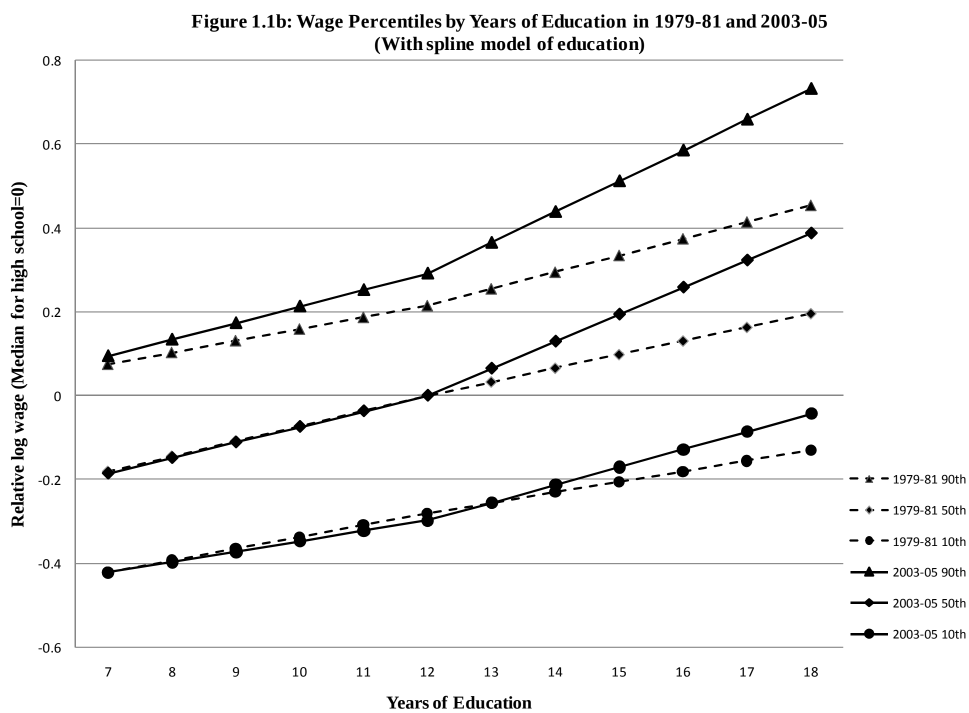


Figure 1.1 Wage Percentiles by Years of Education (continued)

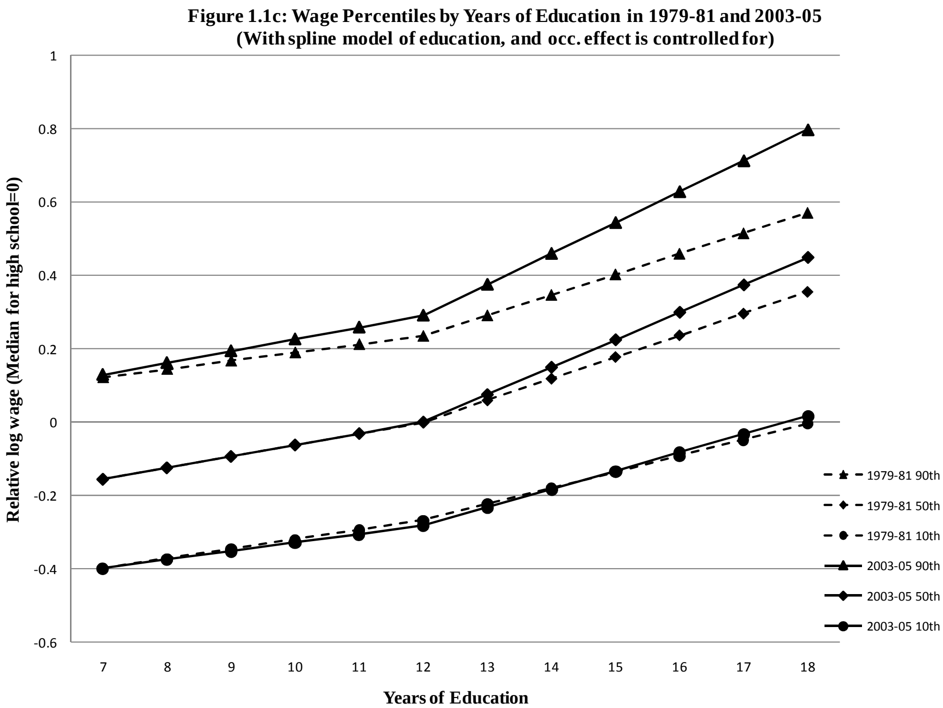


Figure 1.2 90th-10th Wage Gap Growth

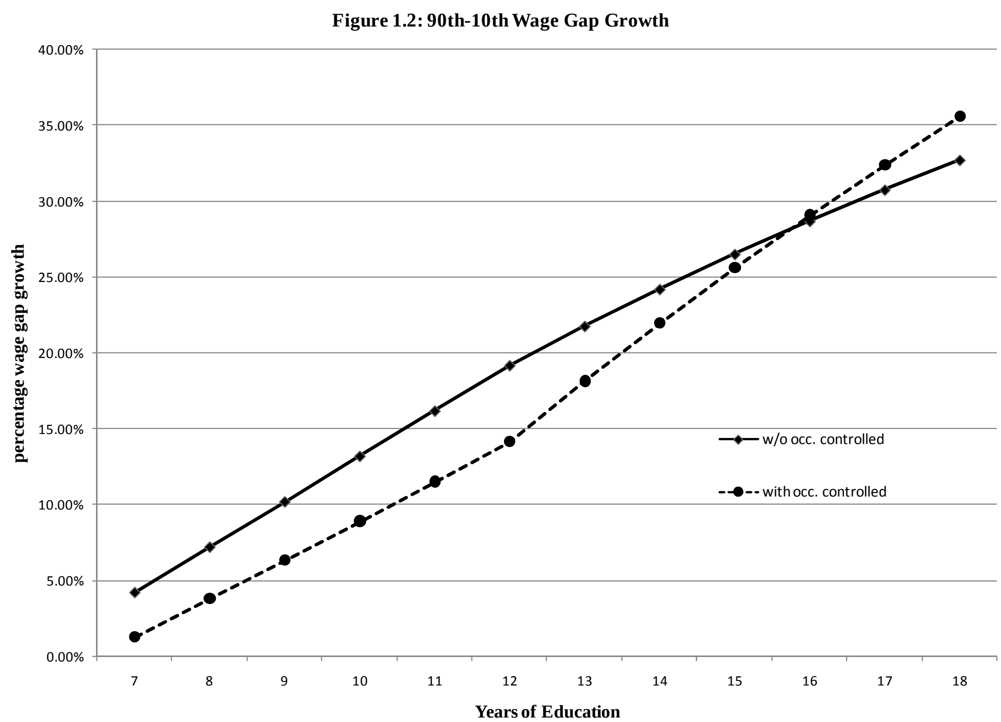


Table 1.1 Data Summary by Occupations

	1979-81			2003-05		
	No. of Obs.	% of Samp.	Std. Dev.	No. of Obs.	% of Samp.	Std. Dev.
Sample Size	222661			189655		
Ave. Edu.	12.8917		2.9142	13.52002		2.9265
Ave. Exp.	18.3455		12.6016	20.32041		11.1281
Edu.>12	96967	43.55%		101857	53.71%	
Edu.>=16	52697	23.67%		59905	31.59%	

Occ.Code	No. of Obs.	% of Samp.	Edu>12	%of Hi_Edu.	No. of Obs.	% of Samp.	Edu>12	%of Hi_Edu.
1+2	34610	15.54%	24045	69.47%	32730	13.41%	26800	81.88%
3	2150	0.97%	1890	87.91%	8197	3.36%	7427	90.61%
4	13415	6.02%	10475	78.08%	8784	3.60%	7664	87.25%
5	4002	1.80%	3558	88.91%	2948	1.21%	2654	90.03%
6	2104	0.94%	1933	91.87%	2971	1.22%	2651	89.23%
7	1239	0.56%	1217	98.22%	2042	0.84%	1989	97.40%
8	6838	3.07%	6691	97.85%	7794	3.19%	7412	95.10%
9	3026	1.36%	2447	80.87%	3589	1.47%	2942	81.97%
10	2370	1.06%	2127	89.75%	5087	2.08%	4635	91.11%
11	504	0.23%	214	42.46%	1122	0.46%	572	50.98%
12	5997	2.69%	2934	48.92%	8175	3.35%	5210	63.73%
13	2727	1.22%	736	26.99%	10339	4.24%	2951	28.54%
14	6113	2.75%	1050	17.18%	9654	3.95%	2176	22.54%
15	1079	0.48%	444	41.15%	2523	1.03%	1191	47.21%
16	12677	5.69%	7895	62.28%	23663	9.69%	14604	61.72%
17	16654	7.48%	7357	44.18%	17227	7.06%	9037	52.46%
18	3209	1.44%	553	17.23%	2687	1.10%	525	19.54%
19+21	60607	27.22%	12239	20.19%	51748	21.20%	14125	27.30%
20	27215	12.22%	6530	23.99%	18060	7.40%	7096	39.29%
22	16125	7.24%	2632	16.32%	24772	10.15%	6623	26.74%

Note:
1. The first column in Table 1 is the occupation code. See Appendix 1 for the occupations corresponding to the Occ. Code.
2. Under each period, the four columns from left to the right are: Number of observations in each occupation; the percentage of occupation's observations over whole sample; the number of observations in each occupation whose education is greater than 12; the percentage of observations whose education greater than 12 over the occupation’s total number.

Table 1.2 Statistics of the General Occupation Groups

Professional Occupation Group
(Occ. code 1 to10, except 6)

	Variable	Obs.	Mean	Std. Dev.	Min	Max
1979	Education	67650	15.08454	2.38826	0	18
	Experience	67650	17.71007	11.47421	1	56
	Post-Secondary	67650	3.17082	2.203313	0	6
2003	Education	58925	15.71723	2.179074	0	18
	Experience	58925	20.03659	10.43109	1	51.5
	Post-Secondary	58925	3.756029	2.072275	0	6

Production and Services Group
(Occ. code 6, 11 to 22)

	Variable	Obs.	Mean	Std. Dev.	Min	Max
1979	Education	155011	11.9347	2.5875	0	18
	Experience	155011	18.6228	13.0534	1	57
	Post-Secondary	155011	0.7666	1.4405	0	6
2003	Education	130730	12.5297	2.6697	0	18
	Experience	130730	20.4483	11.4261	1	57
	Post-Secondary	130730	1.1256	1.6942	0	6

Table 1.3 OLS Estimates of Equation (1) and Equation (2)

	Equation (1)		Equation (2)	
	79-81	03-05	79-81	03-05
Return to:				
Education	0.0599*** (0.0016)	0.0070*** (0.0018)	0.0633*** (0.0006)	0.0630*** (0.0008)
Education Square/10	0.0015** (0.0006)	0.0341*** (0.0007)		
Post Secondary Edu.			0.0004 (0.0008)	0.0452*** (0.001)
Experience	0.0585*** (0.0012)	0.0628*** (0.0016)	0.0583*** (0.0012)	0.0613*** (0.0016)
Experience Square/10	-0.023*** (0.001)	- 0.0224*** (0.0014)	-0.0228*** (0.001)	- 0.0207*** (0.0014)
Experience Cube/100	0.0041*** (0.0003)	0.0030*** (0.0004)	0.004*** (0.0003)	0.0024*** (0.0004)
Experience Quad/1000	-0.0003*** (0)	-0.0001** (0)	-0.0003*** (0)	0.000 (0)
Constant	0.6869*** (0.0107)	0.6379*** (0.0129)	0.6681*** (0.0081)	0.4482*** (0.0105)
Adjusted R Square	21.60%	21.59%	31.57%	31.42%

Note: Single, double and triple asterisks denote significance at 10%, 5% and 1% level respectively.

Table 1.4 OLS Estimates of Equation (3)

Variables	Estimated Returns		Returns to a year of Post-secondary Edu.	
	79-81	03-05	79-81	03-05
Constant	0.2626***	0.2896***		
Education	0.0515***	0.0532***		
Post-secondary Edu.	-0.0483***	-0.0112**		
exp	0.0551***	0.0526***		
exp2 / 10	-0.0218***	-0.0165***		
exp3 / 100	0.0038***	0.0016***		
exp4 / 1000	-0.0002***	0.0000		
Returns to Occ. dummies				
occ1_2	0.6621***	0.575***		
occ3	0.8551***	0.7005***		
occ4	0.7206***	0.5939***		
occ5	0.765***	0.4465***		
occ6	0.2699***	0.3513***		
occ7	0.8008***	0.3561***		
occ8	0.4609***	0.4236***		
occ9	0.6582***	0.5155***		
occ10	0.4874***	0.3513***		
occ11	0.2491***	0.0835**		
occ12	0.398***	0.3028***		
occ13	0.1896***	0.0172		
occ14	0.2991***	0.1172***		
occ15	0.2618***	0.1168***		
occ16	0.4827***	0.3084***		
occ17	0.5377***	0.2825***		
occ19b	0.6106***	0.3758***		
occ20	0.6357***	0.4177***		
occ22	0.5237***	0.2426***		
Returns to post-secondary Edu.				
occ_int1_2	0.063***	0.048***	0.0662	0.0900
occ_int3	0.0425***	0.0305***	0.0457	0.0725
occ_int4	0.0616***	0.045***	0.0648	0.0871
occ_int5	0.0503***	0.0487***	0.0536	0.0907
occ_int6	0.0205**	0.0017	0.0237	0.0437
occ_int7	0.0535***	0.0937***	0.0568	0.1357
occ_int8	0.0471***	0.0217***	0.0503	0.0637
occ_int9	0.0417***	0.0236***	0.0449	0.0657
occ_int10	0.0661***	0.0809***	0.0693	0.1229

Table 1.4: OLS Estimates of Equation (3) (Continued)

Variables	Estimated Returns		Returns to a year of Post-secondary Edu.	
	79-81	03-05	79-81	03-05
occ_int11	0.0597***	0.0153	0.0630	0.0573
occ_int12	0.0765***	0.0366***	0.0797	0.0786
occ_int13			0.0032	0.0420
occ_int14	0.0197**	0.0068	0.0230	0.0488
occ_int15	0.0497***	0.0152**	0.0530	0.0572
occ_int16	0.0807***	0.0674***	0.0840	0.1094
occ_int17	0.0406***	0.0187***	0.0439	0.0607
occ_int18	0.0366***	0.0138*	0.0399	0.0558
occ_int19	0.0387***	0.002	0.0419	0.0440
occ_int20	0.0392***	0.0127**	0.0424	0.0547
occ_int22	0.0261***	0.0124**	0.0293	0.0544
Adjusted R Square	30.68%	39.98%		
Average			0.0489	0.0717
Standard dev.			0.0198	0.0267

Note:

1. The first two columns report the estimates from equation 3. Single, double and triple asterisks denote significance at 10%, 5% and 1% level respectively.
2. The third and fourth columns report the computed returns to post-secondary education for each occupation, as well as the average and standard deviation of the returns.

Table 1.5 Quantile Regressions: without occupations

A. Quadratic function of education, by equation (1)

	Median		10th Quantile		90th Quantile	
	79-81	03-05	79-81	03-05	79-81	03-05
Log wage Return to:						
Education	0.0765***	0.0057**	0.0566***	-0.0048*	0.0203***	0.0079**
Educ. Square/10	-0.0036***	0.0373***	-0.0016	0.0278***	0.0202***	0.041***
Experience	0.0654***	0.0653***	0.0453***	0.0342***	0.0544***	0.0852***
Exp. Square/10	-0.0258***	-0.023***	-0.0158***	-0.0078**	-0.0201***	-0.0364***
Exp. Cube/100	0.0046***	0.0031***	0.0022***	-0.0002	0.0035***	0.0067***
Exp. Quad/1000	-0.0003***	-0.0001*	-0.0001	0.0001*	-0.0002***	-0.0004***
Constant	0.5328***	0.5727***	0.3419***	0.5389***	1.3662***	0.9248***

B. Spline model of education, by equation (2)

	Median		10th Quantile		90th Quantile	
	79-81	03-05	79-81	03-05	79-81	03-05
Log wage Return to:						
Education	0.0723***	0.0665***	0.0561***	0.0442***	0.0559***	0.0705***
Post-secondary Educ.	-0.0073***	0.0488***	-0.006***	0.0317***	0.0239***	0.0608***
Experience	0.0655***	0.0629***	0.0449***	0.0311***	0.0539***	0.0838***
Exp. Square/10	-0.0261***	-0.0204***	-0.0153***	-0.0045**	-0.0195***	-0.035***
Exp. Cube/100	0.0047***	0.0022***	0.0020***	-0.0014*	0.0033***	0.0063***
Exp. Quad/1000	-0.0003***	0.0000	-0.0001	0.0003***	-0.0002***	-0.0004***
Constant	0.5365***	0.3738***	0.3303***	0.3494***	1.2242***	0.7462***

Note:
1. Single, double and triple asterisks denote significance at 10%, 5% and 1% level respectively.
2. Table 4A responds to Figure 1; Table 4B responds to Figure 2.

Table 1.6 Quantile Regressions: return to post-secondary education controlled for by occupations

	Base Period (79-81)			End Period (03-05)		
	Median	10^{th} Quantile	90^{th} Quantile	Median	10^{th} Quantile	90^{th} Quantile
Education	0.0581***	0.0494***	0.0425***	0.0552***	0.041***	0.0573***
Post-secondary Edu.	-0.0584***	-0.0857***	0.0058***	-0.0079***	-0.0528***	0.0387***
Constant	0.1800***	-0.2023***	0.8272***	0.2308***	0.1733***	0.5992***
Additional Post-Secondary Educ. Payoff to occ. (δ_i):						
occ_int1+2	0.0712***	0.1032***	0.0165*	0.0525***	0.0996***	-0.0159**
occ_int3	0.0538***	0.0714***	0.0008	0.0345***	0.0787***	-0.0249**
occ_int4	0.072***	0.0954***	0.0164*	0.0478***	0.0939***	-0.0099
occ_int5	0.0621***	0.0751***	0.0111	0.0476***	0.0816***	0.0121
occ_int6	0.0332***	0.047***	-0.0298**	0.0073	0.045***	-0.0461***
occ_int7	0.0837***	0.11***	-0.0101	0.1099***	0.1175***	0.0214
occ_int8	0.0528***	0.0958***	-0.0004	0.0155**	0.0914***	-0.0285**
occ_int9	0.0529***	0.0598***	0.0148	0.0228**	0.0598***	-0.0144
occ_int10	0.072***	0.0481***	0.0711***	0.0905***	0.0841***	0.054***
occ_int11	0.0544***	0.0858***	0.0503**	0.0019	0.0388**	0.0183
occ_int12	0.085***	0.1013***	0.0307**	0.052***	0.0602***	-0.0134*
occ_int13						
occ_int14	0.0251**	0.0323**	-0.0076	-0.0029	0.0307***	-0.0167*
occ_int15	0.0575***	0.0611***	0.0353**	0.0124	0.0436***	-0.0117
occ_int16	0.0963***	0.0961***	0.0439***	0.0738***	0.0742***	0.048***
occ_int17	0.0427***	0.0669***	0.0128	0.0152**	0.0464***	-0.0076
occ_int18	0.0401***	0.0468**	0.0338**	0.007	0.0103	0.0056
occ_int19+21	0.0448***	0.0627***	0.0054	0.0038	0.0361***	-0.0328***
occ_int20	0.0434***	0.078***	-0.0004	0.011**	0.066***	-0.0407***
occ_int22	0.0304***	0.0498***	-0.001	-0.0069	0.0261***	0.0268**

Notes:

1. All quantile regressions also include quartic function of experience and occupation dummies.
2. Single, double and triple asterisks denote significance at 10%, 5% and 1% level respectively.

Table 1.7 NLS Estimates of the Variance Components Model

	1979-81	2003-05
Wage Return to:		
Education	0.0714***	0.0786***
	(0.0001)	(0.0001)
Post-secondary Education	-0.0095***	0.0269***
	(0.0001)	(0.0002)
Experience	0.0404***	0.0474***
	(0.0001)	(0.0002)
Experience Square/10	-0.0094***	-0.0111***
	(0.0001)	(0.0002)
Experience Cube/100	0.0003***	-0.0001**
	(0.0000)	(0.0001)
Experience Quad/1000	0.0001***	0.0002***
	(0.0000)	(0.0000)
Unobserved Ability	1.0669***	0.7967***
(Constant)	(0.0007)	(0.0011)
Heterogeneous Return Component Variance:		
Unobserved ability	0.1015***	0.1639***
(σ_a^2)	(0.0014)	(0.0033)
Education	0.1112***	0.1141***
(σ_b^2)	(0.0034)	(0.002)
Experience	0.1519***	0.1893***
(σ_c^2)	(0.0064)	(0.0074)
Fraction of between-group variance explained by model	94.50%	95.98%

Note: Single, double and triple asterisks denote significance at 10%, 5% and 1% level respectively.

Table 1.8 Decomposition of the 1979-81 to 2003-2005 Change in the Variance of Wage

	Change in Variance		
	Between Group	Within Group	Total
Price effects:			
High school and less	0.0021	0.0047	0.0068
	[4.4%]	[13.8%]	[8.3%]
Post-secondary Education	0.0321	0.0114	0.0435
	[66.2%]	[33.7%]	[52.8%]
Experience	0.0027	0.0057	0.0084
	[5.5%]	[16.9%]	[10.2%]
Unobserved Ability		-0.0042	-0.0042
		[-12.4%]	[-5.1%]
Variance Component change (Edu. & Exp.)		0.0137	0.0137
		[40.6%]	[16.7%]
Composition Effects (Distribution of Edu.&Exp.)	0.0116	0.0025	0.0141
	[23.9%]	[7.5%]	[17.1%]
Total changes between the two periods	0.0485	0.0338	0.0823
	[100%]	[100%]	[100%]
Total change as a percentage of the base period level	100.1%	20.1%	38.5%

Note: Percentage of the total column change is in square brackets.

