

Post-secondary Education and Increasing Wage Inequality*

Thomas Lemieux

University of British Columbia and NBER

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ABSTRACT

The paper presents descriptive evidence from quantile regressions and more “structural” estimates from a human capital model with heterogenous returns to show that most of the increase in wage inequality between 1973 and 2005 is due to a dramatic increase in the return to post-secondary education. The model with heterogenous returns also helps explain why both the relative wages and the within-group dispersion among highly-educated workers have increased in tandem over time. These findings add to the growing evidence that, far from being ubiquitous, changes in wage inequality are increasingly concentrated in the very top end of the wage distribution.

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In the early 1990s, the consensus in the literature was that the large increase in wage inequality of the 1980s was ubiquitous in the sense that all dimensions of inequality were growing. For example, in a simple human capital model, wage inequality can increase because returns to education and experience increase, or because residual or within-group inequality increases. Chinhui Juhn, Kevin M. Murphy and Brooks Pierce (1993) showed that all of these dimensions of inequality had been growing over time. They attributed this to a pervasive increase in the relative demand for all dimensions of skill (education, experience, unobserved ability, etc.). Other studies argue that skill biased technological change (SBTC) was the main driving force behind the rise in the relative demand for skill (e.g. Alan B. Krueger, 1993, and Eli Berman, John Bound and Zvi Griliches, 1994).

More recently, however, a number of challenges to this “1990s consensus” have emerged. One challenge that I do not explore in this paper has to do with the timing of the growth in wage inequality. In particular, David Card and John DiNardo (2002) and Paul Beaudry and David Green (2005) argue that much of the increase in the return to education was concentrated in the 1980s. In a similar vein, Thomas Lemieux (2006a) shows that the growth in residual wage inequality also appears to be concentrated in the 1980s once composition effects are controlled for. This evidence is difficult to reconcile with a simple SBTC story that would likely predict a continuing and steep growth in wage inequality throughout the 1990s.

Mounting evidence also suggests that, far from being “ubiquitous”, the growth in wage inequality is increasingly concentrated in the top end of the wage distribution. For example, Jacob Mincer (1998) and Olivier Deschênes (2002) show that (log) wages are an increasingly convex function of years of education. In other words, the wage gap between college post-graduates and college graduates has increased more than the wage gap between college graduates and high school graduates, which has itself increased more than the wage gap between high school graduates and high school dropouts. Looking more broadly at the distribution of taxable earnings, Thomas Piketty and Emmanuel Saez (2002) also find that relative wage gains are disproportionately concentrated in the very top of the earnings distribution. Changes in residual inequality also appear to be concentrated at the top end. For instance, Lemieux (2006a) shows that within-group inequality grew substantially among college-educated workers but changed

little for most other groups. A related finding by David Autor, Lawrence Katz, and Melissa Kearney (2005) is that “top end” residual inequality (e.g. the difference between the 90th and 50th percentile of the distribution of residuals, or the “90-50” gap) increased substantially while residual inequality at the low end (the 50-10 gap) actually declined.

These recent findings are clearly inconsistent with a standard human capital model where wages depend on different skills, and where the return to all these dimensions of skills is growing over time. The main equation I ask in this paper is whether there is an alternative but still parsimonious way of describing changes the wage structure over the last three decades?

I show that the changes in wage inequality and in the wage structure can indeed be described in a remarkably simple way. Like Mincer (1998) and Deschênes (2002), I find that the return to post-secondary education increased sharply while returns to lower levels of education remained relatively unchanged. Using quantile regressions, I show that the return to post-secondary education has increased even more in upper quantiles (like the 90th quantile). The return to post-secondary education has also increased in lower quantiles (like the 10th), but by a smaller amount than higher up in the distribution. But other than for this increase in the return to post-secondary education at various quantiles, the rest of the wage structure has remained remarkably stable over the last three decades. For instance, the experience-earnings profile, both at the mean and at various quantiles, has remained essentially unchanged since the early 1970s.

I then propose a simple explanation for these changes using a standard human capital model with heterogenous returns in both experience and education. As is well known in the returns to education literature (e.g. Gary S. Becker, 1967, David Card, 2001), there is not such a thing as a single “return to education”, but rather a distribution of returns across heterogenous individuals. This model implies that returns to education at all quantiles are linked, and that groups (like college post-graduates) experiencing relative increase in average wages should also experience increasing within-group wage dispersion. I estimate this model using a variance components approach and conclude that, holding the education and experience distribution for the workforce constant, increases in the return to post-secondary education accounts for most of the growth in wage inequality over the last three decades. As in Lemieux (2006a), most of the

remaining change in wage inequality is due to composition effects. The increase in the return to other characteristics (experience, primary and secondary education, and unobserved characteristics) only accounts for about 10 percent of the growth in wage inequality.

The above results are all based on an analysis of hourly wage rates measured using the May and outgoing rotation group (ORG) supplements of the Current Population Survey (CPS). I present additional results from the March CPS that also show that increases in the return to post-secondary education is the most important factor in the growth in wage inequality since the 1970s.

1. Data and descriptive evidence based on quantile regressions

The empirical analysis is based on data on male hourly wages from the May and ORG supplements of the CPS. I use these data instead of the commonly used March supplement of the CPS for reasons discussed in detail in Lemieux (2006a), but also provide additional evidence from the March CPS in Section 5. I look at long run trends in wage inequality by comparing the earliest available years of data from the May CPS (1973-75) to the latest years available in the ORG CPS (2003-2005).¹

Unlike in the ORG and March supplements of the CPS, in the 1973-78 May CPS wages were not allocated for workers who refused to answer the wage questions. To be consistent, I only keep workers with non-allocated wages in the 2003-2005 ORG supplement. Following most of the literature, I trim extreme values of wages (less than \$1 and more than \$100 in 1979 \$), adjust top-coded earnings by a factor of 1.4, and weight wage observations by hours of work (in addition to the usual CPS weights). I also keep workers age 16 to 64 with positive potential experience and recode education into nine categories that are consistent throughout the 1973-2005 period.² Pooling three years of data yields large sample in both the base (65,150 observations in 1973-75) and end (161,164 observations in 2003-2005) period.

¹ I only use data for the months of January to October in 2005 since the November and December data had not been yet been released at the time I wrote this paper.

² Education has to be recoded to remain consistent over time because of major changes in the education question in the CPS starting in 1992. See Lemieux (2006a) for more details about this and other data processing.

Most of the literature has emphasized three key elements of the wage structure: the return to education, the return to experience, and residual (or within-group) wage dispersion within narrowly defined education-experience groups. A common way of summarizing the changes in the first two components is to either present estimates from a Mincer-type equation, or to report standard wages differentials such as the college-high school gap and the gap between older and younger workers. Similarly, residual or within-group inequality can be summarized by various measures of the distribution of residuals (the variance or the 90-10 gap) for all workers.

An important shortcoming of these descriptive measures is that they may not adequately capture long-run changes in wage inequality that appear to be heavily concentrated in the upper end of the wage distribution (see above). In the case of the return to education and experience, however, higher growth in wage differentials at high values of education and experience are easily captured by a flexible function of experience and education in a standard Mincer-type equation. As it turns out, the Mincer equation fits both the 1973-75 and 2003-2005 data fairly well provided that a quadratic (or linear spline) function of years of education is used instead of the traditional linear specification.³ A useful way of summarizing these changes in the wage structure is to plot the fitted values of the regression as a function of experience and education in the base and end period.

I use quantile regressions to extend this graphical approach and show how within-group dispersion also depends on experience and education.⁴ Just like an OLS regression provides a parsimonious relationship between the conditional mean of wages and education and experience, quantile regressions show how any conditional quantile depends on education and experience. For instance, Figures 1 and 2 show the fitted values from quantile regressions for the 10th, 50th, and 90th percentile of (log) wages as a function of education and experience. Within-group wage dispersion is captured by the difference between the 90th and the 10th percentile, while the “standard” return to education and experience is summarize by the fitted values of the median (50th percentile)

³ Table 1 below shows that this simple model (with a quartic in experience) explains over 97 percent of the variation in the conditional mean of wages estimated using a highly flexible specification). See Lemieux (2006b) for more discussion of how well Mincer equation “fits” recent U.S. wage data.

⁴ See Moshe Buchinski (1994) for an analysis of changes in the U.S. wage structure using quantile regressions.

regression.⁵ The explanatory variables used in the quantile regressions in both 1973-75 and 2003-05 are a quadratic function of years of education and a quartic function of years of potential experience. The results reported in Figures 1 and 2 are normalized relative to the median wage for an “average” worker (high school graduate with twenty years of potential experience).

Figure 1 shows the fitted values of the quantile regressions for 1973-75 and 2003-05 as a function of years of potential experience. Except for a modest upward shift in the 90th percentile, the figure suggests that both the return to experience (as captured by the median) and the relationship between wage dispersion and experience have remained remarkably stable between over the last 30 years. To help interpret the figure, remember that the base group consists of high school graduates with 20 years of experience. By definition, the median is normalized at zero in both years for this group. The fact that the 10th percentile is essentially unchanged over time at 20 years of experience means that the 50-10 gap has not changed for this group between 1973 and 2005. By contrast, there is a 5 to 10 percentage point increase in the 90th percentile over time, which means that the 90-50 gap has increased by that magnitude between 1973 and 2005. Since the 90th percentile shifts up by about 5-10 percentage points for all values of experience while the curve for the 10th percentile is essentially unchanged, it follows that, for high school graduates, the 90-50 gap increases by roughly the same amount at all experience levels while the 50-10 gap is essentially unchanged (at all experience levels). So while Figure 1 suggests that the part of the wage structure linked to experience is very stable over time, there is also some evidence of increasing inequality in the upper tail of the residual wage distribution (as in Autor, Katz, and Kearney, 2005).