Table 1.9 NLS Estimates of the Variance Components Model: post-secondary education are classified by occupations

	1979-81		2003-05	
Wage Return to:				
Education	0.0585***		0.0667***	
Post-secondary Education	-0.0555***		-0.0282***	
Experience	0.0384***		0.0413***	
Exp. Square /10	-0.0094***		-0.0087***	
Exp. Cube /100	0.0004***		-0.0004***	
Exp. Quad /1000	0.0001***		0.0002***	
Constant	0.5782***		0.5783***	
Post-Secondary Edu. By Occupations (δ_i):				
occ_int1+2	0.0611***	0.0641	0.0495***	0.0880
occ_int3	0.0401***	0.0431	0.0310***	0.0695
occ_int4	0.0595***	0.0625	0.0460***	0.0845
occ_int5	0.0475***	0.0504	0.0497***	0.0882
occ_int6	0.0237***	0.0266	0.0047***	0.0432
occ_int7	0.0465***	0.0494	0.0908***	0.1293
occ_int8	0.0396***	0.0426	0.0218***	0.0603
occ_int9	0.0400***	0.0430	0.0253***	0.0638
occ_int10	0.0665***	0.0694	0.0815***	0.1200
occ_int11	0.0537***	0.0567	0.0156***	0.0542
occ_int12	0.0725***	0.0755	0.0370***	0.0755
occ_int13		0.0030		0.0385
occ_int14	0.0178***	0.0207	0.0072***	0.0457
occ_int15	0.0461***	0.0491	0.0177***	0.0562
occ_int16	0.0783***	0.0812	0.0688***	0.1074
occ_int17	0.039***	0.0419	0.0203***	0.0588
occ_int18	0.0365***	0.0394	0.0174***	0.0559
occ_int19+21	0.0367***	0.0397	0.0021**	0.0406
occ_int20	0.0369***	0.0398	0.0117***	0.0502
occ_int22	0.0242***	0.0272	0.0127***	0.0512
Average		0.0463		0.0690
Std. Dev.		0.0189		0.0263
Heterogeneous Return Component Variance:				
Unobserved ability (σ_a^2)	0.0558***		0.0522***	
Education (σ_b^2)	0.1598***		0.1448***	
Experience (σ_c^2)	0.2501***		0.3909***	
Fraction of between-group variance explained by model	93.34%		96.02%	

Notes: 1. Both estimations also include occupation dummies.
2. Occ.18 is dropped in occupation dummy and Occ. 13 in interactive dummy.
3. Single, double and triple asterisks denote significance at 10%, 5% and 1% level respectively.

Table 1.10 Decomposition of the 1979-81 to 2003-2005 Change in the Variance of Wage: post-secondary education are classified by occupations

	Change in Variance		
	Between Group	Within Group	Total
Price effects:			
High school and less	0.0025	0.0065	0.0090
	[4.6%]	[22.9%]	[10.9%]
Post-secondary Education	0.0191	0.0072	0.0263
	[35.4%]	[25.3%]	[31.9%]
Post-secondary Education Through Occupations	0.0039	0.0003	0.0042
	[7.3%]	[0.9%]	[5.1%]
Experience	0.0020	0.0055	0.0075
	[3.8%]	[19.3%]	[9.2%]
Unobserved Ability	0.0100	-0.0274	-0.0173
	[18.6%]	[-96.3%]	[-21.1%]
Variance Component change (Edu. & Exp.)		0.0159	0.0159
		[56.0%]	[19.3%]
Composition Effects (Distribution of Edu.&Exp.)	0.0202	0.0207	0.0409
	[37.5%]	[72.9%]	[49.7%]
Total changes between the two periods	0.0539	0.0284	0.0823
	[100%]	[100%]	[100%]
Total change as a percentage of the base period level	79.9%	19.5%	38.5%

Note: Percentage of the total column change is in square brackets.

Table 1.11 NLS Estimates of the Variance Components Model: Post-secondary education are classified by professionals occupations

	1979-81		2003-05	
Wage Return to:				
Education	0.052***		0.0849***	
Post-secondary Education	-0.0098***		-0.0257***	
Experience	0.0419***		0.0465***	
Exp. Square /10	-0.008***		-0.0088***	
Exp. Cube /100	-0.0003**		-0.0011***	
Exp. Quad /1000	0.0001***		0.0003***	
Constant	1.0598***		0.7736***	
Post-Secondary Edu. By Occupations (δ_i):				
occ_int1+2	0.0266***	0.0687	0.0293***	0.0885
occ_int3	0.0057***	0.0479	0.0115***	0.0707
occ_int4	0.0237***	0.0659	0.0271***	0.0863
occ_int5	0.014***	0.0562	0.0298***	0.0890
occ_int7	0.0163***	0.0585	0.0745***	0.1337
occ_int8		0.0422		0.0592
occ_int9	0.0042***	0.0464	0.0043***	0.0635
occ_int10	0.029***	0.0711	0.061***	0.1202
Average		0.0571		0.0889
Std. Dev.		0.0109		0.0263
Heterogeneous Return Component Variance:				
Unobserved ability (σ_a^2)	0.0636***		0.0989***	
Education (σ_b^2)	0.095***		0.0766***	
Experience (σ_c^2)	0.1685***		0.1827***	
Fraction of between-group variance explained by model	91.26%		90.65%	

Notes:

1. Both estimations also include occupation dummies.
2. Occ.8 is dropped in both occupation dummy and interactive dummy.
3. Single, double and triple asterisks denote significance at 10%, 5% and 1% level respectively.

Table 1.12 Decomposition of the 1979-81 to 2003-2005 Change in the Variance of Wage: post-secondary education are classified by professional occupations

	Change in Variance		
	Between Group	Within Group	Total
Price effects:			
High school and less	0.0016	0.0197	0.0213
	[12.0%]	[51.9%]	[41.6%]
Post-secondary Education	0.0170	0.0097	0.0268
	[129.6%]	[25.6%]	[52.3%]
Post-secondary Education Through Occupations	-0.0010	-0.0024	-0.0034
	[-7.3%]	[-6.4%]	[-6.6%]
Experience	-0.0010	0.0022	0.0012
	[-7.3%]	[5.7%]	[2.3%]
Unobserved Ability	-0.0018	-0.0042	-0.0061
	[-14.0%]	[-11.1%]	[-11.9%]
Variance Component change (Edu. & Exp.)		-0.0023	-0.0023
		[-5.9%]	[-4.4%]
Composition Effects (Distribution of Edu.& Exp.)	-0.0027	0.0129	0.0102
	[-20.2%]	[33.9%]	[20.0%]
Total changes between the two periods	0.0132	0.0380	0.0512
Total change as a percentage of the base period level	28.50%	24.12%	25.13%

Note: Percentage of the total column change is in square brackets.

Table 1.13 NLS Estimates of the Variance Components Model: post-secondary education are classified by production and services occupations

	1979-81		2003-05	
Wage Return to:				
Education	0.0565***		0.0657***	
Post-secondary Education	-0.0542***		-0.0268***	
Experience	0.0395***		0.0387***	
Exp. Square /10	-0.0121***		-0.0079***	
Exp. Cube /100	0.0012***		-0.0006***	
Exp. Quad /1000	0.0000		0.0002***	
Constant	0.6027***		0.6057***	
Post-Secondary Edu. By Occupations (δ_i):				
occ_int6	0.0255***	0.0278	0.0047***	0.0435
occ_int11	0.0523***	0.0546	0.0152***	0.0540
occ_int12	0.07***	0.0723	0.0358***	0.0747
occ_int13		0.0023		0.0388
occ_int14	0.0165***	0.0188	0.0069***	0.0457
occ_int15	0.0453***	0.0476	0.0174***	0.0562
occ_int16	0.0772***	0.0794	0.0678***	0.1067
occ_int17	0.0378***	0.0400	0.0197***	0.0585
occ_int18	0.0357***	0.0380	0.0171***	0.0559
occ_int19+21	0.0356***	0.0378	0.0017**	0.0405
occ_int20	0.0352***	0.0374	0.0107***	0.0495
occ_int22	0.0224***	0.0247	0.0128***	0.0516
Average		0.0401		0.0563
Std. Dev.		0.0216		0.0185
Heterogeneous Return Component Variance:				
Unobserved ability (σ_a^2)	0.0461***		0.0442***	
Education (σ_b^2)	0.3196***		0.3137***	
Experience (σ_c^2)	0.2844***		0.3532***	
Fraction of between- group variance explained by model	91.29%		93.09%	

Notes:

1. Both estimations also include occupation dummies.
2. Occ.13 is dropped in interactive dummies of college education and occupation.
3. Single, double and triple asterisks denote significance at 10%, 5% and 1% level respectively.

Table 1.14 Decomposition of the 1979-81 to 2003-2005 Change in the Variance of Wage: Post-secondary education are classified by production and services occupations

	Change in Variance		
	Between Group	Within Group	Total
Price effects:			
High school and less	0.0026	0.0120	0.0146
	[16.0%]	[49.8%]	[36.2%]
Post-secondary Education	0.0031	0.0042	0.0073
	[18.9%]	[17.7%]	[18.1%]
Post-secondary Education Through Occupations	-0.0001	0.0000	-0.0001
	[-0.4%]	[-0.0%]	[-0.2%]
Experience	0.0028	0.0058	0.0087
	[17.4%]	[24.3%]	[21.6%]
Unobserved Ability	-0.0058	-0.0242	-0.0299
	[-35.6%]	[-100.7%]	[-74.5%]
Variance Component change (Edu. & Exp.)		0.0072	0.0072
		[30.2%]	[18.0%]
Composition Effects (Skill level of Edu. & Exp.)	0.0135	0.0189	0.0324
	[83.3%]	[78.7%]	[80.6%]
Total changes between the two periods	0.0045	0.0058	0.0103
Total change as a percentage of the base period level	35.79%	16.99%	21.56%

Note: Percentage of the total column change is in square brackets.

CHAPTER 2 - U.S. Immigration Wage Differentials across the Wage Distributions: 1990 to 2006

2.1 Introduction

Accumulating evidence suggests that, when the wage differential between immigrants and natives is compared, the entire wage distribution should be considered. Depending on where in the distribution the comparison is made, a comparison based on distributions may have implications that differ from the conventional approach of comparing means (see for example, LaLonde and Topel, 1992 and Yuengert, 1994). One of the first papers to study immigration wage differentials along with the earning distributions was by Bucher and DiNardo (2002). They studied the wage gap between natives and immigrants based on a comparison of wage densities. To compare the wage distributions across different periods, their work used U.S. decennial Census data from 1960 to 1990, and the wage densities were estimated based on a non-parametric method, Kernel density estimator. They suggest that after controlling for structural change in the labor market and changes in the skill level of the immigrant cohort, the distribution of immigrant wages does not move significantly relative to the distribution of native wages.

Following the idea of comparing wage distributions, Chiswick *et al*. (2006) compared the wage differential of native-immigrant earnings at different quantiles of the wage distribution. In contrast to Bucher and DiNardo, their wage distribution estimation was based on quantile regression methodology. Using 2000 Census data, they highlighted the impact of English skill levels for immigrants on wage differentials. They found that the immigrant-native wage gap varies with different income levels, and it is relatively larger in the lower wage deciles.

The present research follows this trend to study immigrant wage differentials based on earning distributions, and it takes advantage of recently available data to extend the study beyond 2000 census data.[20] The paper is motivated in part by an observation by Borjas and Friedberg (2007) of a turnaround of the growth in the immigrant-native wage differential. According to U.S. Census data from 1960 to 2000, they showed that the earnings of immigrants relative to

[20] Most U.S. immigrant wage studies use Census data that is up to 2000. One exception is Smith (2006), who uses CPS data of 2002.

native workers declined continuously from 1960 to 1990, but the trend was reversed between 1990 and 2000. Borjas and Friedberg suggest that the increase of H1B visa immigrants explains this upturn in the earnings of recent immigrants, because H1B immigrants are not only highly educated but also equipped with the skills that are demanded in the U.S. labor market.

One objective of the present study is to test whether the narrowing of wage differentials has continued after 2000. Thus, 1990 to 2006 data is used to examine how the wage differential is distributed and developed at different wage levels. By comparing estimated earning distributions, we check whether the narrowing of the wage differential exists through the whole distribution, or is concentrated in a fraction of the distribution. In addition, taking advantage of a recently developed decomposition method, we attempt to ascertain which economic factors determine the size and the growth of the wage differential. Specifically, we want to know how factors, such as skills, prices or market structure, contribute to the wage gap at different levels of wage distribution and how they affect the growth of the wage gap.

Based on Census data from 1990 and 2000, our research agrees with early findings that the immigrant-native wage differential declined from 1990 to 2000 at all wage deciles, after the difference in skill characteristics is controlled for. However, this decline did not continue after 2000. According to 2006 American Community Survey (ACS) data, we find an expansion of the wage gap between recent immigrants and native workers from 2000 to 2006, whether we measure the raw gap or the gap after including basic controls. Using a decomposition approach based on quantile regressions, we find that in each period of 1990, 2000, and 2006, the wage differential was most pronounced in the lower end to the median level of the wage distribution. The major reason for the existing wage differential is the skill differences between immigrants and native workers. However, within the observed wage differential, the proportion due to the difference in skill prices has grown larger over time. Decomposing the growth of the wage differential between recent immigrants and natives from 1990 to 2006, we find the growth is relatively larger at the top and bottom end of the wage distribution, and the reason for the growth is due to the faster skill growth of native workers compared to skill growth among the recently arrived immigrants.

The rest of the paper is organized as the follows. Section 2 introduces data and presents descriptive statistics. Section 3 discuses the results from quantile regression analysis, in which 3a focuses on the measurement of the immigrant-native differentials at various wage percentiles, and 3b focuses on the immigrant-native difference in returns to labor market skills. Section 4 describes the approach of decomposition based on the quantile regression method and presents the results. Section 5 decomposes and discusses the growth of the immigrant-native wage differentials between 1990 and 2006. A summary and conclusion are offered in Section 6.

2.2 Data and Descriptive Statistics

Census data are standard source of information in existing studies of immigrant wage, so we include the 1% Public Use Microdata Sample (PUMS) Files of 1990 and 2000 Census for our analysis. To take advantage of recently released data, we also include data from the 2006 American Community Survey (ACS), which is also a 1% sample of US population. All these data are provided by an online dataset of IPUMS-USA, a machine-readable database by the Minnesota Population Center (Ruggles *et al*, 2004).

The data in our study includes full-time male workers between the age of 25 and 64, excluding self-employed workers and the military. Specifically, these are male workers in the 1% US census of 1990, 2000, and ACS 2006 who are not in school, employed but not by self-owned business or the military service branches, worked last year, and were not absent from work due to layoff or on vacation. Among these workers, immigrants are defined as those born outside of the United States and not to U.S. parents. In addition, because the immigrants who arrived in the United States within the last five years better represent the composition change of immigrants, we discuss these so-called recently arrived immigrants separately from the overall immigrants. This separation also partially controls for cohort effects. A summary of data is presented in Table 2.1.

Following the lead of other work on immigrant wages, we choose the basic labor market characteristics as control variables for analyzing hourly log wages. Years of education, in a range of 0 to 22, is recoded from the educational attainment recorded in PUMS data.[21] Potential experience is calculated as age minus years of education minus six.[22] The data roughly records the English proficiency of workers, so English skill levels are controlled for by dummy variables in our analysis. In addition, race and metropolitan dummies are included. The hourly wage is computed using the yearly earning divided by usual working hours, and the wage is adjusted to its equivalence of the 1989 dollar value for cross-time comparison.

[21] The education attainment is originally recorded as degrees and grades, so the “years of education” is estimated.
[22] The observations with negative potential experience are then dropped.

Table 2.1 shows that, in all three years, immigrant male workers on average earn a lower hourly wage than native male workers, but they also on average have a lower educational attainment and less market experience. The changes of average log wage are small for all three groups, but difference in trends are noticeable. The average log wage of native workers slightly increased over time, while the average wage for all immigrants decreased. The average log wage of recent immigrants first increased from 1990 to 2000, but then decreased in 2006 to a level lower than 1990.

The average schooling of overall immigrants is lower than native workers. By 2006, the schooling gap is 1.48 years, a slight reduction from a gap of 1.7 years in 1990. Recent immigrants in 2000 and 2006 are more educated compared to all immigrants of the same period, indicating progress in the educational attainment among recent immigrants. Native workers also made gains in their educational attainment at the same time but at a slower pace, so immigrants are slowly catching up in terms of the schooling. The variation of schooling among the immigrants is considerably larger than among native workers, indicated by the variance of schooling for immigrants, which is about two times larger than the variance for native workers.[23]

The relative experience of all immigrants compared to natives was positive in 1990, which was 1.2 years more than native workers, but it became negative in 2000 as -0.3 yeasr and in 2006 as -1.1 years.[24] The change can be partly explained by looking at the average experience of recent immigrants. In 1990, recent immigrants had 3 years less potential experience than native workers, and the gap became 6.5 years in 2006. This indicates that recent immigrants are younger and less experienced than immigrants who arrived earlier. As discussed in Smith (2006), such a trend can be attributed to two facts: the baby boom made native-born workers older in the past 50 years, and immigrants have become younger as the pace of immigration has quickened.

According to the measure of English skill in census data, "Poor English” is a dummy variable that is defined to be “one” for those who reported that they do not speak English well, or do not speak English at all. It is “zero” for those who speak only English and for those who reported they speak English well or very well. By this measure, the proportion of good English

[23] A relevant finding is in Smith (2006) is that the immigrants are more highly represented in both the lowest and highest rungs of the education ladder. According to the Borjas (1987) model, this is because immigration decision is a self-selection result either by the more-than-average skilled labors (positive-selection) from a country where there is less wage inequality than the U.S., or by less-than-average skilled labors (negative selection) from a country where there is more wage inequality.

[24] Because this “potential” experience is estimated from age minus years of education, if immigrants in general are more likely to experience a layoff period after graduation, the experience of immigrants is overestimated.

speakers among all immigrants and recent immigrants has decreased over time. This contrasts with the fact that the schooling of recent immigrants has increased at the same time. A possible explanation is could be that more immigrants in later years, though with more years of schooling, are from non-English speaking countries. Finally, immigrant workers are more likely to work in metropolitan areas.

An overview of observed wage differentials in which wage densities are compared is presented in Figures 2.1 and 2.2. Figure 2.1 shows the differential between all immigrants and native workers, and Figure 2.2 shows the differential between recent immigrants and native workers. The wage densities are constructed with Gaussian kernel estimates using the optimal bandwidth that minimizes the mean integrated squared error if the data were Gaussian.[25] As shown in Figure 2.1, compared to native workers, the wage distribution of immigrant workers is less symmetric and centered near the lower-than-median wage of native workers. In contrast, the differential at the upper tail and at the very bottom is small. Accordingly, immigrants are more likely to fall in the lower tail of wage distribution and less likely to be in the middle range. Figure 2.2 shows a similar pattern of differential between recent immigrants and natives. Recent immigrants are more likely to earn a wage at the lower end of the wage distribution, even compared to the all immigrant cohort.

2.3 Estimated Differentials by Quantile Regressions

2.3.1 Wage differential after control variables

In this section, we measure immigrant-native wage differentials at different wage percentiles, using the quantile regression method and pooling data for both natives and immigrants. The wage differentials are measured by the coefficients of an immigration dummy variable at each wage decile. Because immigrant and native labor data are pooled together, the same standard of wage quantiles is applied to both groups. Wage differentials are estimated in two ways: 1) the observed, raw wage differential, and 2) the wage differential after skill variables have been controlled for. Results shown in Table 2.2a compare all immigrants to natives, and in Table 2.2b compare recent immigrants to natives.

[25] We use STATA 10 to estimate the Kernel Densities, and the optimal bandwidth is set as default.

In Table 2.2, the first rows under each year present the observed wage differential from the 10th to the 90th wage percentiles. The differentials are measured by the coefficient of the immigration dummy "b" in the following equation:

$$w_i = a + b * d_{im}. \quad (1)$$

Equation (1) is estimated by quantile regressions at the 10th, 20th ... 90th wage deciles, in which w_i is the log hourly wage, a is a constant, and d_{im} is a dummy variable for overall immigrants in Table 2.2a, and for recent immigrants in Table 3.2b. Because no control variables are included in equation (1), b measures the raw wage differential that is directly observed at each wage decile.

The second line under each year in Table 2.2 presents the wage differential after controlling for the skill differences. The differentials are measured by the coefficients of immigration dummy for each decile in the following equation:

$$w_i = a + x_i\beta + b * d_{im}. \quad (2)$$

Equation (2) is estimated by quantile regressions at the 10th, 20th ... 90th wage deciles, in which x_i accounts for the skill characteristics listed in Table 2.1, and β is a vector of log wage returns to labor market skill characteristics. The coefficient b measures the wage differential after control it for the skill variables. With a common β for the natives and immigrants, equation (2) implies the same returns to labor market skill characteristics for both groups. We will see later that this "same price" assumption is unrealistic. Here we need a simple measure of the wage differential after controlling for the difference in skills and prices. As skill variables are included, the wage gap measured by equation (2) is the part of the differential that is neither explained by price differences nor by skill differences. Let's call it "the wage gap after controls" to distinguish it from the raw wage gap measure.

Let's first look at the wage gap between all immigrants and native workers, as shown in Table 2.2a. Two patterns are common in all three years. First, the wage gaps are found to be largest among the workers who earn a lower-than-medium wage, and the wage gap decreases as one moves up to higher wage levels. This pattern remains true for both the raw wage gap and the wage gap after controls. Alternatively, this trend can be clearly read through Figure 2.3, which is also measured using equation (1) and (2), but depicts "b" from every wage percentile. Another common pattern in all three periods is that the wage gaps after controls are much smaller than the raw wage gap, and they are generally less than 20 percent of the raw gaps. This means more than

80 percent of the raw wage gaps, depending on the wage deciles, are explainable by controlling for basic labor skills.

Using Table 2.2a for a cross-time comparison, we see the raw wage gap between all immigrant and native workers continuously growing from 1990 to 2006 in all wage deciles except for the 10th and the 90th. On the other hand, the wage gaps measured after controlling for skills at the 10th to 40th wage deciles first enlarged from 1990 to 2000, and then decreased from 2000 to 2006. From 1990 to 2006, the negative, after-control wage differentials at the lower end of the wage distribution is more than doubled. The after-control wage differentials at the upper end of the wage distribution were positive in 1990, but they became either smaller or negative in 2006.

In Table 2.2b, which presents the recent immigrant-native wage gap, the pattern still holds true that the wage gap is largest at the lower end of the wage distribution and getting smaller while moving up to the higher end. What is different in Table 2.2b is that the wage gaps after controlling for skills account for a large proportion of the raw gap, which ranges from one-half to one-fourth, depending on which wage deciles are compared. Thus, controlling for basic skills explains only about half of the observed wage gap between recent immigrants and native workers.

Another difference between Tables 2.2a and 2.2b comes from the different patterns of raw gap growth over time. In Table 2.2b, the raw wage gap between recent immigrants and natives is increasing strictly from 1990 to 2006 at the 10th and the 20th wage deciles. The raw wage gaps at the 30th to 70th and the 90th wage deciles first decrease from 1990 to 2000, but end up being larger in 2006. The raw gaps at all wage deciles, except the 80th, are larger in 2006 compared to 1990, and the size of increases are particularly large in the lower end of the distribution from the 10th to 40th wage deciles.

In terms of the gaps after controls, Table 2.2b shows that wage gaps between recent immigrants and natives were smaller in 2000 than in 1990. This is consistent with a finding in Borjas and Friedberg (2007), in which they found the long-term trend of the immigration wage gap increasing from 1960 to 1990 was turned around in the late 1990s. However, according to the data from the 2006 ACS, the immigrant-native wage gap recovered in 2006, though it did not return to the size it was in 1990. From 1990 to 2000, the wage differential reduction occurs mostly around the median of wage distribution, i.e., the 40th to 60th, and changes little at the lower end, the 10th and 20th deciles. This result illustrates the advantage of making the wage comparison over distributions rather than basing it on point estimations like means: the conclusion could be different, depending on at which point the comparison is made.

In summary, the estimates in Table 2.2 illustrate that, between all immigrants and natives, both the raw wage gap and the wage gap after controls are concentrated at the lower end of wage distributions, and they both increased from 1990 to 2006. The raw wage gap between recent immigrants and natives also becomes larger over the same time, but the gaps after controls became smaller with fluctuation. Again, the estimates of wage gap that control for skill differences in Table 2.2 is restricted by an assumption that immigrants and natives are paid the same for their labor market skills. In the next section, we will find out how skills were compensated differently in these groups.

2.3.2 Different returns/prices to skills

In this section, quantile regressions at each percentile (or 1%) are estimated separately for immigrants, recent immigrants, and natives, so there are 99 quantile regressions for each group. Thus, the returns to human capital are allowed to differ for immigrants and natives. The equation for quantile regression estimation is the same as equation (2), except that the dummy variable for immigrant workers is dropped. To save space, only the estimates for the 10^{th}, 50^{th}, and 90^{th} are presented in Table 2.3. Corresponding OLS estimates are included for comparison. As expected with the given sample size, the coefficients are estimated fairly precisely, i.e., the standard errors are relatively small.

According to the OLS results shown in Table 2.3, in all three selected periods, the returns to education and experience are higher for native workers than for the immigrants. Such a result is typical when the focus is on the conditional mean. In contrast, the quantile regression analysis shows that the increments in earnings associated with skills vary across the earnings distributions. Taking 2006 as an example, we see that for all three groups the log wage return to education at the lower end of wage distributions is lower than it is at the higher end. At the same quantile of each group, the wage percentage increment for one more year of education is greatest for native workers, lower for overall immigrants, and lowest for recent immigrants. The latter result suggests that, as staying time in the U.S. increases, an immigrant’s schooling becomes more effective as wage determinent.

The lower payoff for immigrants' schooling has been well documented in extant studies. Some evidence suggests that the difference in returns to schooling between U.S. immigrants and native workers is due to a less-than-perfect international transferability of human capital, which can be due to the country of original language, differences in education quality (see Chiswick, 1978 and 1979; Bratsberg and Ragan, 2002), and/or a mismatch of education and occupations among the foreign born workers (Chiswick and Miller, 2005).

The quantile regression analysis of different periods produced an interesting finding for a cross-time comparison of the education premium at different wage levels. Table 2.3 shows a large increase in the return to education among the native workers over time, especially at the upper end of the wage distribution. However, such growth in returns is less obvious for all immigrants and almost nonexistent for recent immigrants.

In the U.S. labor market, the growth of returns to education concentrated on the upper end of wage distribution has been discussed extensively in extant wage inequality studies, and the reasons for it have been attributed to the general growth of demand for skills and the trend toward skill biased technological change (SBTC) that favors higher education skills (see i.e. Deschênes, 2001 and Lemieux, 2006a).

This trend of increasing returns to education affected native workers and immigrants differently. Though the growth in the education premium also exists for all immigrants, the growth is a much smaller than it is for native workers. On the other hand, the effect does not even exist for the recently arrived immigrants. Even worse, the recent immigrant workers at the upper end of wage distribution, who are more likely to attain higher education than median and lower wage workers, even encountered a decrease in the return to education in 2006, compared to their counterparts in 1990.

Such a result suggests that, although the recent trend toward skill biased demand in the U.S. labor market has increased the return to schooling, the effect does not immediately affect immigrants who have just arrived. After some time in which their education skills are transferred to fit the domestic labor market, immigrants merged into the trend, though not fully, in that their education premium also increased. Such a result is also intuitively reasonable. The recently arrived immigrants lack country-specific information and, perhaps, language fluency. After arriving, recent immigrants need time to collect relevant information and transfer their education skills so the skills have a market value similar to those of native workers.[26]

As with education, the returns to experience for the native born are higher than for immigrants in general. However, in contrast to the case of the education premium, recent immigrants are advantaged compared to overall immigrants in returns to experience. Taking workers with 20 years of experience as an example and using the OLS result, the average return to experience for a native worker in 2006 is 0.70 log points. The numbers for immigrants and recent immigrants are 0.28 and 0.33. Based on the quantile analysis, the recent immigrants at the higher end of the wage distribution have a higher return to experience. The experience return for high-wage recent immigrants is not only higher than it is for overall immigrants, but also higher than it is for natives at the same wage quantile.

Again, what's more interesting about the return to experience is evident in a closer examination of the different wage levels. Among the native workers, the difference in the return to experience is not large between the 10th, 50th and 90th wage percentiles. However, for the recent immigrants, the difference is so big that the workers at 90th wage percentile in all three years earned a return to experience about 4 times higher than the workers at the 10th percentile. In addition, in all three years, the returns to experience for the recent immigrants at the 90th wage decile are higher than they are for native workers at the same wage level. This suggests that the recent immigrants who successfully earn a wage at the top level of the wage distribution have market experience that is highly valued or demanded in the U.S. labor market. However, this higher return to experience does not accrue to overall immigrants, which is a puzzling result. A possible explanation is that these are generally temporary immigrants, but then the question is why they do not stay in the U.S. to take the advantage of the high returns to experience.

Another notable immigrant-native earning difference evident in Table 2.3 is that the intercept in the immigrants' wage equation is much larger than the one in the natives' wage equation.[27] Such a result is not unique to our data. A similar result was reported by Chiswick et al, (2006), whose study based on 2000 U.S. census data. Though the result is not supposed to be random, there is no explicit discussion about why the difference in constants is generated. A possible explanation of such difference is the well known "self selectivity" effect of immigrants.

[26] See Kubotsky (2001) for a detailed discussion about immigrants' human capital transfer.
[27] This size difference of constants in earning equations is relevant to our later discussion about the decomposition of the growth of the wage differentials, so it is addressed here.

Immigrant workers do not represent a random sample of the population from foreign countries, because the immigration decision could be correlated to motivation and ability. In other words, immigrants in general have more unobservable abilities regardless of their observable skills. If the regression equation does not include such unobservable ability or motivation variables, such correlation is shown in the intercept.[28]

2.4 Counterfactual Analysis

In this section, we use the estimates of 99 quantile regressions for each group to decompose the wage difference between native and immigrant log wage distributions. The decomposition accounts for a component that is due to the difference in labor market characteristics between native and immigrant workers, as well as the different returns to the skill characteristics. This decomposition is in the same sprit as the Blinder (1973) and Oaxaca (1973) decomposition method, except that, rather than identifying the sources of the difference between the means of two distributions, we explain the differences by quantiles between the native and the immigrant log wage distributions.

There are different techniques available in the literature for decomposing the differences in wage distributions based on quantile regression techniques, i.e., see Melly (2005). We use the approach developed by Mechado and Mata (2005). The basic idea is to generate two counterfactual wage densities: (i) the immigrant log wage density that would arise if immigrants were given natives' labor market characteristics but continued to be paid like immigrants; (ii) the wage density that would arise if immigrants retained their labor market characteristics but these characteristics were paid like natives.

We follow the Machado-Mata approach almost exactly to construct the counterfactual density. The approach can be summarized as the following steps.

Step 1. Start with 0.01, pick 99 numbers from (0, 1) with the equal distance of 0.01, namely $\theta_1, \theta_2, \ldots, \theta_{99}$.

Step 2. Use the immigrant dataset and quantile regression approach to estimate vectors, $b^{im}(\theta_i)$, for $i = 1 \ldots 99$. The superscript "im" indicates the coefficients are estimated from the immigrant dataset. θ_i is from Step 1. The quantile regressions are estimated using equation (2)

[28] In this situation, if a regression equation does not include ability or motivation variables, the intercept would be upward-biased and the coefficients or returns to skill characteristics would be downward-biased. For a more detailed discussion about the self-selection of immigrants, see Borjas (1987) and Chiswick (1999).

without the immigrant dummy variable. Note that steps 1 and 2 actually performed in section 3b, and part of the result from performing theses steps has been shown in Table 2.3.

Step 3. Make m draws at random with replacements from the native workers dataset, denoted by X_j^{na}, for $j = 1, \dots, m$. The superscript "na" indicates the observations are from the native worker dataset.

Step 4. Generate the counterfactual density as $\{y_j | y_j = x_j^{na} b^{im}(\theta_i)$, where $b^{im}(\theta_i)$ is randomly chosen from $\{b^{im}(\theta_i)\ as\ i = 1, \dots 99\}\}$, for $j = 1 \dots m$.

We make m equal 4500, so the resulting counterfactual wage density is estimated from 4500 counterfactual observations. The second counterfactual density (ii) is estimated by reversing the roles of immigrant and native workers in steps 2 and 3.

Figures 2.4 and 2.5 illustrate a comparison of the marginal and counterfactual densities of log wages by applying the method described above.[29] A marginal density is estimated using the conditional wages of step 2, which are expected wages conditional on skill characteristics and without the residual from the observed wages. Consequently, Figures 2.4 and 2.5 are able to answer this question: how much of the wage differential along the wage distributions can be removed if the immigrants' or recent immigrants' labor market skills are paid like native workers? Figure 2.4 shows the difference between all immigrants and natives, and Figure 2.5 between recent immigrants and natives. The solid line represents the marginal wage density of native workers, and the dashed line the density of immigrant workers. The dash-dot line represents the counterfactual wage density of immigrant workers if their labor skills were paid like the natives.

According to Figure 2.4, in all three periods, the dash-dot line is close to the dashed line and distant from the solid line. Thus, assuming the same skill prices is not influential in wage differential reduction. This suggests that the existing wage differential in each period is primarily explained by the differences in the labor skills, rather than the price difference of these skills.[30] However, though not the primary source of the wage gap, the price difference becomes more important to account for the wage gap over time. This can be seen by the fact that, among the

[29] The terms of "marginal density" and "marginal distribution" is borrowed from Machado and Mata (2005). The marginal densities are estimated using the marginal wage effects estimated from quantile regressions.
[30] Alternatively, we can address the same question by generate the counterfactual density which would arise as immigrants have the same skill distributions as the native workers, but just these skills are paid as immigrants. Such a counterfactual density is also practiced, and it was close to the wage density of native workers, so it is confirmed that the wage difference is mainly due to the skill differences not the return the skills.

three periods, the largest movement of the counterfactual density from the dashed line to the solid line is observed for year 2006. In addition, a comparison of the dash-dot and dashed line shows that giving the same skill prices is particularly helpful for the immigrants whose wage is slightly lower than average. For example, in 2006, if the immigrants were paid the same return of skills as natives, there would be some immigrants whose wages were originally in the 1 to 2 log wage point range to move to the 3 to 4 point range.[31]

Figure 2.5 shows wage differentials between recent immigrants and native workers. In contrast to Figure 2.4, the counterfactual densities for all three years are making a larger move from the immigrant density toward the native density. Accordingly, the price difference is a more important source for the observed wage differential for recent immigrants, compared to the case of all immigrants. This is consistent with our earlier finding that skill characteristics are valued at even lower prices for recent immigrants.

In summary, Figures 2.4 and 2.5 shows that in both cases of recent immigrants and all immigrants, the skill gap is the main source for the observed wage differential, but an increasing proportion of the immigration wage gap is attributable to the price differences of observable skills. The disadvantage in the skill prices is greatest among the newly arrived immigrants, and it becomes less severe as the immigrants stay in the U.S. for a longer time. As the effect from price difference decreases, the major wage differential between all immigrants and native workers can be attributed to the skill differences.

If the wage gap is mainly caused by the skill differences, then we want to identify how each of the labor market characteristics contributes to the existing wage gap. To determine this, we build counterfactual densities with the assumption that the immigrant and native workers have the same distribution of *one* particular skill characteristic. In this case, the counterfactual density reflects how one skill characteristic contributes to the observed wage gap. The procedure to calculate the counterfactual densities is similar to the one described in the above 4 steps, except that, in step 3, the randomly drawn sample of skill observations X_j is collected from immigrants, so it is denoted as X_j^{im}. This X_j^{im} is collected with a restriction that *one* skill distribution among the drawn sample of immigrants is identical to the native workers. For example, if we are interested in the counterfactual wage distribution of immigrants if their

[31] There is a negative effect at the lower end of distribution in 2006, where if immigrants' skills are paid like natives, they would actually earn less. This is due to the skill price substitute including a smaller constant from native workers, or the basic pay without education or experience.

schooling is distributed as it is for native workers, the X_j^{im} in step 3 is randomly selected to create an immigrant sample that has the same distribution of schooling as the native workers. The counterfactual distributions are shown in Figures 2.6 and 2.7 for all and recent immigrants, respectively. Because similar patterns hold, only figures for 1990 and 2006 are presented for comparison.

Before we examine the figures, it is worth noting that, while the initial purpose here is to isolate the effect of one skill characteristic from the others, if there is correlation between skills, this approach may actually draw a sample that also features a different distribution of a related skill besides the target skill. For example, better education may imply better English skills. Therefore, when we examine the counterfactual wage distribution in case that immigrants' schooling distribution is like native workers', the drawn sample of immigrants will have more schooling compared to all immigrants. A byproduct of this drawn sample is that those in the sample may also on average have better English skills. In this case, the demonstrated impact may not exclusively result from the change in schooling distribution. This is, on the other hand, a meaningful outcome, because it is reasonable to have more educated people with better language skills when the impact of education on wage differential is examined.

The top graphs in Figures 2.6 and 2.7 illustrate the counterfactual wage density of immigrants that would arise if the immigrant workers' schooling distribution were the same as the native workers. The dash-dot line presents the counterfactual wage density that would arise if immigrants' schooling distribution were like native workers, while the return to education is still in the same pattern for immigrants. Because assuming the same schooling distribution affects the wage gap similarly in all three years, we use the 2006 result as an example. The means of the three densities are 2.34, 2.53, and 2.46 for immigrants, natives, and the counterfactual ones, respectively. In terms of the means, the wage gap is largely associated with schooling differences. Based on Figures 2.6 and 2.7, giving immigrants the same schooling distribution as natives would help some immigrants to move from the wage range between 1 to 2 log wage points to the range between 2 to 3.5 log wage points. In other words, the impact is focused on those slightly below and slightly above the median wage, and less noticeable at the extremes.

In contrast to education, when assuming the immigrants' experience distribution were the same as the natives', it has little impact on the wage densities. The middle graphs in Figures 2.6

and 2.7 show that in all three years the counterfactual wage density is very close to the original wage density of immigrants, leaving the wage gap little changed.

By assuming that the English proficiency of immigrants was same distributed as the native workers, wage gap at the lower tail was expected to be particularly reduced, because lack of English efficiency is supposed to be a major issue that affects the wages of low income immigrant workers. As shown by the bottom graph in Figure 2.7, assuming the same distribution of English skills between immigrants and natives reduced the wage gap similarly to the case of assuming same distribution of schooling, but giving same English skills is particularly effective in gap reduction at the lower end of the wage distribution. As argued earlier, the impact showing in the middle and higher wage range could be caused by the correlation between education and English proficiency.

Figures 2.8 and 2.9 show the counterfactual wage gaps that exist between recent immigrants and native workers, as if the recent immigrants were the same as natives in terms of skill distributions with respect to schooling, experience, or English efficiency. The result is similar to Figures 2.6 and 2.7, except for the effect of experience. In all three years, the experience difference affected the wage gap more dramatically than the case of all immigrants. Such a result is expected because the recent immigrants typically have less experience than the other two groups, as shown in Table 2.1.

2.5 Wage differential Growth: 1990 vs. 2006

In the previous section, we examined the wage gap composition *within* each period. In this section, we explore how the wage gap composition has changed *over time*. Specifically, we decompose the immigrant/native wage differential growth into the causal factors that are associated with the relative skill differential growth and that are relevant to the wage structure change. On one hand, the wage structure in the U.S. has changed in favor of highly educated workers, as we have seen in Table 2.3. However, the increasing returns to education among the native workers did not work the same way as it did for the immigrants. Such change in the wage structure could potentially increase the wage gap between immigrants and native workers. On the other hand, recent immigrants in the later period are better educated compared to early immigrants, and the relative skill growth could reduce the wage differential.

The effect of the wage structure change in the U.S. on the immigration wage differential has been documented in the literatures. For example, Lubotsky (2001) uses CPS and SIPP data from the 1990s to study the effect of the wage structure change on the immigrant-native wage gap. We take a different approach in our study by examining the impact of the wage structure change separately for immigrants and native workers, rather than assuming that a general wage structure change affects both groups in the same way. With this approach, an increase in the return to education only applies to the native workers, and not necessarily to recent immigrant workers, which is consistent with our earlier finding.

We use the standard approach of the Blinder/Oaxaca framework and decompose the change of the immigrant-native wage gap into the relative skill change and the wage structure change. The growth to be decomposed occurred between 1990 and 2006. The following equation illustrates this idea:

$$\begin{aligned}\Delta G &= \left[N_{S_{06}}^{P_{06}} - I_{S_{06}}^{P_{06}}\right] - \left[N_{S_{90}}^{P_{90}} - I_{S_{90}}^{P_{90}}\right] \\ &= \left[\left(N_{S_{06}}^{P_{06}} - N_{S_{90}}^{P_{06}}\right) - \left(I_{S_{06}}^{P_{06}} - I_{S_{90}}^{P_{06}}\right)\right] + \left[\left(N_{S_{90}}^{P_{06}} - N_{S_{90}}^{P_{90}}\right) - \left(I_{S_{90}}^{P_{06}} - I_{S_{90}}^{P_{90}}\right)\right] \qquad (3)\end{aligned}$$

where ΔG is the change of the wage gap between 1990 and 2006. N_{Sx}^{Py} refers to the wage of native workers (denoted as *N*) with skills (denoted as *S* in subscript) in year *x* and wage structure (denoted as *P* as price in superscript) of year *y*. I_{Sx}^{Py} is defined analogously for immigrants. The first row of equation (3) simply defines the differential growth between the two periods. The second line of equation (3) is constructed by adding and subtracting the term $N_{S_{90}}^{P_{06}} - I_{S_{90}}^{P_{06}}$.

According to the second row of equation (3), the first bracket measures the wage differential growth due to the relative growth of skills, or by covariates. Because the wage structure of each group is set to be the same as the second period, it measures a would-be growth in case that labor skills of each group are updated to the second period, but the returns to skills are unchanged. Note that the two groups are still paid different skill prices in the same period, only the *cross-time price change within each group* is eliminated. Similarly, the second bracket measures the wage differential growth attributed to the changes in the wage structure, or by coefficients. Because all covariates are from the first period, the second bracket in equation (3) measures the would-be growth in case that the wage structure is updated to the second period, but the skill level of each group is unchanged.[32]

[32] Alternative approach is computed. The results are only different in terms of the scales, but in the same direction.

Using the same decomposition method as described in the steps 1 to 4, we can build the counterfactual densities representing the cases of $N_{S_{90}}^{P_{06}}$ and $I_{S_{90}}^{P_{06}}$, so the decomposition can be made in every percentage or any moment of the wage distribution. Because the recent immigrants better represent the composition change of immigrant workers, the decomposition comparison is made between the recent immigrants and native workers. The decomposition results at the wage percentiles of 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} are presented in Table 2.4.

The first or "raw gap" column in Table 2.4 presents the observed wage differentials of different wage quantiles and their changes. The observed wage differential is computed by differencing the log wage of recent immigrants and native born workers.[33] The changes are all positive, indicating the raw gaps at all wage levels are enlarged from 1990 to 2006. We have seen in Table 2.2 and Figure 2.3 that the raw wage gap in both periods is concentrated from the lower end to the medium level of wage distribution. In contrast, the growth of the wage gap is concentrated at both ends of the wage distribution. The growth is 3.5 percent at the 10^{th} percentile and 11.6 percent at the 90^{th} wage percentile. The growth at the median is less than 1 percent.

The column of "estimated marginal gap" in Table 2.4 presents the marginal wage gaps and their changes. The marginal wage gaps are estimated in the same way as we draw Figures 2.4 and 2.5, and they measure the portion of the raw wage gap that is explained by skills and wage structures. The marginal wage is calculated using the estimated coefficients multiplied by observable skill variables. Therefore, the marginal wage gaps can be decomposed into the parts by changes in covariates or by the changes in coefficients. The difference between the observed wage gap growth and the marginal growth is attributed to the residuals, which are listed in the third entry of the "aggregate contribution" column in Table 2.4. For example, the majority of the observed wage gap growth at the 10th wage decile is due to the gap in residuals, which is 0.065 minus 0.014. In contrast, the wage gap growth at the higher end, the 75^{th} and 90^{th} deciles, is mostly attributed to the changes in relative skills and the returns to the skills.

The decomposition result is shown in the "aggregate contribution" column of Table 2.4. The first entry of the column presents the change of marginal wage gap that is due to the covariates, or "relative skill change," which in equation (3) is described as $\left(N_{S_{06}}^{P_{06}} - N_{S_{90}}^{P_{06}}\right) -$

[33] The observed immigration wage gap decomposed in this section is corresponding to the raw wage gap in Table 2, the one that is not controlled by skill characteristics.

$\left(I_{S_{06}}^{P_{06}} - I_{S_{90}}^{P_{06}}\right)$. Again, this is the counterfactual wage differential growth that would arise if the skill distributions of immigrants and native workers are updated from 1990 to 2006 while the wage structure is kept the same as it was in 2006. According to our simulation, both $\left(N_{S_{06}}^{P_{06}} - N_{S_{90}}^{P_{06}}\right)$ and $\left(I_{S_{06}}^{P_{06}} - I_{S_{90}}^{P_{06}}\right)$ are positive in all wage levels, as shown in Table 2.5, so both groups generally became more "skilled" and would make higher wages with this level of skills in 1990. However, as the progress for natives is greater than immigrants at all levels, the net outcome is an increase of the wage gap by covariates. Therefore, without the change in wage structures, the relative growth in skills could have increased the wage gap more than observed. To understand this increasing skill differential, let's reconsider Table 2.1.

As shown in Table 2.1, the most obvious skill growth of natives relative to immigrants is in experience. The recent immigrants in 2006 are younger and less experienced, compared to those in 1990. At the same time, the experience of native workers increased by 13 percent. This leads to a much larger skill gap in labor market experience in 2006. In terms of English skills, five percent fewer of the recent immigrants in 2006 "speak English well," compared to 1990. In summary, the growing skill advantage of natives over recent immigrants enlarged the wage differential, but this is primarily due to the recent immigrants being younger than their counterparts in 1990.

The change of the wage structure drives the wage gap in the opposite direction of the skill attributes change, but this is due to an ambiguous change in the intercept in the wage equations. The second entry in the "aggregate contribution" column shows the marginal wage gap change that is due to the coefficient or price change of each group between 1990 and 2006. In equation (3), this is described as $\left(N_{S_{90}}^{P_{06}} - N_{S_{90}}^{P_{90}}\right) - \left(I_{S_{90}}^{P_{06}} - I_{S_{90}}^{P_{90}}\right)$, which measures wage differential growth that would occor if the returns to skills for immigrants and native workers are respectively updated to 2006, while the skill distributions for each group remain the same as it was in 1990. Note that, when we compute this counterfactual growth, we update all of the coefficients from the later period to the early period within each group, including the intercept of each group. As shown in the second entry of the "aggregate contribution" column, the results are negative at all wage deciles, so the change in wage structures would have reduced the wage gap between immigrants and native workers over time.

To be more clear about the impact of the wage structure change within each group, the result of $\left(N_{S_{90}}^{P_{06}} - N_{S_{90}}^{P_{90}}\right)$ and $\left(I_{S_{90}}^{P_{06}} - I_{S_{90}}^{P_{90}}\right)$ are listed in Table 2.5. Both $\left(N_{S_{90}}^{P_{06}} - N_{S_{90}}^{P_{90}}\right)$ and $\left(I_{S_{90}}^{P_{06}} - I_{S_{90}}^{P_{90}}\right)$ are negative in all quantiles, so both natives and recent immigrants would have earned less in 1990 if they were paid based on the wage structure of 2006. The negative price effect is more severe among the native workers. Therefore, the wage gap reduction is not a result of a relative increase of the returns to skills of immigrants, but a result of a more severe reduction in skill prices among the native workers.

This outcome of negative price effect on wages is surprising: we observed in Table 2.3 that the skill prices, at least for native workers, have greatly increased. To understand the negative effect of 2006 skill prices, let's reconsider Tables 2.3a and 2.3c. Comparing the OLS estimates from 1990 and 2006, we see that the returns for education and experience have increased for a typical native worker, while the corresponding prices for immigrants changed little or decreased. If these are the only change in skill prices, updating the wage structure would result in a positive wage growth for natives and a negative one for immigrants, and it would be an overall positive growth in wage differential. However, the intercept in the wage equation also changed. The intercept typically refers to the basic return with zero education and experience. For natives it decreased from 0.87 in 1990 to 0.48 in 2006. As can be easily tested, this is the negative factor that offsets the potential wage growth of natives by skill price increases in education and experience.[34]

In summary, the main finding based on Tables 3.4 and 3.5 is that, from 1990 to 2006, the growth in wage differential is concentrated at the bottom and top ends of the wage distribution, and the change at median wage level is almost nonexistent. The main source for this growth is the enlarged skill difference between the recent immigrants and natives, particularly due to the lack of experience among younger recent immigrants. In terms of implications, the recent growth of the wage gap should not raise concerns for new immigrants lack of competitively with natives, since the gap growth is a outcome of the new immigrants being younger. The impact from the wage structure change is negative overall, which is a consequence by two opposing forces. The traditional skill prices for education and experiences have increased in favor of natives relative to

[34] In another simulation to compute $\left(\mathrm{N}_{\mathrm{S}_{90}}^{\mathrm{P}_{06}} - \mathrm{N}_{\mathrm{S}_{90}}^{\mathrm{P}_{90}}\right)$ and $\left(\mathrm{I}_{\mathrm{S}_{90}}^{\mathrm{P}_{06}} - \mathrm{I}_{\mathrm{S}_{90}}^{\mathrm{P}_{90}}\right)$, skill prices are updated without intercept. The results are as expected: native workers wage increases in all wage levels and immigrants' wage decreases. However, it is not clear what the meaning of the counterfactual wage change is by leaving out the intercept.

immigrants, but the overall negative outcome is caused by a decrease in the intercept in natives' wage equation, while the intercept does not change as much for immigrants.

2.6 Conclusion

To analyze the recent growth of immigrant/native wage differentials, this paper compares PUMS data from 1990 and 2000, and ACS data from 2006, and applies a decomposition method based on quantile regressions. The empirical results show that the wage disadvantage of immigrants was concentrated in the bottom half of the wage distribution, and the scale of the wage disadvantage is becoming larger over the selected periods. The main reason for the wage differential is the labor market skill disadvantage of immigrants. The proportion in the wage differential that can be attributed to the skill price differences is becoming larger over time. This is because the advantage of natives in returns to schooling and experience has been growing, as there is an increasing demand for skills in U.S. labor market, which raises the skill prices.

Between all immigrants and natives, the wage differential after controlling for labor market skills first expanded from 1990 to 2000 and then decreased from 2000 to 2006. In contrast, the after-control wage differential between recent immigrants and natives first decreased from 1990 to 2000 and then expanded from 2000 to 2006. The overall growth of the recent immigrant/native wage differential between 1990 and 2006 is small, but the growth is concentrated at the top and bottom ends of the wage distribution. Our growth decomposition shows the main reason for the growth is that recent immigrants being younger and having less market experience than their counterparts, which results in a larger gap in market experience, compared to the contemporary native workers.

Our analysis of skill price differences shows that the recent trend of increasing returns to the U.S. labor market skills does not affect immigrants as much as it does native workers, and it does not have any impact on recent immigrants. Compared to native workers, recent immigrants at high wage percentiles enjoy a higher return to their experience.

Table 2.1 Descriptive Statistics for Men: Native-Born, Immigrants, and Recent Immigrants, by Year

	1990			2000			2006		
Variable Name	Natives	Immigrants	Recent Immigrants	Natives	Immigrants	Recent Immigrants	Natives	Immigrants	Recent Immigrants
Observations	360110	34237	6164	388109	55493	9859	403592	70565	10135
Log hourly wages	2.52	2.38	2.15	2.53	2.35	2.21	2.54	2.33	2.13
	(0.62)	(0.71)	(0.74)	(0.65)	(0.75)	(0.81)	(0.67)	(0.74)	(0.77)
Education	13.45	11.72	11.66	13.81	12.11	12.36	14.08	12.6	12.65
	(2.88)	(5.25)	(5.5)	(2.64)	(4.98)	(5.13)	(2.6)	(4.7)	(4.84)
Experience	21.11	22.32	17.9	22.31	21.98	17.13	23.97	22.84	17.43
	(10.87)	(11.41)	(10.22)	(10.25)	(10.85)	(9.94)	(10.56)	(10.87)	(9.78)
Metropolitan	57.42%	75.43%	76.88%	52.24%	77.47%	75.23%	73.84%	88.38%	86.08%
Black	7.86%	6.13%	5.99%	8.34%	5.84%	4.45%	7.58%	6.59%	6.63%
Asian	0.71%	22.16%	28.21%	0.71%	22.46%	23.18%	1.01%	24.17%	22.66%
Other race	2.28%	21.36%	21.40%	3.94%	30.36%	28.58%	4.08%	24.59%	23.12%
English wellness	99.58%	75.34%	58.83%	99.59%	73.10%	57.84%	99.62%	71.05%	53.85%

1. Table contains sample averages; sample standard errors in parentheses.
2. “White” is omitted as it serves as control group of all races.
3. “English wellness” is a dummy variable, which is defined to be “zero” if a worker speaks only English, or reports to speak English very well or well. It is “one” if a worker speaks English unwell or do not speak English.

Table 2.2 Estimated Immigration Wage Gaps by Percentiles

Table 2.2a. Estimated Immigration Wage Gaps by Percentiles: Native Born vs. All Immigrants

Quantiles	10th	20th	30th	40th	50th	60th	70th	80th	90th
1990									
Observed Gap	-0.247	-0.262	-0.260	-0.208	-0.178	-0.127	-0.090	-0.017	0.000
Gap after Controls	-0.050	-0.039	-0.029	-0.014	0.004	0.020	0.033	0.054	0.096
2000									
Observed Gap	-0.324	-0.325	-0.298	-0.261	-0.227	-0.182	-0.133	-0.056	0.010
Gap after Controls	-0.107	-0.082	-0.063	-0.045	-0.029	-0.009	0.012	0.038	0.086
2006									
Observed Gap	-0.306	-0.325	-0.319	-0.300	-0.260	-0.203	-0.144	-0.074	-0.032
Gap after Controls	-0.089	-0.076	-0.062	-0.041	-0.023	-0.007	0.012	0.032	0.058

Table 2.2b. Estimated Immigration Wage Gaps by Percentiles: Native Born vs. Recent Immigrants

Quantiles	10th	20th	30th	40th	50th	60th	70th	80th	90th
1990									
Observed Gap	-0.431	-0.470	-0.514	-0.506	-0.494	-0.427	-0.362	-0.245	-0.101
Gap after Controls	-0.288	-0.286	-0.269	-0.256	-0.218	-0.179	-0.117	-0.067	0.034
2000									
Observed Gap	-0.468	-0.508	-0.504	-0.472	-0.439	-0.357	-0.252	-0.083	0.011
Gap after Controls	-0.284	-0.249	-0.204	-0.157	-0.098	-0.049	-0.003	0.046	0.105
2006									
Observed Gap	-0.496	-0.528	-0.544	-0.549	-0.511	-0.490	-0.365	-0.241	-0.161
Gap after Controls	-0.277	-0.278	-0.242	-0.197	-0.146	-0.112	-0.074	-0.036	0.019

1. All estimates in Table 2 are significant at 5% level;
2. Results in the second rows of each year are estimated with the control variables listed in Table1.

Table 2.3 OLS and Quantile Regression Estimates

Table 2.3.a OLS and Quantile Regression Estimates, 1990 U.S. Census, 1% PUMS

Variable	Natives				Immigrants				Recent Immigrants			
	OLS	Quantile			OLS	Quantile			OLS	Quantile		
		0.1	0.5	0.9		0.1	0.5	0.9		0.1	0.5	0.9
Constant	0.8745	0.3414	0.8441	1.3727	1.2896	0.7799	1.265	1.8651	1.3193	0.9174	1.3558	1.6475
	(0.0062)	(0.0123)	(0.0064)	(0.0091)	(0.0199)	(0.0343)	(0.0219)	(0.033)	(0.0503)	(0.0744)	(0.0575)	(0.0871)
Education	0.0822	0.0759	0.0848	0.0882	0.0589	0.0503	0.0614	0.0615	0.0519	0.0393	0.0515	0.0666
	(0.0003)	(0.0007)	(0.0004)	(0.0005)	(0.0008)	(0.0014)	(0.0009)	(0.0014)	(0.0021)	(0.0026)	(0.0023)	(0.0038)
Exp	0.0348	0.0348	0.037	0.0332	0.0295	0.0204	0.0302	0.0345	0.0305	0.0098	0.0232	0.0537
	(0.0004)	(0.0007)	(0.0004)	(0.0005)	(0.0012)	(0.0019)	(0.0012)	(0.0019)	(0.003)	(0.0053)	(0.0036)	(0.0043)
Exp Squared /100	-0.0464	-0.0558	-0.0497	-0.0364	-0.0336	-0.0216	-0.0332	-0.039	-0.0454	-0.0133	-0.0316	-0.077
	(0.0007)	(0.0014)	(0.0008)	(0.0011)	(0.0022)	(0.0037)	(0.0023)	(0.0036)	(0.0062)	(0.0121)	(0.0077)	(0.0077)
Black	-0.1894	-0.2419	-0.1937	-0.1463	-0.1768	-0.1285	-0.1962	-0.2074	-0.179	-0.0353	-0.1623	-0.2742
	(0.0034)	(0.0073)	(0.004)	(0.0053)	(0.014)	(0.0273)	(0.0159)	(0.0211)	(0.0368)	(0.034)	(0.041)	(0.0581)
Asian	0.0651	0.0979	0.0634	0.0596	-0.0821	-0.1046	-0.0827	-0.0638	-0.0591	-0.0816	-0.0641	0.038
	(0.0109)	(0.0182)	(0.0105)	(0.0124)	(0.0085)	(0.0148)	(0.0097)	(0.0149)	(0.0206)	(0.0303)	(0.0238)	(0.0425)
Other Races	-0.1093	-0.1727	-0.1088	-0.0491	-0.129	-0.1085	-0.1247	-0.1635	-0.2014	-0.1672	-0.1747	-0.2889
	(0.0062)	(0.0133)	(0.0069)	(0.009)	(0.009)	(0.0154)	(0.01)	(0.0146)	(0.0233)	(0.0321)	(0.0219)	(0.0379)
Metropolitan	0.1451	0.1592	0.146	0.1257	0.0937	0.0903	0.0897	0.0847	0.0469	0.0342	0.0376	0.0467
	(0.0019)	(0.0038)	(0.0019)	(0.0027)	(0.0076)	(0.0134)	(0.0087)	(0.0125)	(0.02)	(0.0302)	(0.0215)	(0.0359)
Speak English Unwell	-0.0378	-0.0834	-0.059	0.0742	-0.2595	-0.2634	-0.2905	-0.2018	-0.2329	-0.1763	-0.2316	-0.248
	(0.0143)	(0.0263)	(0.0137)	(0.0241)	(0.0086)	(0.0144)	(0.0097)	(0.0148)	(0.0197)	(0.0269)	(0.0203)	(0.0357)

Standard errors are in parenthesizes.

Table 2.3b. OLS and Quantile Regression Estimates, 2000 U.S. Census, 1% PUMS

Variable	Natives				Immigrants				Recent Immigrants			
	OLS	Quantile			OLS	Quantile			OLS	Quantile		
		0.1	0.5	0.9		0.1	0.5	0.9		0.1	0.5	0.9
Constant	0.7698	0.3935	0.7416	1.141	1.4087	0.9172	1.3499	1.9725	1.5064	1.0045	1.6532	1.7838
	(0.0068)	(0.0125)	(0.0069)	(0.0109)	(0.0175)	(0.0268)	(0.0189)	(0.0304)	(0.0426)	(0.0725)	(0.0506)	(0.0721)
Education	0.0916	0.0775	0.0925	0.1049	0.0587	0.0423	0.0616	0.0663	0.0519	0.0351	0.0465	0.0718
	(0.0004)	(0.0007)	(0.0004)	(0.0006)	(0.0007)	(0.0011)	(0.0008)	(0.0013)	(0.0018)	(0.003)	(0.0021)	(0.0033)
Exp	0.0306	0.0295	0.0324	0.0296	0.0149	0.0129	0.0148	0.0178	0.0121	0.0005	0.0037	0.0339
	(0.0004)	(0.0007)	(0.0004)	(0.0007)	(0.001)	(0.0015)	(0.0011)	(0.0017)	(0.0025)	(0.0044)	(0.003)	(0.0042)
Exp Squared	-0.0433	-0.0515	-0.0458	-0.0317	-0.0116	-0.0151	-0.0099	-0.011	-0.0157	-0.0033	-0.0008	-0.0411
/100	(0.0008)	(0.0015)	(0.0008)	(0.0014)	(0.002)	(0.0029)	(0.0023)	(0.0033)	(0.0053)	(0.01)	(0.006)	(0.0094)
Black	-0.1813	-0.2302	-0.1816	-0.1418	-0.1429	-0.055	-0.1115	-0.2084	-0.2043	-0.0761	-0.2075	-0.2254
	(0.0034)	(0.0065)	(0.0036)	(0.005)	(0.0124)	(0.02)	(0.0125)	(0.019)	(0.0354)	(0.0429)	(0.03)	(0.0366)
Asian	0.0266	-0.0169	0.0326	0.0347	0.0273	-0.0215	0.0491	0.0474	0.1189	0.0462	0.189	0.1535
	(0.0112)	(0.0263)	(0.0101)	(0.0164)	(0.0075)	(0.0137)	(0.0086)	(0.0133)	(0.0188)	(0.0306)	(0.0277)	(0.0314)
Other Races	-0.1218	-0.1644	-0.1185	-0.0717	-0.1068	-0.073	-0.102	-0.1563	-0.14	-0.0802	-0.1333	-0.16
	(0.0049)	(0.009)	(0.005)	(0.008)	(0.007)	(0.0099)	(0.0072)	(0.0123)	(0.0177)	(0.0315)	(0.0184)	(0.0319)
Metropolitan	0.1831	0.1456	0.1778	0.2184	0.097	0.0661	0.0993	0.1164	0.1025	0.0771	0.084	0.1187
	(0.0019)	(0.0036)	(0.0019)	(0.0031)	(0.0067)	(0.0098)	(0.0071)	(0.0125)	(0.0165)	(0.0297)	(0.0186)	(0.0268)
Speak English	-0.0446	-0.1402	-0.0656	0.0476	-0.2662	-0.2577	-0.2839	-0.2061	-0.3383	-0.2166	-0.3859	-0.3546
Unwell	(0.0148)	(0.0263)	(0.0163)	(0.0288)	(0.0071)	(0.01)	(0.0076)	(0.0128)	(0.0168)	(0.0282)	(0.0191)	(0.0297)

Standard errors are in parenthesizes.

Table 2.3c. OLS and Quantile Regression Estimates, 2006 ACS

Variable	Natives				Immigrants				Recent Immigrants			
	OLS	Quantile			OLS	Quantile			OLS	Quantile		
		0.1	0.5	0.9		0.1	0.5	0.9		0.1	0.5	0.9
Constant	0.4835	0.0624	0.4372	0.856	1.2627	0.8256	1.2333	1.7749	1.3969	1.0958	1.4994	1.6958
	(0.007)	(0.0125)	(0.0066)	(0.0119)	(0.016)	(0.0243)	(0.0175)	(0.0263)	(0.0428)	(0.0574)	(0.0467)	(0.0631)
Education	0.1038	0.0905	0.1062	0.1182	0.066	0.047	0.0674	0.0751	0.0529	0.0298	0.0474	0.0688
	(0.0004)	(0.0007)	(0.0004)	(0.0006)	(0.0007)	(0.001)	(0.0007)	(0.0011)	(0.0018)	(0.0021)	(0.002)	(0.003)
Exp	0.0363	0.037	0.0381	0.0364	0.0144	0.0103	0.0143	0.0184	0.0172	-0.0008	0.0119	0.0429
	(0.0004)	(0.0007)	(0.0004)	(0.0007)	(0.0009)	(0.0013)	(0.001)	(0.0014)	(0.0024)	(0.0031)	(0.0026)	(0.0033)
Exp Squared /100	-0.0585	-0.0688	-0.0614	-0.0503	-0.0131	-0.0112	-0.012	-0.0137	-0.0281	-0.0001	-0.0208	-0.0595
	(0.0008)	(0.0014)	(0.0008)	(0.0014)	(0.0017)	(0.0024)	(0.0019)	(0.0028)	(0.0053)	(0.0059)	(0.005)	(0.007)
Black	-0.2286	-0.28	-0.2215	-0.1915	-0.1783	-0.1185	-0.169	-0.2359	-0.2295	-0.1273	-0.2197	-0.3098
	(0.0036)	(0.0077)	(0.0036)	(0.0057)	(0.0099)	(0.014)	(0.0098)	(0.0181)	(0.0272)	(0.0378)	(0.0283)	(0.058)
Asian	0.0254	-0.0143	0.0363	0.0314	0.0514	-0.0028	0.0952	0.0552	0.0575	0.0044	0.125	0.0781
	(0.0094)	(0.0156)	(0.009)	(0.0115)	(0.0062)	(0.0111)	(0.0075)	(0.0102)	(0.0175)	(0.0254)	(0.0246)	(0.0252)
Other Races	-0.1113	-0.1649	-0.1075	-0.078	-0.1053	-0.0723	-0.0895	-0.1337	-0.1266	-0.1003	-0.0987	-0.1512
	(0.0048)	(0.0083)	(0.0048)	(0.0093)	(0.0061)	(0.009)	(0.0061)	(0.0104)	(0.0168)	(0.0195)	(0.0168)	(0.0266)
Metropolitan	0.2015	0.1751	0.1972	0.225	0.1217	0.107	0.116	0.1342	0.0949	0.0581	0.0805	0.1297
	(0.0022)	(0.0038)	(0.002)	(0.0035)	(0.0074)	(0.0111)	(0.0084)	(0.0129)	(0.0188)	(0.0298)	(0.0173)	(0.0263)
Speak English Unwell	-0.0672	-0.1666	-0.0869	0.0535	-0.3078	-0.2316	-0.3138	-0.3142	-0.3773	-0.2266	-0.3964	-0.5179
	(0.0152)	(0.026)	(0.022)	(0.0286)	(0.006)	(0.009)	(0.0064)	(0.0103)	(0.0161)	(0.0214)	(0.0191)	(0.026)

Standard errors are in parenthesizes.

Table 2.4 Decomposition of the Changes in the Wage distribution, Recent Immigrants vs. Native-Born

	Raw Gap				Est. Marginal Gap			Aggregate Contributions		
	1990	2006	Change	%Change	1990	2006	Change	Covariates	Coefficients	Residuals
10th	0.431	0.496	0.065	3.50%	0.476	0.490	0.014	0.080	-0.066	0.051
25th	0.523	0.547	0.023	1.09%	0.504	0.538	0.034	0.093	-0.060	-0.010
50th	0.494	0.511	0.017	0.84%	0.457	0.492	0.035	0.111	-0.076	-0.018
75th	0.313	0.325	0.012	0.94%	0.320	0.330	0.011	0.109	-0.098	0.001
90th	0.101	0.162	0.061	11.59%	0.145	0.207	0.062	0.100	-0.038	-0.001

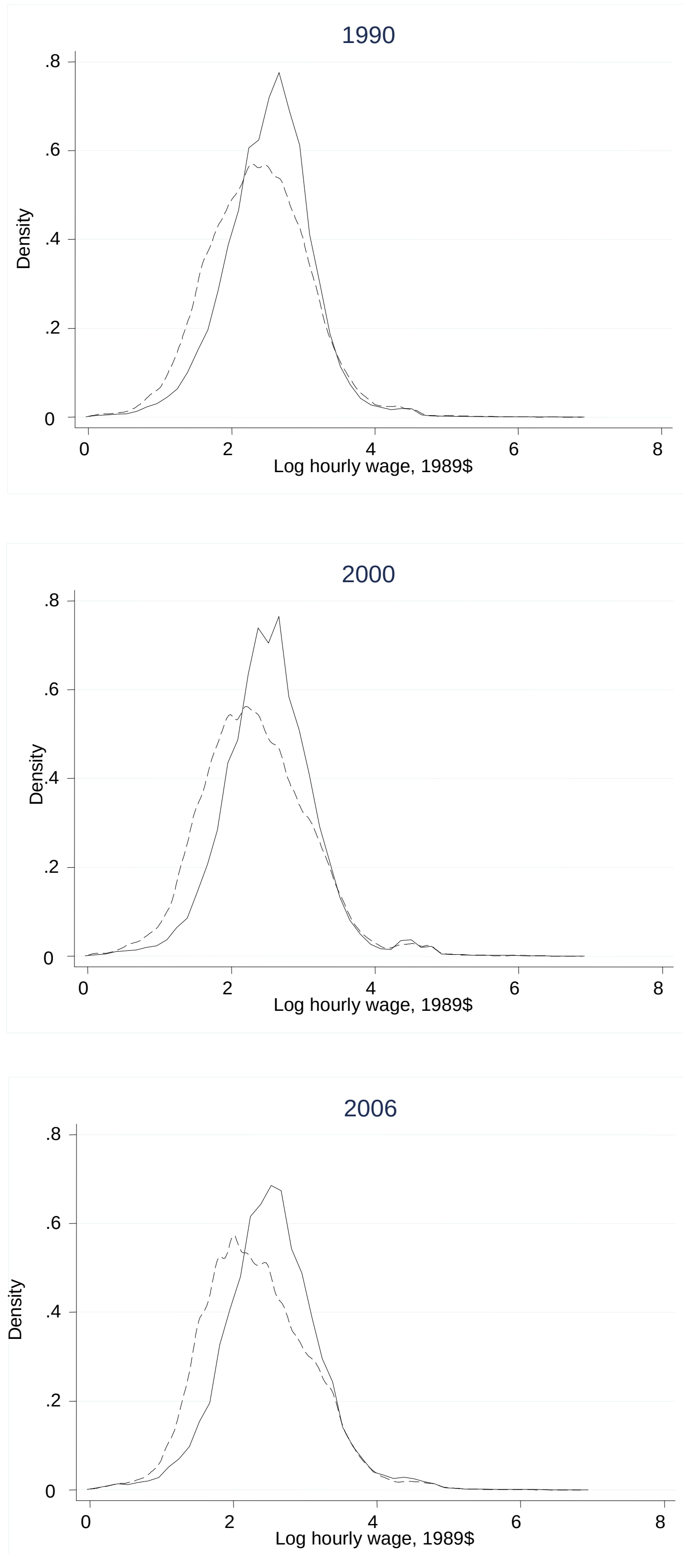
The observed gap change is decomposed to marginal changes and the changes by residuals, so the “Change” under “Raw Gap” is equal to the sum of the “change” under “Estimated Marginal Gap” plus the “Residuals”. The marginal change is further decomposed to divide it between skills and prices, which are represented by the “Covariates” and “Coefficients”, respectively. Thus, the change under “estimated marginal gap” is equal to the sum of “Covariates” plus “Coefficients”.

Table 2.5 Components of the decomposition for Immigrant-native Wage Gap Change

	$N_{S_{06}}^{P_{06}} - N_{S_{90}}^{P_{06}}$	$I_{S_{06}}^{P_{06}} - I_{S_{90}}^{P_{06}}$	$N_{S_{90}}^{P_{06}} - N_{S_{90}}^{P_{90}}$	$I_{S_{90}}^{P_{06}} - I_{S_{90}}^{P_{90}}$
10th	0.1254	0.0455	-0.1394	-0.0737
25th	0.1260	0.0326	-0.1447	-0.0851
50th	0.1278	0.0171	-0.136	-0.0601
75th	0.1315	0.0229	-0.0949	0.0032
90th	0.1366	0.0364	-0.0308	0.0076

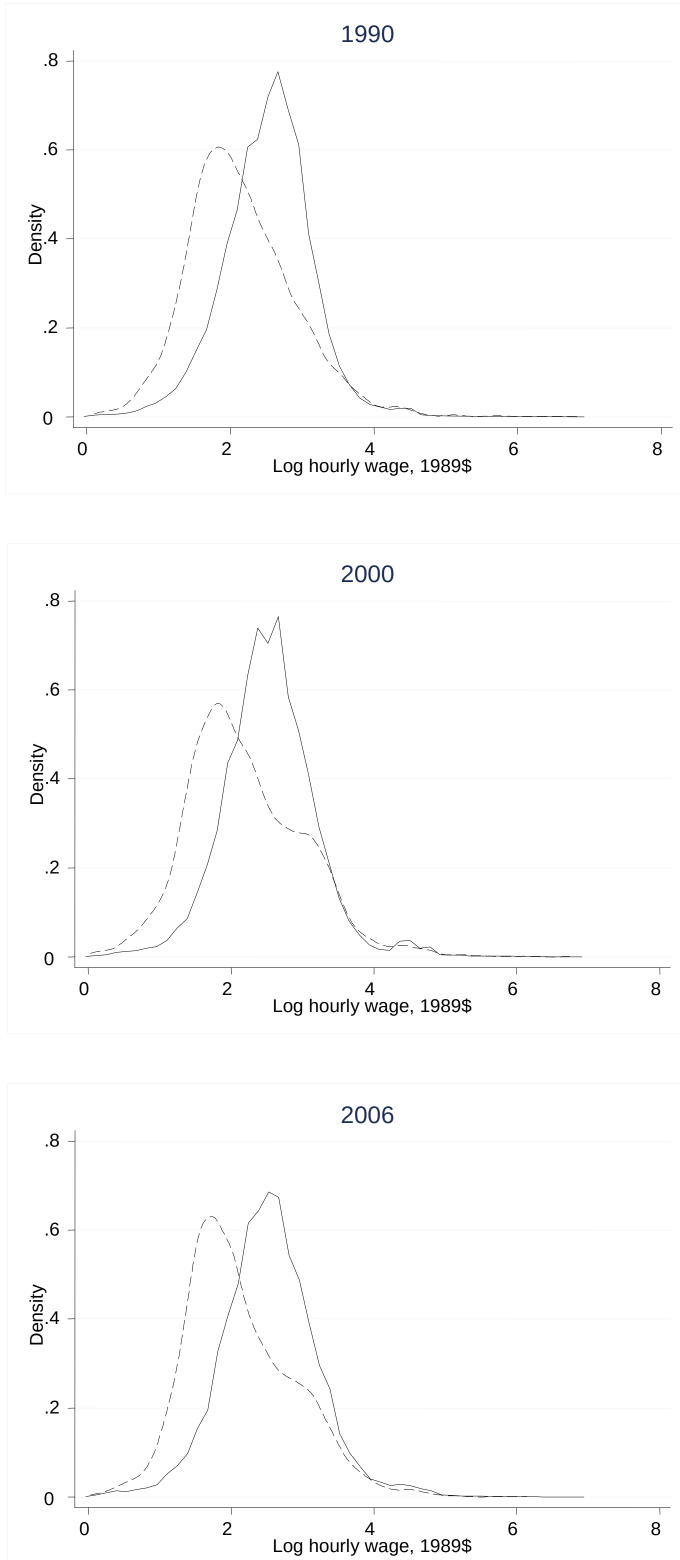
The differences of the first two columns in Table 2.5 is equal to the “Covariates” in Table 2.4, and the differences of the last two columns of Table 2.5 are equal to the “Coefficients” in Table 2.4.

Figure 2.1 Density of Log Wages, Native Born vs. All Immigrants



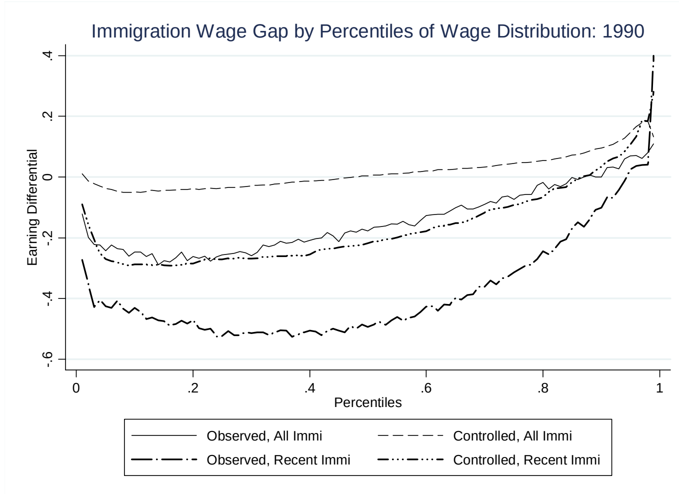
Solid line is for Native born; Dash line is for All Immigrants

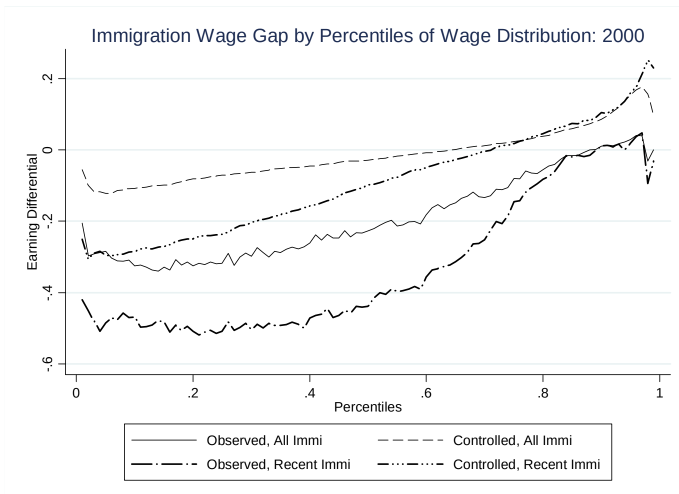
Figure 2.2 Density of Log Wages, Native Born vs. Recent Immigrants



Solid line is for Native born; Dash line is for All Immigrants

Figure 2.3 Wage Differentials by Percentiles in 1990, 2000 and 2006





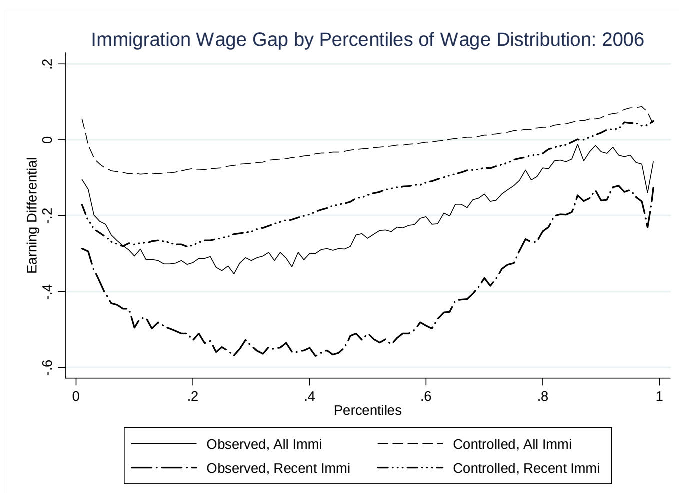
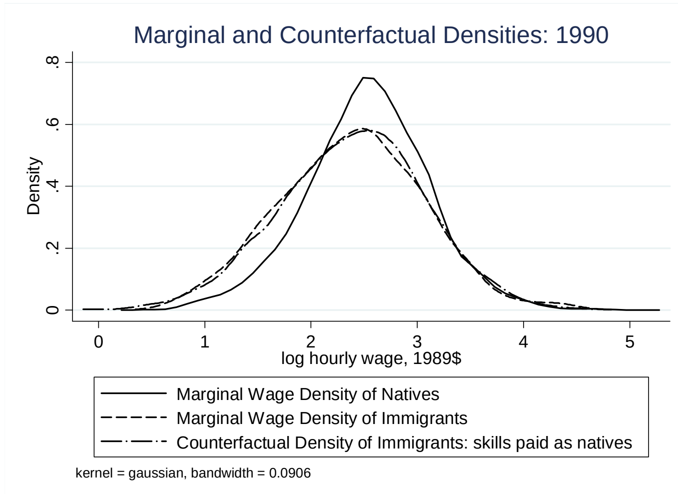
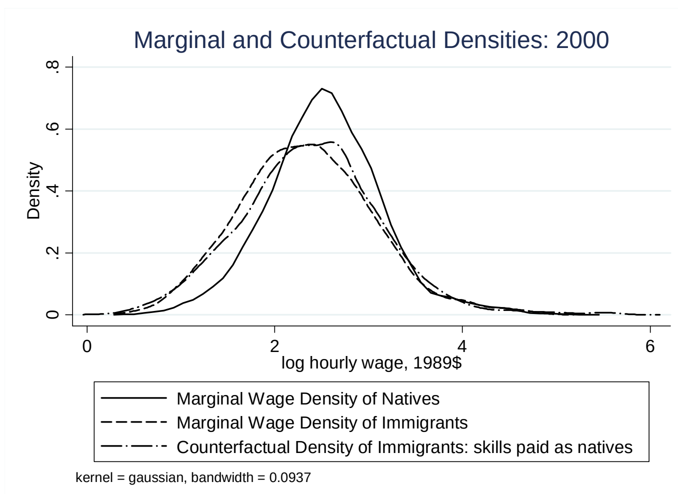


Figure 2.4 Marginal and Counterfactual Wage Densities: Natives vs. All Immigrants

(What if immigrants' skills are paid as natives?)





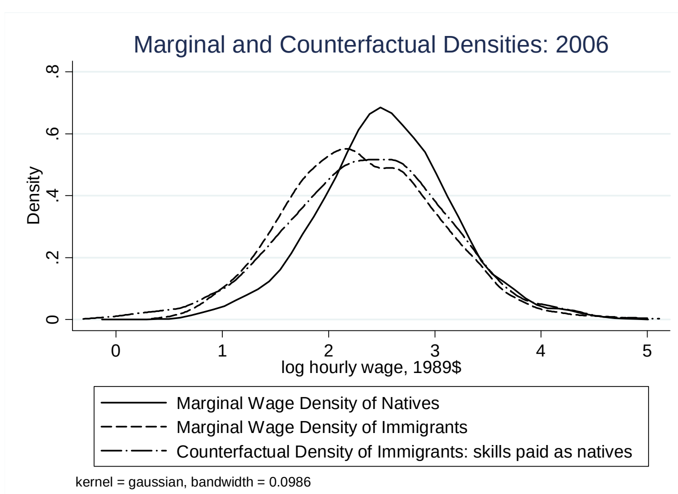
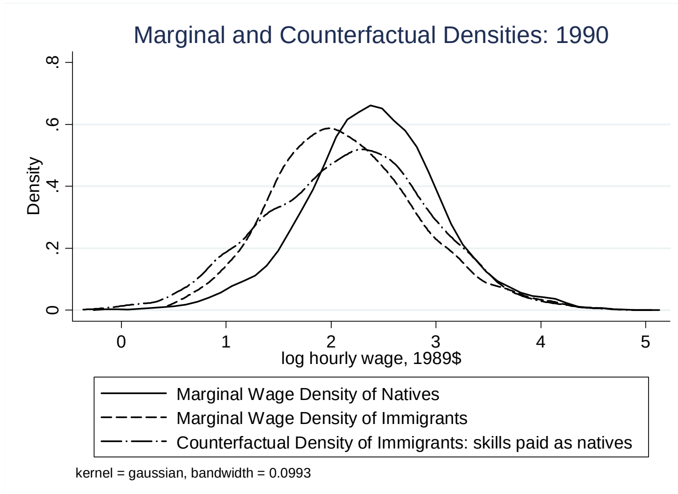
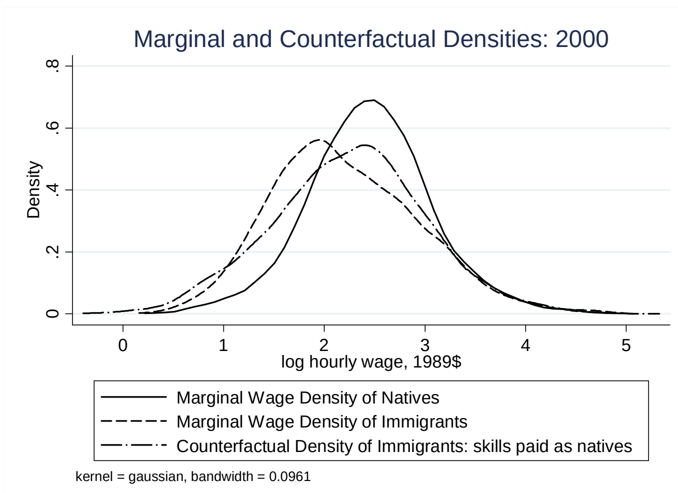


Figure 2.5 Marginal and Counterfactual Wage Densities: Natives vs. Recent Immigrants

(What if *recent* immigrants' skills are paid as natives?)





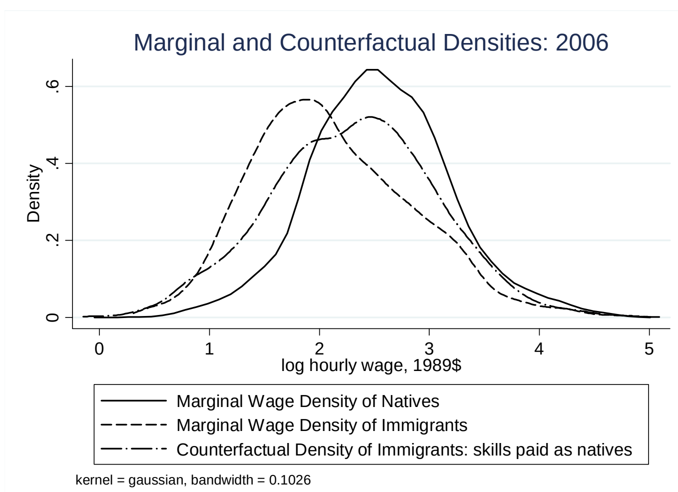


Figure 2.6 Log Wage Densities: All Immigrants vs. Natives, 1990

(What if one skill factor had been same distributed between all immigrants and natives?)

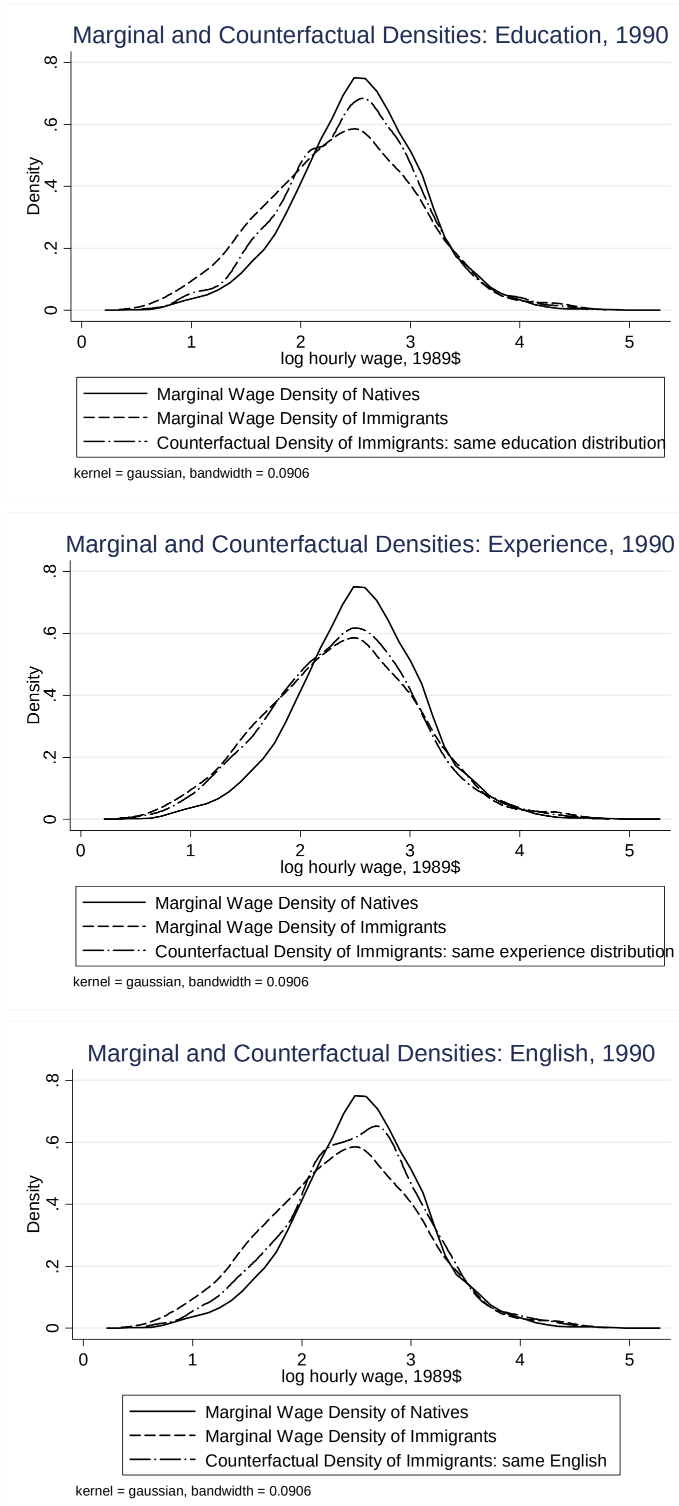
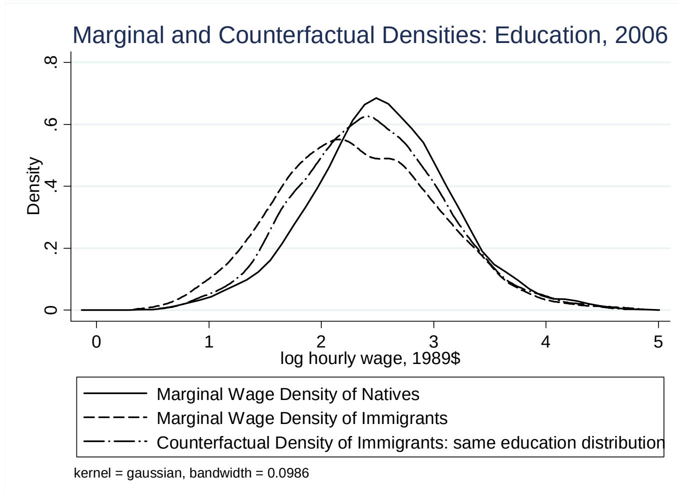
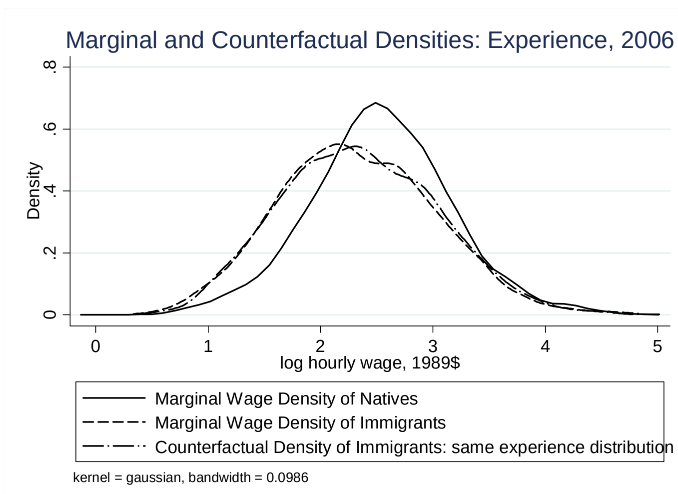


Figure 2.7 Log Wage Densities: All Immigrants vs. Natives, 2006

(What if one skill factor had been same distributed between all immigrants and natives?)





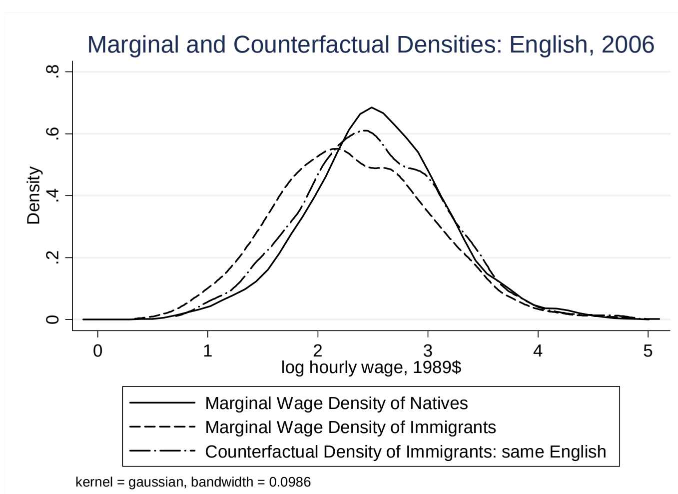


Figure 2.8 Log Wage Densities: Recent Immigrants vs. Natives, 1990

(What if one skill factor had been same distributed between recent immigrants and natives?)

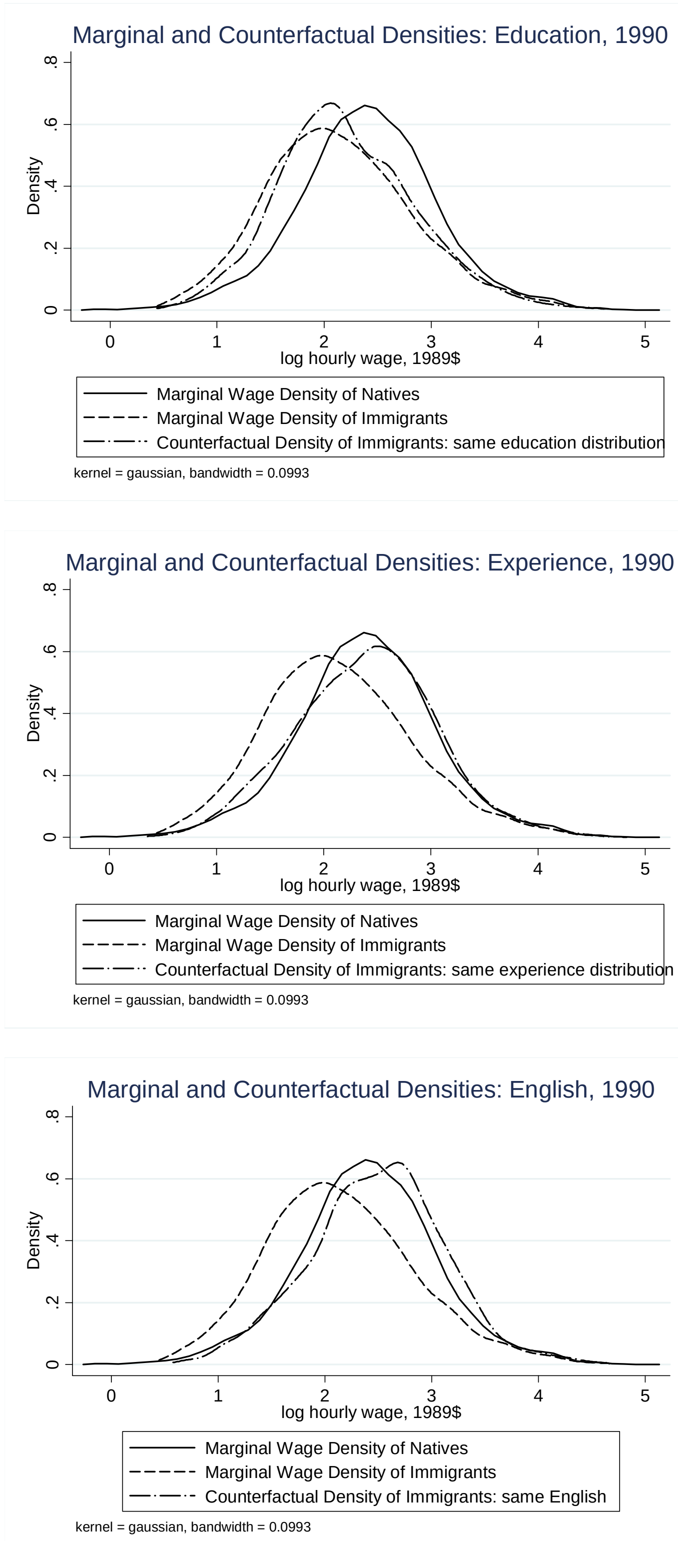
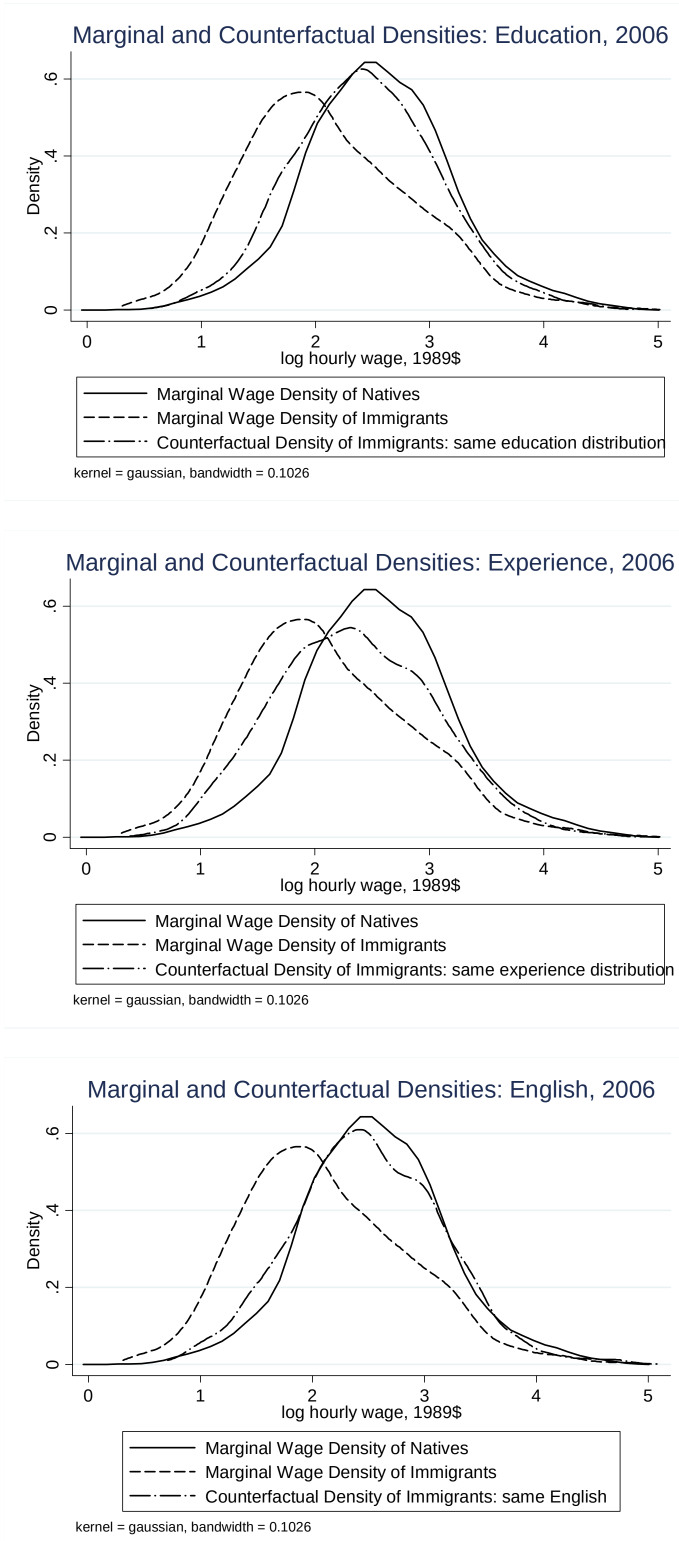


Figure 2.9 Log Wage Densities: Recent Immigrants vs. Natives, 2006

(What if one skill factor had been same distributed between recent immigrants and natives?)



CHAPTER 3 - Admission Standards and Student Effort: An Example[35]

3.1 Introduction

Workers with college degrees tend to earn more than those without.[36] This notion is a key motivation for many students. Combined with the notion of education externalities, it also motivates much government policy. Governments around the world participate in funding education and anticipate higher enrollment and a higher paid workforce in return.[37]

Such responses to the college premium rely on hopeful assumptions regarding the process of human capital accumulation. Colleges combine student time and school resources to generate human capital. Through this process, graduates acquire more human capital than non-graduates. With increased human capital, the marginal product of a graduate is higher and the college premium is a simple reflection of improved productivity.[38]

When these assumption hold, students are right to expect higher human capital and wages from schooling. Furthermore, governments are right to expect higher average income from policies which increase enrollment. In settings with externalities, government can expect an amplification of this positive impact. However, different assumptions of the human capital accumulation process often preserve private returns to college while leading to quite different expectations for government policy. Most famously, Spence (1973) and Arrow (1973) show that education can serve simply to signal innate ability. In this case, governments cannot increase average wages through expanding enrollment but able students expect higher wages through stratification allowed by schooling.[39]

Blankenau and Camera (2006, 2009) highlight another 'weak link in this chain of events' from expanding schooling to expanding skill. They include student effort as an input into the production of human capital. Subsequent to the enrollment decision, students decide whether to make an imperfectly observable effort investment in human capital. Some students earn a degree

[35] This essay is coauthored with my dissertation advisor Dr. William Blankenau.
[36] See Goldin and Katz (2007) for a comprehensive historical review of the college premium.
[37] Education at a Glance (2008), Table B2.4 shows that on average public spending on education accounted for 5 % of GDP in OECD countries in 2005. Of this, 1.5% of GDP was spent on tertiary education.
[38] This is the standard human capital approach of Becker (1964) and Ben Porath (1967).
[39] The literature on signaling is immense. See Bedard (2001) as an example of recent evidence supporting its empirical relevance.

but avoid effort. These students earn a degree only as a means of mimicking truly skilled agents. This allows them to appropriate some of the returns intended for the skilled. In this environment, graduates have a higher income on average. However, by encouraging an increased share of students to mimic skilled workers rather than earn skill, some government policies which encourage enrollment can lower average human capital and wages in equilibrium.

A further example is provided by Costrell (1994) and Betts (1998). They consider environments where government or colleges can directly affect enrollment by setting education standards. A key feature of both papers is that firms cannot observe ability but only credentials. As such, students put forth no effort beyond what is required to earn the degree. Costrell shows that in this setting increasing enrollment through lower standards can yield lower average output and wages. In Betts' model, low standards have no effect on the human capital at either end of the ability distribution but in the center force a quality/quantity trade-off. Thus there is again a negative side effect of increasing enrollment.

These papers encourage caution in drawing policy implications from the correlation between schooling and wages. In environments where the correlation arises endogenously, more schooling may nonetheless fail to yield higher average wages. This paper reiterates the call for caution by showing another example where more education can be poor policy.[40]

In our paper, government (or colleges) choose enrollment by selecting education standards. In this sense, it is related to the work by Costrell and Betts.[41] However, two key mechanism at work in our model are not present in theirs. The first mechanism is an education externality along the lines of Acemoglu (1996), though simplified. In his model, as in ours, the return to investment by agents and firms is increasing in the investment of their counterpart in production. A friction arises since investments must be made prior to matching. As such, investment decisions are based on the expected productivity in a match and are muted by fear of unproductive matches. When all students are skilled, an increase in their numbers improves expectations of a productive match for firms. They respond with greater investment and this increases expected returns to all skilled workers. Hence the externality. When standards are high

[40] In Costrell (1994) and Betts (1998) the focus is on selected standards in relation to optimal standards. Since too high or low standards are suboptimal lowering standards under some circumstances is poor policy.
[41] Other recent theoretical work on standards includes Gary-Bobo, et al. (2008) and Epple, et al. (2006). However, they are primarily interested optimization of objective functions of the university, an issue not considered here.

in our model, all students who earn degrees also earn skill. When this holds, the Acemoglu externality results in favorable outcomes from lower standards.

The second mechanism is a market failure in the spirit of Blankenau and Camera (2006, 2009). The setting is one in which firms can post skilled positions at a cost or unskilled positions at no cost. Heterogeneity in the cost assures that some, and maybe all, will post skilled positions. Workers take an exam, earning a score directly related to ability and government chooses the cutoff score for admission. Once enrolled, workers can earn a degree at a cost normalized to zero or skill at a positive cost. Heterogeneity in ability maps into heterogeneity in the cost of skill. This assures that some, and maybe all, enrollees will earn skill. After agents and firms have made investment decisions, they are randomly matched for purposes of production. Skilled firms and skilled workers benefit only in reciprocal matches; i.e. only when their production counterpart is also skilled. Matches with a skilled firm and unskilled degree holder provide a benefit only to the worker. With this benefit positive, workers for whom skill acquisition is costly may choose to remain unskilled. This is the source of market failure.

This gives an example of the perils of standards set too high or too low or equivalently of enrollment set too low or too high. When standards are high, the externality outlined above goes unexploited. With few graduates, firms have a low probability of being matched to a graduate and so few post skilled positions. As such, graduates have a low probability of being matched with a skilled firm. Relaxing standards benefits all through the externality. However, beyond a cutoff point the marginal worker finds the cost of skill too high and instead remains unskilled. As an equilibrium outcome, firms no longer increase investment in response to increased enrollment. While graduates continue to earn more than non-graduates in equilibrium, a larger share of graduates are in unproductive matches.

The key problem is that firms know that some degree holders are unskilled and that in hiring them they will gain nothing from having created a skilled position. Too few skilled positions will be created for graduates and many will find themselves working in unskilled positions. There is significant anecdotal evidence of this which will be discussed in the subsequent version of this paper.

In Section 1 we consider the model with the return structure above set exogenously. In the subsequent section we describe environments that give rise to this structure. In Section 4 we consider generalizations. The first generalization demonstrates that low standards can lead to fewer skilled postings. The second shows that our results are robust to the case where exam scores give imperfect information regarding an agent's true ability to acquire skill. Section 5 provides a summary and conclusion.

3.2 A Simple Case

We present a stylized model with several key features. Government funds college for those who gain admission. Admission is based on entrance exam scores and enrollment is regulated through the choice of the cutoff score. Those who go to college have the opportunity to become skilled by incurring an effort cost. They also have an opportunity to earn a degree but no skill at a lower effort cost. Firms can create unskilled or skilled jobs. Skilled jobs are more costly to create and can pay off only if the firm hires a skilled worker.

In this section we take as given that earning a degree increases the expected wage even if no skill is earned while earning skill provides a higher expected wage. We also take as given that the expected gross profit of creating a skilled position exceeds that of creating an unskilled position. There are many settings that could give rise to these relationships and we sketch several example environments in Section 3. However, there are two advantages to simply assuming them for now. First, it highlights that our results hold for any setting generating the relationships. Secondly, it allows us to delay some of the complexity of the model in order to focus first on the implications of these relationships.

3.2.1 Workers

We consider a static economy populated by a mass of workers, a mass of firms, and a government. Workers are heterogeneous in innate ability and are indexed by

$$j = j(a) \tag{1}$$

with $\frac{\partial j(a)}{\partial a} < 0$ so that higher ability agents have lower indices. We drop the a notation in this when no confusion arises. Let the continuous increasing cdf $\mathrm{J}(j)$ be the distribution of j with j normalized such that $j \in [0,1]$. For tractability we initially assume a uniform distribution where $\mathrm{J}(j) = j$. As the period begins, each worker j takes an exam and receives a grade g_j which is inversely related to j (and thus directly related with ability) such that $g_j > g_{j'}$ for all $j < j'$. Government sets a cutoff point for the exam, g, such that $g_0 \leq g \leq g_1$. Workers who score at this level or above costlessly can attend college. Let j_g identify the worker for whom $g_j = g$. This worker and those with a lower index can attend college.

This education environment is useful in that it allows simple analytical results. It also reflects the reality of many education systems where competitive exams are required for enrollment and tuition is then free or heavily subsidized.[42] It is a less precise description of other economies and so it is useful to point out that our specification generalizes along several dimensions. First, we can add a tuition cost without consequence. All that is required is that some set of workers is constrained in college attendance by standards; i.e. the private expected gain to college for this set exceeds the tuition but they are not admitted. Secondly, rather than thinking about increasing or decreasing standards, we can think of decreasing or increasing the capacity of the education system. So long as students are ordered such that, for example, the most able are the first to attend and the least able are the last, the two interpretations are equivalent. Increasing capacity will require a lowering of standards. A minor caveat to this assertion is discussed in Section 4.1.

Contingent on attending college, workers decide whether to make an effort investment to gain skill. This effort cost is worker-specific and the effort required by worker j to become skilled is

$$E_j = e\big(j(a)\big)^{\eta} \tag{2}$$

where $e > 0$ is a scalar governing the cost and η gauges the curvature of this function. Notice that this function gauges how the cost of earning skill depends on ability. Those enrolled can instead earn a degree but no skill at a lower effort cost normalized to zero. We normalize wages so that the wage of a worker with no degree is zero. Workers with a degree but no skill on average find more favorable employment than those without degrees and the expected wage is given by $G_d > 0$. Workers with a degree and skill have an expected wage of $G_s > G_d$. In this simple environment, wage and consumption are equivalent. Assuming lifetime utility to be linear in consumption and effort we have

$$V_{s,j} = G_s - ej^{\eta};\ V_{d,j} = G_d;\ V_{u,j} = 0$$

where $V_{s,j}$, $V_{d,j}$, and $V_{u,j}$ are expected utility as a skilled worker, a schooled worker (i.e. a worker possessing a degree but no skill) and an unskilled worker (no degree). Notice that $V_{d,j}$ and $V_{u,j}$

[42] China is a good example. The subsequent version of this paper will elaborate.

are common for all workers. Heterogeneity along these lines is easy to handle but heterogeneity in effort costs proves sufficient to make our points.

Since $G_d > 0$ and the effort cost of a degree is 0, each eligible worker strictly prefers to go to college and the share of the population going to college is j_g.[43] Thus the only meaningful decision made by workers is whether to obtain skill contingent on being admitted to college. A worker will choose skill if $V_{s,j} > V_{d,j}$; i.e. if

$$G_s - G_d \geq ej^{\eta}. \tag{3}$$

The left-hand side of this is the increased expected wage when skill is earned. Since the structure assures that ej^{η} is strictly increasing with $ej^{\eta} \in \left[0, ej_g^{\eta}\right]$, this holds for all degree holders if $G_s - G_d > ej_g^{\eta}$. In this case $j_s = j_g$ where j_s is the highest indexed agent who earns skill. All workers with a lower index will be skilled and the remainder will be unskilled so that in this case the mass of skilled graduates equals the mass of graduates. Otherwise equation (3) will hold with equality for some worker j_s where now $j_s < j_g$. The mass of skilled workers in this case is smaller than the mass of graduates. Considering the two cases we have

$$j_s = \begin{cases} j_g & \text{if} \;\; G_s - G_d > ej_g^{\eta} \\ \left(\frac{G_s - G_d}{e}\right)^{\frac{1}{\eta}} & \text{if} \;\; 0 \leq G_s - G_d \leq ej_g^{\eta} \end{cases}. \tag{4}$$

Note that the share of the population with skill is j_s, the share of the population with degrees is $j_g \geq j_s$ and the share of the degree holders with skill is $\frac{j_s}{j_g}$.

3.2.2 Firms

We index firms by i. Let the continuous increasing cdf $\mathrm{I}(i)$ be the distribution of i with i normalized such that $i \in [0,1]$ Again we assume a uniform distribution so that $\mathrm{I}(i) = i$. Taking labor outcomes as given, firms create job openings in order to maximize expected profits. There are two types of openings that a firm might create: skilled and unskilled. Firms are heterogeneous in their ability to create skilled openings. The cost to firm i of creating a skilled position is C_i=ci^{β} while the cost of creating an unskilled position is normalized to 0. An unskilled position earns profits normalized to 0 while a skilled position yields expected profits net of job creation costs equal to $p_s - \mathrm{c}i^{\beta}$ where $p_s > 0$ is the gross expected profits from a

[43] Results are identical with a positive effort cost of schooling or a tuition cost small enough that G_d always compensates for the cost.

skilled position. The environment assures that some firms will create skilled vacancies and we refer to these as skilled firms.

A firm will be skilled if $p_s - \mathrm{c}i^{\beta} \geq 0$. Since the structure assures that $\mathrm{c}i^{\beta}$ is strictly increasing with $\mathrm{c}i^{\beta} \in [0, c]$, this holds for all firms if $p_s > c$. Otherwise it will hold with equality for some firm which we refer to as i_s. All firms with a lower index will be skilled and the remainder will be unskilled so that the share of skilled firms will be i_s. Thus

$$i_s = \begin{cases} 1 & \text{if } \ P_s > c \\ (c^{-1}P_s)^{\frac{1}{\beta}} & \text{if } \ 0 \leq P_s \leq c \end{cases}. \tag{5}$$

3.2.3 Equilibrium

After firms and workers have made their decisions regarding skill acquisition and job creation, bilateral matching occurs. The production technology is such that an unskilled firm matched with any worker generates output normalized to zero. With no output, the gain to working for such a firm, whether skilled, schooled, or unskilled, is 0. Furthermore, any firm matched with an unskilled worker yields output of zero and thus no gain to the worker.

The interesting features of our model stem from the cases where workers with degrees are matched with skilled firms. By our assumption that $G_d > 0$, schooled workers have an expected gain in such cases and by our assumption that $G_s > G_d$, those with skill have a larger expected gain. Let $G > 0$ be the expected wage increment of a skilled worker when matched with a skilled firm. Then since i_s is the chance of such a match occurring

$$G_s - G_d = i_s G. \tag{6}$$

From the firm's perspective, gains can occur only if the firm is matched with a skilled worker. A skilled firm's expected profit then depends on the share of workers with skill and the expected gain in a skilled match. Letting $P > 0$ be the firm's expected gain in a skilled match we have

$$P_s = j_s P. \tag{7}$$

It proves convenient to define $W = Ge^{-1}$ and $F = Pc^{-1}$. Notice that for any workers with a degree, the benefit-cost ratio of skill is $\frac{i_s}{j^{\eta}}\frac{G}{e} = \frac{i_s}{j^{\eta}}W$. Thus W is a scalar determining the rate of return to skill for workers in a best match. Similarly, F is a scalar determining the rate of return for firms from creating a skilled opening in a best match. With these definitions we can use equations (6) and (7) to rewrite equations (4) and (5) as

$$j_s = \begin{cases} j_g & \text{if } Gi_s > ej_g^{\eta} \\ (Wi_s)^{\frac{1}{\eta}} & \text{if } 0 \le Gi_s \le ej_g^{\eta} \end{cases} \tag{8}$$

$$i_s = \begin{cases} 1 & \text{if } Pj_s > c \\ (Fj_s)^{\frac{1}{\beta}} & \text{if } 0 \le Pj_s \le c \end{cases}. \tag{9}$$

As mentioned in the introduction, the model blends some features of Acemoglu (1996) and Blankenau and Camera (2006, 2009). In Acemoglu's paper, firms and workers also make uncoordinated investment decisions prior to random matching. Thus as in our model firms and workers have to make decisions based on the expected productivity of their production partner. In our model entities face a dichotomous choice to invest or not. This is to match the dichotomous choices faced by workers in going to college and by firms in posting jobs requiring degrees. Acemoglu is not concerned with the college choice per se and entities in his model choose a level of investment. However, an equivalent coordination problem results in an equivalent externality. We see this in equations (8) and (9). Except for corner solutions (i.e. when $j_s < j_g$ and $j_s < 1$) an increase in skilled workers motivates an increase in skilled firms and vice versa.

Absent the Blankenau and Camera market failure, policy implications from our model would align closely with those in Acemoglu. In his model, anything that increases investment by workers would increase investment by firms and improve outcomes through this externality. In ours, anything that increases the number of students would increase the number of skilled workers and in turn would increase the number of skilled firms. With the market failure however the chain of events can break down at its first link. An increase in the number of students may not increase the number of skilled workers. While the remaining link is unbroken, it is also unexploited when there is no gain in skill.

To see this more clearly, we consider equilibrium outcomes. An equilibrium in this setting is a set ($j_s \in (0, j_g]$, $i_s \in (0,1]$) such that j_s satisfies equation (8) with workers taking i_s and j_g as given and i_s satisfies equation (9) with firms taking j_s and j_g as given. Proposition 1 below characterizes the equilibrium.

Proposition 1. Let $\tilde{j} \equiv \left(FW^{\beta}\right)^{\frac{1}{\beta\eta - 1}}$. If $W^{\frac{1}{\eta}}F > 1$

$$
(j_s, i_s) = \begin{cases} \left(j_g, \left(Fj_g\right)^{\frac{1}{\beta}}\right) & \text{if } j_g < F^{-1} \\ \left(j_g, 1\right) & \text{if } F^{-1} < j_g < W^{\frac{1}{\eta}}. \\ \left(W^{\frac{1}{\eta}}, 1\right) & \text{if } j_g > W^{\frac{1}{\eta}} \end{cases} \tag{10}
$$

and if $W^{\frac{1}{\eta}}F < 1$

$$
(j_s, i_s) = \begin{cases} \left(j_g, \left(Fj_g\right)^{\frac{1}{\beta}}\right) & \text{if } j_g < \tilde{j} \\ \left(\tilde{j}\,, \left(F^{\eta}W\right)^{\frac{1}{\beta\eta-1}}\right) & \text{if } j_g > \tilde{j} \end{cases}. \tag{11}
$$

Proposition 1 shows that there are two distinct cases delineated by $W^{\frac{1}{\eta}}F$. When this value is greater than 1, (j_s, i_s) is governed by equation (10) and when it is smaller, they are governed by equation (11). The first line of each shows that with j_g sufficiently small, (j_s, i_s) is the same in each case. With j_g small, any worker allowed entrance to college has a relatively low cost of acquiring skill and all choose to do so; i.e. $j_s = j_g$. From the firm´s perspective, the relative scarcity of skilled workers makes creating skilled positions less attractive and few skilled positions are created. Here $i_s = \left(Fj_g\right)^{\frac{1}{\beta}}$. In this case, a loosening of standards, that is a rise in j_g, yields more skilled workers, more skilled firms and has no negative effect on the average skill level of graduates.

As j_g rises, the cost to the marginal worker of obtaining skill increases, making skill acquisition less attractive for the marginal agent. At the same time, the number of skilled firms rises, increasing the chances of being matched with a skilled firm. This makes skill acquisition more attractive. Eventually, though, the return does not justify the high effort cost for the marginal agent and a group of schooled workers arises ($j_s < j_g$).

The cases delineated by $W^{\frac{1}{\eta}}F$ differ in whether $j_s < j_g$, arises when all firms are skilled (equation (10)) or when a subset of firms are skilled (equation (11)). When F is larger, i_s is larger for any given j_g and thus more readily hits its upper bound of 1. The proposition shows that for F large enough, this upper bound is reached when $j_s < j_g$. When F is smaller, the upper bound is never reached as discussed below.

We will focus mostly on the case where $W^{\frac{1}{\eta}}F < 1$. However, we first point out some interesting features of the other case. As mentioned above, with j_g small, increasing enrollment yields more skilled workers and firms. Furthermore, when j_g exceeds F^{-1}, an equilibrium arises where all graduates are skilled and all are matched with skilled firms as in the second line of equation (10). It seems that this setting is one in which lowering standards (increasing j_g) would be most advisable. However, the third line shows the perils of low standards in this case. When j_g is sufficiently large, some workers find it best to be schooled workers even with $i_s = 1$. Lowering standards further yields no increase to the average skill level of the population and decreases the average skill level of a college graduate.

The case where $W^{\frac{1}{\eta}}F < 1$ is more relevant since it assures $i_s < 1$and we do not observe $i_s = 1$ in actual economies. It is also more interesting since it allows the case where both j_s and i_s are interior solutions. With $j_g < \tilde{j}$ lowering education standards has a positive effect on both the number of skilled workers and the number of skilled firms as discussed above.

We refer to matches with a skilled worker and a skilled firm as productive matches. With $j_g < \tilde{j}$ the number of such matches, $j_s i_s$, clearly increases as standards fall. Unproductive matches occur when at least one party to a match is not skilled; i.e. they occur with probability $1 - j_s i_s$. Changing the composition of matches in favor of skilled matches and away from unproductive matches is one positive effect of lower standards. However, even in this simple setting the model demonstrates a potential problem with lowering standards: while the number of unproductive matches falls, the number of wasteful unproductive matches can rise.

To see it, note that unproductive matches can be of three types. If both parties to the match are unskilled, the match represents no wasted effort; neither the worker nor the firm has unrequited costly potential. The number of such matches is $(1 - j_s)(1 - i_s)$ and they are clearly less prevalent when j_s and i_s increase. In other unproductive matches, one party has skill and the other does not. These matches imply a wasted effort on the part of the skilled party. They have paid a cost to become skilled but end up in an unproductive situation. In the case of workers, there is also a wasted tuition payment by government. We refer to a skilled worker in an unproductive match as underemployed. The number of such matches is $j_s(1 - i_s)$. We refer to a skilled firm in an unproductive match as underperforming since it has the potential to be productive but is unable to hire the requisite skilled labor. The number of such matches is $(1 - j_s)i_s$. Corollary 1 summarizes the effect of lower standards when j_g is small.

Corollary 1. Let $j_g < \tilde{j}$ and $W^{\frac{1}{\eta}}F < 1$. As enrollment standards are lowered (as $j_g$increases) there are more skilled firms, more skilled workers, and more productive matches. The share of degree holders with skill is constant at 1. For $j_g < (>) \frac{1}{1+\beta}$ there are more (fewer) underperforming firms. For $j_g < (>) \left(\frac{\beta}{1+\beta}\right)^{\beta} \frac{1}{F}$ there are more (fewer) underemployed graduates. However, the share of degree holders who are underemployed is lower.

The first claim (second sentence) restates that j_s , i_s, and $j_s i_s$ are increasing in j_g. The second is a restatement of $j_s = j_g$. The third claim is proven in the appendix. An implication is that in a neighborhood of $j_g = 0$ lowering standards yields more wasteful unproductive matches of each type. The reason is that with j_g low, i_s is low so that skilled workers will be unlikely to match with skilled firms and j_s is low so that skilled firms will be unlikely to match with skilled workers. Lower standards can increase underemployment over the entire range $j_g \in [0, \tilde{j}]$ if $\tilde{j} < \frac{1}{1+\beta}$ and can increase underperformance by skilled firms over this range if $\tilde{j} < \left(\frac{\beta}{1+\beta}\right)^{\beta} \frac{1}{F}$.

We emphasize that these results stem solely from the matching structure. Since all degree holders are skilled, the option of being a schooled worker is never chosen and this feature of our model is not operative. Thus lower standards have no negative effect on the average skill of graduates. Lowering standards simply increases human capital and firms respond positively. The potential increase in wasteful unproductive matches is an artifact of more skill subjected to random matching. This problem is more severe when graduates (and hence skilled firms) are few in number, i.e. when j_g is small. When $j_g > \left(\frac{\beta}{1+\beta}\right)^{\beta} \frac{1}{F}$, further increases in the number of college graduates will decrease the number of underemployed graduates so long as all earn skill.

While increasing graduates can increase the number of underemployed skilled workers, the final claim states that at as a share of degree holders, underemployment always falls. Since the number of underemployed workers is $j_s(1 - i_s)$, this as a share of degree holders is simply $(1 - i_s)$. Thus the algebra of the claim is simple. The intuition is also straightforward. More skilled agents begets more skilled firms so each skilled worker has a better chance of an appropriate match. Thus a larger share of those with skill are in skilled matches.

The above policy implications only hold when all graduates choose to earn skill. When j_g exceeds the $\tilde{j}$ threshold a group of unskilled graduates emerges and the implications of a further lowering of standards are much different. These are summarized in Corollary 2.

Corollary 2. Let $j_g > \tilde{j}$ and $W^{\frac{1}{\eta}}F < 1$. As enrollment standards are lowered there is no change in the number of skilled firms, skilled workers, or skilled matches. The share of degree holders with skill falls and there are more underemployed graduates. The number of underperforming firms does not change but the share of such firm employing college graduates rises.

As j_g crosses a threshold, the marginal worker finds that the expected return to skill does not compensate for the effort cost of its acquisition. As a result, this worker opts for the lower expected wage of being a schooled agent. Beyond this threshold, additional students will make the same decision so that j_s no longer increases in j_g. With no additional skilled workers, the number of skilled firms does not expand. The mechanism driving the earlier results is shut down. As a result both j_s and i_s are independent of j_g beyond the threshold. This is clear from the second line of equation (11) and is stated as the first claim of Corollary 2.

The second claim is evident from rising enrollment with a fixed number of skilled workers and skilled firms. A group of degree holders with no skill arises with sufficiently low standards and expands as standards continue to fall. Since no new skilled positions are created as enrollment rises, the number of underemployed college graduates rises.

Since this new class of workers does not acquire skill, this is not wasteful of student effort. Also, workers and firms with skill are no less likely to be in a productive match. Thus the cost of the failure is not wasted effort or lower output but rather futile education expenditures.

The third claim points out that with j_s and i_s fixed, there is no change in the number of underperforming skilled firms. However, if we consider firms who are able to hire college graduates, we find that their average productivity will be lower. This is because more skilled firms are hiring graduates but the same number are in fact hiring skilled workers. Thus two measures of economic performance are adversely affected: the underemployment rate of degree holders and the average productivity of degree holders who find skilled positions. While neither the number of skilled workers nor skilled matches falls, skilled workers may nonetheless be made worse off by lower standards. It is shown in Section 3 that if the skill level of a worker is difficult for a firm to assess, the expected wage to a skilled worker may decrease in response to the lower expected output from hiring a degree holder.

In summary, lowering standards can have a variety of effects. When j_g is small these can be both positive and negative. On the negative side, lower standards may increase the number of underemployed skilled workers and/or underperforming skilled firms. On the positive side, lower standards increase the number of skilled workers, the number of skilled firms, and output. When j_g is larger, the ability of government to increase output through allowing greater enrollment is eliminated and the only results are negative. Increasing j_g beyond a threshold increases the number of graduates but has no effect on the number of skilled workers. Thus the number of unskilled graduates is positive and increasing in j_g. While underemployment among the skilled does not increase, there are more graduates in unskilled positions so that apparent underemployment rises. Furthermore, though output does not fall, the productivity of firms contingent of being matched with a skilled worker falls.

While lowering standards (or increasing enrollment) beyond a threshold proves to be poor policy, the model is suggestive of more robust policies for improving outcomes. Recall that F and W are the rates of return for skilled firms and workers in best matches. It is easy to suggest ways in which government might influence either. Lower corporate income taxes, subsidies to skilled firms, or lowering the cost of posting a skilled position might increase F.[44] Lower income taxes (or less progressive income taxes) might lower W. Lowering the private cost of acquiring skill, perhaps through improved education quality, would have the same effect. Rather than complicating the model with the particulars of such policies at this point, we simply argue that these rates of return might be influenced by policy. Corollary 3 shows how outcomes respond to changes in F and W.

Corollary 3. When $j_g < \tilde{j}$, an increase in F increases i_s and has no effect on j_s while an increase in W has no effect on either i_s or j_s . When $j_g > \tilde{j}$, an increase in either F or W increases both i_s and j_s. An increase in either also increases $\tilde{j}$.

The corollary, which derives directly from equations (10) and (11), shows that increasing the rate of return for firms is always helpful. When standards are high (j_s low), it motivates more firms to post skilled positions. As a result more of the graduates land high paying jobs. When

[44] Investment tax credits can be considered an example of lowering the cost of posting a skilled position.

standards are lower, this effect still operates and another kicks in. Due to improved chances of a skilled match, more students earn skill. This causes an even greater increase in the number of firms posting skilled positions.

Increasing the returns to skilled labor is not effective when all earn skill. Since government is choosing admission and all agents are already choosing skill, there is no margin along which the increased return can work to increase skill. However when standards are low and some students choose to earn no skill, increasing returns to skill can be helpful. It motives a larger share of the workforce to earn skill, and through this increases also the number of skilled postings.

There is a large literature suggesting that with production externalities government has a role in funding education. Often this work focuses on tuition subsidies (ex. Hanushek, Leung and Yilmaz (2004)). Our work complements this by considering an environment where the externalities arise endogenously. By evaluating the source of the externalities we show that subsidizing firms can be an appropriate response to what we typically think of as an education externality. In fact, from equation (11) we see that with $j_g < \tilde{j}$ it is the only sort of subsidy that is effective since changes in W have no effect. Concerning education, our work also focusses on the need for subsidies to quality rather than to tuition. In this, it mirrors the findings of Blankenau and Camera (2009).

3.3 Foundations

There are several key assumptions that give rise to the results above. First, there needs to be some advantage to going to school even if the worker does not become skilled; i.e. $G_d > 0$. Second, earning skill must have an additional advantage; i.e. $G_s > G_d$. Finally, firms must have some expected benefit from creating a skilled position; $P_s > 0$. In this section we describe several example environment that can support these assumptions. We then discuss some possible extensions to this foundation that would preserve the key findings. The main point is that a variety of intuitive settings can support the required assumptions.

3.3.1 Productive schooling

Suppose that in any match the wage is set to zY where Y is the output from the match and $z \in (0,1)$ is the exogenously determined share paid to the worker. A match between a skilled worker and a skilled firm yields output of Y_h. Since a skilled worker matches with a skilled firm with probability i_s we have

$$G_s = i_s z Y_h \ .$$

Similarly, a match between a schooled worker and a skilled firm yields output of Y_l where $0 < Y_l < Y_h$. This gives

$$G_d = i_s z Y_l \ .$$

Thus $G_s > G_d > 0$ as required.

We assume that firms pay a fixed cost of production. For unskilled firms this is normalized to 0 and for skilled firms it is equal to C. The firm matches with a skilled worker with probability j_s and with a schooled worker with probability $(j_g - j_s)$. Thus the benefit to being a skilled firm is

$$P_s = j_s\big((1-z)Y_h - C\big) + \big(j_g - j_s\big)\big((1-z)Y_l - C\big).$$

To simplify the algebra, we assumed in the previous section that firms benefit only when matched with skilled agents. It is easy to relax the assumption so that firms benefit in any match and benefit more in a skilled match. However, numerical solutions are required and little is gained in terms of intuition. Thus we preserve the assumption by setting $C = (1-z)Y_l$. Then $P_s = j_s\big((1-z)Y_h - C\big)$ so that the final assumption is also satisfied. To be more explicit, in this setting $W = \frac{z(Y_h - Y_l)}{e}$ and $F = \frac{(1-z)Y_h - C}{c}$. With theses definitions, the math from the previous section applies directly. Results are similar when $0 < C < (1-z)Y_l$ though closed form solutions are not available.

3.3.2 Asymmetric information

An alternative foundation builds on an information asymmetry and also maps directly into setting in the previous section. Consider an economy where the information structure is similar to that in Blankenau and Camera (2006, 2009). Suppose that in any match the wage is set to $zE(Y)$ where $E(Y)$ is the expected output from the match and $z \in (0,1)$ is the exogenously determined share paid to the worker. The output expectation is contingent on information available prior to production. A match between a skilled worker and a skilled firm yields output of $Y > 0$ while all other matches yield output normalized to 0. As a result, if the skill level of a degree holder is observable, schooled workers will always earn 0. This violates $G_d > 0$. If instead the skill level cannot be observed, the expected output from a match with a degree holder is $Y\frac{j_s}{j_g}$. Thus the common wage for all degree holders is $zY\frac{j_s}{j_g}$. This violates $G_s > G_d$.

To satisfy both restrictions, we assume that the skill level of a worker is revealed with probability $\theta \in (0,1)$. The idea here is that the degree only indicates that a worker has had an opportunity to earn skill, not that the opportunity was taken. As such the firm may request additional information such as grades, letters of recommendation, and interview assessments. These give additional but noisy information and may reveal a worker's skill level.

In this setting schooled workers earn $zY\frac{j_s}{j_g}$ when they are matched with a skilled firm and are not recognized and they earn nothing otherwise. In other matches they earn 0. Since we have already shown that $i_s, j_s > 0$, we have

$$G_d = i_s(1-\theta)zY\frac{j_s}{j_g} > 0 \tag{12}$$

as required. Skilled workers earn zY when they are matched with a skilled firm and recognized. Otherwise they earn the same as a schooled worker. Thus

$$G_s = i_s\theta zY + G_d \tag{13}$$

and obviously $G_s - G_d = i_s\theta zY > 0$. It is straightforward to show that in this setting

$$P_s = (1-z)j_sY > 0 \tag{14}$$

so that the final assumption is also satisfied. To be more explicit, in this setting $W = \frac{\theta zY}{e}$ and $F = \frac{(1-z)Y}{c}$ so that the math above applies directly.

This setting makes explicit the effect of j_g on the expected wages of different types of workers and on the productivity of skilled firms. We summarize these is Corollary 4.

Corollary 4. Let $W^{\frac{1}{\eta}}F < 1$ and $j_g > \left(FW^{\beta}\right)^{\frac{1}{\beta\eta-1}}$ in the environment described above. Then an increase in j_g decreases the expected wage of both skilled workers and schooled workers and decreases the expected output of a match with a skilled firm and a degree holder.

The information asymmetry presents the worker with the option of mimicking a skilled worker by earning identical credentials. In cases where the skill level is obscured, the schooled workers appropriate some of the rent due skilled workers. The share of rent confiscated by schooled workers rises as the share of schooled workers rises. Thus lower standards do not lower the productivity of a skilled worker but rather lower the share of output retained by the worker.

Schooled workers are also hurt by an enrollment expansion. With few schooled workers, the expected output of a degree holder is high and the wage to unrecognized degree holders reflects this. As more schooled workers enter the labor force, expected output and wages fall.

Firms are not hurt by the expansion since they are risk averse and wages adjust to keep their expected profit the same whenever matched with a degree holder. However, productivity measures are affected. A larger number of schooled workers will decrease the expected output of a firm who hires a schooled worker.

A variety of generalizations of this setting are possible. For example, one may be concerned that the information asymmetries would be temporary. Production should reveal skill levels and future wages should adjust. However in another setting Blankenau and Camera (2009) generalize a similar information structure to one where workers live several periods. There is uncertainty regarding productivity in the first period but not in subsequent periods. This generalization has little effect on their results. The same is true here. So long as schooled workers can mimic the skilled at least initially, the results hold. Thus for algebraic simplicity, we consider only the static case.

As another example, the split of expected output could be endogenized. All that is required is that workers and firms agree to a split prior to production and that this split be conditional only on information available at that time. It is not important that this split be equal in cases where the skill level is known and unknown but only that it not be a corner in either case.

3.3.3 Different compensation strategies

The foundation provided above shows in a simple setting how information asymmetries can influence the effectiveness of increasing enrollment by lowering the required score for entry to college. Moreover, it is a setting which has proven useful elsewhere in the literature. Its simplicity, though, requires a somewhat cumbersome assumption. The government knows exam scores before college begins but firms do not know initial exam scores when college is completed. If they did, they could work through the calculations above and discern which graduates are skilled and which are not based on exam scores. Instead, for any individual, they only know whether college was completed. Other information is revealed only with probability θ.

It may be reasonable to assume that government does not provide this information and that individuals cannot credibly reveal the information. If anything prevents the perfect transference of this information to firms, we can subsume the possibility of revelation into the parameter θ. So long as $\theta < 1$, our results hold. However, there are several alternatives to this information structure which get around this feature. One alternative which requires a bit more structure is discussed in Section 4.2. The other is a simple reinterpretation of the θ parameter and allows the math above to hold in an identical manner.

Suppose that the skill level is recognized by firms so that they can calculate the skilled agents from the schooled agents. However, only a share of firms use this information to set wages. That is, a share θ of firms compensate degree holders according to their ability and the remainder compensate degree holders according to the expected ability of a degree holder.[45] In the environment above, firms earn the same regardless of the compensation strategy and so this does not violate optimality on their part. There are many reasons a firm might choose to compensate all degree holders equally. For example, there may be a union, wage negotiations or monitoring may be costly, or there may be some residual uncertainty not modeled here. There is in fact a large literature that identifies and explains different compensation strategies by firms. See, for example, Lazear (1986, 2000a, and 2000b). This literature shows why some workers are paid piecemeal so that wages reflect output directly while others are paid a salary which essentially relates pay to input, at least initially. The first case more closely resembles pay according to marginal product and the second more closely resembles pay according to expected marginal output. Our model can be seen as taking as given some exogenous impetus for variation in compensation schemes. As argued above, this wage equality across ability levels need not endure. If it occurs at least initially, our requirements are satisfied.

The math in the previous subsection maps precisely into this new environment. From this we see that the essential requirement is not the information structure but the payment structure. So long as the schooled worker can at times be overcompensated at some cost to the skilled worker, the required conditions for our results can arise.

3.4 Extensions

[45] Pay according to expected ability is a common feature in signaling models. See for example Bedard (2001).

In previous sections, college enrollment influences neither the skill level nor the share of skilled firms unless all students are skilled. This highlights the separation of schooling from skill accumulation in a simple setting but likely understates the importance of enrollment. In this section we consider several environments which allow j_s and i_s to depend on education levels. We then consider how this consideration modifies our findings. We show that despite the more complex setting, the mechanism described above serves to mitigate the effects of increased enrollment on skill accumulation and the creation of skilled jobs.

3.4.1 Generalized cost and return functions

To this point we have implicitly assumed that education quality is stable as enrollment increases. To see it, note that as enrollment increases, the effort cost of earning skill is fixed for a particular agent. This is why in Section 2.1 we could state that expanding and using capacity was the same as lowering standards. There is evidence however, that per capita government spending on education falls as enrollments rise. For example, OECD Factbook (2009) states that "in many OECD countries the expansion of enrolments, particularly in tertiary education, has not always been paralleled by changes in educational investment." To the extent that per capita expenditures influence education quality, this makes earning skill more difficult for those enrolled.

In this subsection we make assume that the cost of skill can be mitigated by per-student spending on education and that per student spending falls as enrollment rises. Suppose $E_j = e\left(\frac{j_g}{k}\right)^{\alpha} j^{\eta}$ where k is total government spending on education so that $\left(\frac{k}{j_g}\right)$ is expenditure per student. Government finances expenditure through lump-sum taxation.[46] We assume $\alpha \geq 0$ so that the effort cost of skill decreases as per-student expenditure rises. The idea here is that higher quality education makes skill acquisition simpler. In this setting, when j_g increases without a proportional increase in k, per-student expenditure falls. This causes a decrease in educational quality. As a result, it is more difficult for a worker to earn skill.

Proposition 2 demonstrates the extent to which our results generalize to include this effect. This is analogous to the second part of Proposition 1. The first part also generalizes and is given in the unpublished proof available from the authors.

[46] This assures that taxes do not distort choices; i.e. generalizations of equations (8) and (9) are independent of taxes and depend on government only through expenditure.

Proposition 2. In the generalized setting, if $(Wk^{\alpha})^{\frac{1}{\eta+\alpha}}F < 1$

$$(j_s, i_s) = \begin{cases} \left(j_g, (Fj_g)^{\frac{1}{\beta}}\right) & \text{if } j_g < \left(FW^{\beta}k^{\alpha\beta}\right)^{\frac{1}{(\eta+\alpha)\beta-1}} \\ (j^*, i^*) & \text{if } j_g > \left(FW^{\beta}k^{\alpha\beta}\right)^{\frac{1}{(\eta+\alpha)\beta-1}} \end{cases} \tag{15}$$

where $j^* = \left(W^{\beta}Fk^{\alpha\beta}j_g^{-\alpha\beta}\right)^{\frac{1}{\eta\beta-1}}$, $i^* = \left(WF^{\eta}k^{\alpha+1}j_g^{-\alpha}\right)^{\frac{1}{\eta\beta-1}}$. When $(j_s, i_s) = (j^*, i^*)$, the number of skilled firms, skilled workers, and skilled matches fall as enrollment standards are lowered. Furthermore the share of degree holders with skill falls, there are more underemployed graduates, and the share of underemployed graduates rises.

Comparing this with Proposition 1, we see that when $j_g$is small, the results are unchanged except that the cutoff point is different. However, when j_g is large enough to ensure interior solutions for both workers and firms, j_g influences both j_s and i_s. In the earlier case, lower standards failed to bring about more skilled firms, workers or matches. Now, each of these measures falls. Higher enrollment lowers the productivity of education so fewer workers decide to earn skill. Anticipating this, fewer firms create skilled positions.

3.4.2 Imperfect correlation between ability and scores

This final example extends the work in two useful ways. First it provides an alternative information structure. This structure is robust to the concern that agents could identify true ability through knowledge of exam scores. Secondly, it relaxes a somewhat extreme finding of earlier settings. In those settings, once a threshold is reached allowing additional enrollment always means increasing the number of schooled agents without increasing the number of skilled agents. In the current setting, at every grade level there is a distribution of ability levels. As a result, allowing more students can increase both the number of skilled and schooled agents.

Due to imperfections in the examination system and an element of randomness in exam performance, it is possible that some high ability agents perform poorly on entry exams while some low ability agents do well. That is, scores and ability may not be perfectly correlated. In this case uncertainty about productivity remains when exam scores are revealed.

To capture this notion, suppose that agents are assigned both an ability level a and an exam score g. These are realizations of the random variables A and G with joint probability distribution $f_{GA}(g, a)$ and support $g, a \in (0,1)$. Test scores reveal the conditional probability distribution of ability, $f_{A|G}(A|G = g)$ but not the realization of ability. An agent know both a and g while those granting admission know only g. This is a simple way to model the common theme that workers may have information about ability unavailable to government.

In this environment we no longer have a mapping from test scores to ability. Thus defining a cutoff exam score is no longer equivalent to identifying a cutoff ability level and index. As such, we no longer use the j_g notation. Rather than defining a cutoff index, we define a cutoff exam score, g_c. In general, some agents at each ability level will score above this cutoff score and go to college while others will score below and not be admitted.

Unobservable ability removes the possibility of a cutoff ability level for college attendance. Since agents know their ability level, however, their choice of skill upon admission is not changed and there remains a cutoff ability level and index for skill acquisition. It proves more convenient going forward to refer to agents by their ability level rather than their index. Thus there is an ability level, a_s, such that agents with ability above a_s will earn skill if they enroll in college and the remainder will not. This is related to our earlier j_s through the functional relationship in equation (1).

The output and compensation structure are the same as in the previous two subsections and true ability is again revealed with probability θ. That is, an agent receives a share of output with probability θ and otherwise receives the same share of expected output. This gives

$$G_d(g) = i_s(1-\theta)zY\int_{a_s}^{1} f_{A|G}\,da$$

$$G_s(g) = i_s\theta zY + G_d(g).$$

These are equivalent to equations (12) and (13) except that the integral replaces $j_s j_g^{-1}$. This integral is the share of workers with exam score g whose ability exceeds a_s just as $j_s j_g^{-1}$ is the share of graduates with skill in earlier representations.

Agents for whom $a > a_s$ will be skilled only if their exam scores warrant college admission. Thus the share of the population with skill, $\pi(a_s, g_c)$, is

$$\pi(a_s, g_c) = \int_{a_s}^{1}\int_{g_c}^{1} f_{GA}(g, a) \tag{16}$$

and the analog to equation (14) is

$$P_s = (1-z)\pi Y > 0.$$

Considering interior solutions for brevity, the second lines of equations (8) and (9) become

$$j_s(a_s) = (Wi_s)^{\frac{1}{\eta}} \tag{17}$$

and

$$i_s = \left(F\pi(a_s, g_c)\right)^{\frac{1}{\beta}} \tag{18}$$

where again $W = \frac{\theta z Y}{e}$ and $F = \frac{(1-z)Y}{c}$. These differ from their earlier counterparts in that j_s in equation (9) is replaced by π in equation (18).

Equations (1) and (16)-(18) define four equations in j_s, i_s, π, and a_s. Further analysis requires that we specify the relationship between j and a in equation (1) and the joint distribution in equation (16). In general this will require numerical solutions. However, we note that in a special case, the model reverts precisely to the math in Section 3.2. Suppose that we choose some joint distribution $f_{GA}(g, a)$ and use equation (16) to find $\pi(a_s, g_c)$ for an arbitrary a. Then in choosing j_a we simply choose j_a equal to the derived $\pi(a_s, g_c)$. So long as this is decreasing in a, we will have violated none of the assumptions of this section. Furthermore, equations (17) and (18) will reduce to the second lines of equations (8) and (9). As the cases are identical, no new analysis is required.

An example serves to make this more clear. Let

$$f_{GA}(g, a) = 2(1-a) + 4(a-.5)g)$$

with support $g, a \in (0,1)$. With this specification $f_G(g) = f_A(a) = 1$ while $f_{A|G} = f_{G|A} = f_{GA}$. That is, the unconditional distributions of ability and skill are uniform while conditional distributions are given by equation (19).For a given exam score, g, any ability level is possible but the expected level of ability is $\frac{1}{3}(1+g)$. Similarly, for a given ability level, a, any score is possible but the expected score is $\frac{1}{3}(1+a)$. The more able have higher expected test scores and higher test scores indicate a higher expected ability. Using equation (16), we find

$$\pi(a_s, g_c) = (1-g_c)(1-a_s)(1+a_s g_c) .$$

Next we specify equation (1) as

$$j(a) = (1-g_c)(1-a)(1+a g_c) . \tag{20}$$

It is straightforward to show that this is decreasing in a and thus allowable. Clearly if j and a are related as in equation (20), the math from Sections 2 and 3 applies directly. The same is true for any specification where $j(a) = \pi(a_s, g_c)$.

The mapping in equation (20) is useful in that it allows this much richer setting to be an alternative foundation for the simple results in Section 2. A drawback is that the mapping is somewhat contrived since it depends on g_c. It is illuminating to consider why this is needed.

With the current setup, lowering standards increases the number of skilled agents since some share of agents with every score will become skilled. Firms respond to this by creating more skilled positions. Since this effect is not present in the earlier case, the cases cannot be identical unless something undoes this effect.

In equation (20), $j(a)$ is decreasing in g_c. Thus when g_c increases and fewer go to college, the index for agents at every ability level falls. Recall that j, as well as serving as an index, determines the cost of skill as indicated in equations (1) and (2). Because of this, by increasing j at each ability level, we are increasing the private cost of earning skill at each ability level. This serves to decrease the number of skilled agents and firms and counters the upward pressure from lower standards mentioned in the previous paragraph. With equation (20) as the mapping from cost to ability, (from j to a), the two effects precisely offset. This is the same mechanism as developed in Section 4.1 except there we explicitly model the effect as depending on per capita expenditures. The current setting can be given the same interpretation.

We need these effects to offset perfectly only to match the earlier model perfectly. The mechanism at work in Sections 2 and 3 is still operative for different specifications of equation (1). To demonstrate we consider additional possibilities numerically. We find results to be quite similar. A discussion will be provided in a future version of this work.

3.5 Conclusions

In this paper, we extend the framework adopted by Blankenau and Camera (2009, 2006), and construct a model in which firms' investment decision to create skilled vacancies depends on the expectation of skilled labor. This analysis demonstrates that lower education standards do not necessarily result in human capital accumulation or skill section expansion. We show that, in some cases, a lower standard increases underemployed skilled workers, decreases the productivity of skilled firms, and lowers the return of schooled workers. This analysis suggests that a lower standard of education can cause more educated people to work in unskilled positions, which is a type of over-education.

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Appendix A - Occupation Codes and Occupations

Occ. Code	Occupations
1+2	Management occupations + Business and financial operations occupations
3	Computer and mathematical science occupations
4	Architecture and engineering occupations
5	Life, physical, and social science occupations
6	Community and social service occupations
7	Legal occupations
8	Education, training, and library occupations
9	Arts, design, entertainment, sports, and media occupations
10	Healthcare practitioner and technical occupations
11	Healthcare support occupations
12	Protective service occupations
13	Food preparation and serving related occupations
14	Building and grounds cleaning and maintenance occupations
15	Personal care and service occupations
16	Sales and related occupations
17	Office and administrative support occupations
18	Farming, fishing, and forestry occupations
19+21	Construction, extraction and production occupations
20	Installation, maintenance, and repair occupations
22	Transportation and material moving occupations

Note:
1. The occupation classification is based on the most general definition of occupation classification in MORG available since 1994. There are 23 occupations defined including army occupations. Army occupations are not included in my sample.

2. Because the available occupation classification during 1979 to1981 is different, the base period occupations are regrouped based on current classification. It is hard to separate management and business observations in the base period, occupation coded as 1 and 2 in the end period are combined to be consistent. For the same reason, occupations coded as 19 and 21 in the end period are combined.

Appendix B - Proofs for Chapter 3

Proof of proposition 1. Suppose where the dot notation means an interior value. We need to demonstrate that given this supposition, i_s indeed lies between 0 and 1 and that the conditions for $j_s = j_g$ are satisfied. Recall $j_s, i_s > 0$ always so that i_s is interior if $i_s < 1$. Using $j_s = j_g$, from the second line of equation (9) $i_s = \left(Fj_g\right)^{\frac{1}{\beta}}$ so $i_s < 1$ requires $j_g < F^{-1}$. Putting this value of i_s into the first line of equation (8), $j_s = j_g$ requires $G\left(Fj_g\right)^{\frac{1}{\beta}} < ej_g^{\eta}$ or $W\left(Fj_g\right)^{\frac{1}{\beta}} < j_g^{\eta}$ which simplifies to $j_g < \tilde{j}$. Thus to satisfy both $(j_s, i_s) = (j_g, .)$ $i_s < 1$ and $j_s = j_g$, we must have $j_g < min\,[F^{-1}, \tilde{j}]$. It is straightforward to show that $min[F^{-1}, \tilde{j}] = F^{-1}$ when $W^{\frac{1}{\eta}}F > 1$. Thus when $W^{\frac{1}{\eta}}F > 1$, $j_g < F^{-1}$ binds giving the first line of equation (10). When $W^{\frac{1}{\eta}}F < 1$, $min\,[F^{-1}, \tilde{j}] = \tilde{j}$ so that $j_g < \tilde{j}$ binds giving the first line of equation (11).

Next consider the case where $(j_s, i_s) = (.,.)$. In this case, solving the second lines of equations (8) and (9) for j_s and i_s gives $j_s = F^{\frac{1}{\beta\eta-1}}W^{\frac{\beta}{\beta\eta-1}}$ and $i_s = F^{\frac{\eta}{\beta\eta-1}}W^{\frac{1}{\beta\eta-1}}$. We need to demonstrate that both are interior. Since we have shown $j_s, i_s > 0$ this requires only showing that $j_s < j_g$ and $i_s < 1$. Using the above expressions for j_s and i_s this requires $j_g > \tilde{j}$ and $W^{\frac{1}{\eta}}F < 1$, giving the second line of equation (11).

Now consider the case where $(j_s, i_s) = (j_g, 1)$. From equation (9), with $j_s = j_g$, $i_s = 1$ requires $j_g > \frac{c}{P} > F^{-1}$. From equation (8) with $i_s = 1$, $j_s = j_g$ requires $j_g < W^{\frac{1}{\eta}}$. Both can hold only if $W^{\frac{1}{\eta}}F > 1$. This gives the second line of equation (10).

Finally suppose $(j_s, i_s) = (.,1)$. From equation (8) with $i_s = 1$, $j_s < j_g$, requires $j_g > W^{\frac{1}{\eta}}$. In this case, from equation (8), $j_s = W^{\frac{1}{\eta}}$. Putting this into equation (9), $i_s = 1$ requires $PW^{\frac{1}{\eta}} > c$ or $W^{\frac{1}{\eta}}F > 1$. This gives the third line of (10).

Proof of corollary 1: As noted in the text, the first claim (second sentence) restates that j_s, i_s and $j_s i_s$ are increasing in j_g. The second is a restatement of $j_s = j_g$. The fourth requires that

$(1-i_s)$ is decreasing in j_g and thus follows from the direct relationship between i_s and j_g. Thus we only need to prove the third sentence.

The measure of underperforming firms is $i_s(1-j_s)$. From the first line of equation (11) $i_s(1-j_s) = F^{\frac{1}{\beta}} j_g^{\frac{1}{\beta}} - F^{\frac{1}{\beta}} j_g^{\frac{1+\beta}{\beta}}$. Thus $\frac{\partial i_s(1-j_g)}{\partial j_g} \geq 0$ requires $\frac{1}{\beta}(j_g)^{\frac{1}{\beta}-1} - \frac{1+\beta}{\beta} j_g^{\frac{1}{\beta}} > 0$ or $j_g < \frac{1}{1+\beta}$.

The measure of underemployed workers is $j_s(1-i_s)$. From the first line of equation (11) $j_s(1-i_s) = j_g - F^{\frac{1}{\beta}} j_g^{\frac{1+\beta}{\beta}}$. Thus $\frac{\partial j_s(1-i_s)}{\partial j_g} \geq 0$ if $1 - \frac{1+\beta}{\beta} F^{\frac{1}{\beta}} j_g^{\frac{1}{\beta}}$ or $j_g - \frac{1+\beta}{\beta} F^{\frac{1}{\beta}} j_g^{\frac{1}{\beta}} < \left(\frac{\beta}{1+\beta}\right)^{\beta} \frac{1}{F}$.

Proof of proposition 2: The proof is a straightforward generalization of the proof to Proposition 1. This is available from the authors upon request.