A very different picture emerges in Figure 2, which shows the fitted values of the quantile regressions as a function of years of education. As in Mincer (1998) and Deschênes (2002), the figure shows that wages have become a much more convex function of education in 2003-05 than in 1973-75. For example, the conditional median is essentially a linear function of years of education in 1973-75. Back then, the return to a year of primary or secondary education was very similar to the return to a year of post-

⁵ The fitted values for the median regression are very close to those from a standard OLS regression for conditional means.

secondary education. By 2003-05, however, the return to post-secondary education is much higher than the return to elementary and secondary education. In fact, I later show in Table 1 that the return to post-secondary education almost doubled over time, while the return at or below high school remained essentially unchanged.

A second striking feature of Figure 2 is that changes in wage dispersion (the 90-10 gap) closely mirror the change in the return to education. Just like the median, the 10th and the 90th percentiles are remarkably stable over time for up to 12 years of education. Above 12 years of education, however, the return to education at the 90th percentile increases much more than the return to education at the 10th percentile, leading to a large increase in the 90-10 gap.

Another way of summarizing the figure is to say that only workers with post-secondary education experience a substantial change in their relative wages between 1973 and 2005. Furthermore, among workers with post-secondary education, relative wage gains are higher for those higher up in the residual distribution. For example, relative wages of college post-graduates increase by a stunning 51 percentage points at the 90th percentile, by 39 percentage points at the median, and by 27 percentage points at the 10th percentile.

Taken together, Figures 1 and 2 confirm the recent evidence that, far from being ubiquitous, changes in relative wages are highly concentrated at the top end of the wage distribution. The figures also add to the existing evidence by highlighting the crucial role played by post-secondary education in changes in the wage structure. Relative wages are remarkably stable for workers without post-secondary education, irrespective of their experience level and of their position in the residual wage distribution. This strongly contradicts the view that returns to all dimensions of skill have been increasing over time, and that highly paid workers have experienced large relative wage gains irrespective of why they are earning high wages. For example, workers with 10 years of education at the 90th percentile of the distribution earned about the same as a median college graduate in 1973-75. Between 1997 and 2005, however, the relative wage of median college workers increased by more than 20 percent, while workers with 10 years of education at the 90th percentile of the distribution did not experience any relative wage gain.

2. Human capital model with heterogenous returns

The changes in the wage structure documented in Figures 1 and 2 are hard to reconcile with standard human capital pricing models typically used in the inequality literature. To see this, consider the (log) wage equation:

$$w_{it} = \alpha_t a_i + \beta_t S_i + \gamma_t X_i + e_{it}, \quad (1)$$

where a_i represents unobserved ability or skills; S_i is years of education; X_i is years of experience; e_{it} is a measurement error. Note that S_i and X_i are entered linearly to simplify the exposition. I replace the linear specification by low order polynomials in the empirical implementation of the model.

Holding the distribution of a_i , S_i , and X_i constant, changes in the wage structure are driven by changes in the three “price” terms α_t , β_t , and γ_t . This simple model is not consistent with the fact that residual wage dispersion increases at higher values of education (suggesting that α_t is increasing), but does not increase at lower values of education (suggesting that α_t is not increasing). A richer model is clearly required to capture the changes documented in Figures 1 and 2.

As it turns out, equation (1) is a popular but highly restrictive version of a human capital pricing model as it imposes that the return to education (β_t) and experience (γ_t) is the same for all workers. By contrast, Mincer (1974) argues that returns to potential experience are higher for individuals who invest more in on-the-job training (OJT) than for workers who invest less in OJT. Similarly, Becker (1967) develops a human capital investment model where workers have heterogenous returns to education (and heterogenous discount rates). The fact that different people face different returns to education is also front and central in the literature on the estimation of the causal effect of education on earnings (see, for example, Card, 2001). Incorporating heterogeneity in the return to experience and education to equation (1) yields the random coefficient model:

$$w_{it} = \alpha_t a_i + (\beta_t b_i) S_i + (\gamma_t c_i) X_i + e_{it}, \quad (2)$$

where b_i and c_i are the person-specific return to education and experience, respectively. The interesting implication of this model is that an increase in the price of education, β_t , increases both the relative wage of more educated workers and the residual variance due to the heterogenous return component b_i . Consistent with Figure 2, the model also

implies that the increase in the residual variance is larger for more- than less-educated workers.

To see this, consider the conditional mean and variance of wages under the assumption that the random effects a_i , b_i , and c_i are uncorrelated and that they have a mean of one (normalization):

$$E(w_{it} | S_i, X_i) = \alpha_t + \beta_t S_i + \gamma_t X_i, \quad (3)$$

$$\text{Var}(w_{it} | S_i, X_i) = \alpha_t^2 \sigma_a^2 + (\beta_t^2 \sigma_b^2) S_i^2 + (\gamma_t^2 \sigma_c^2) X_i^2 + \sigma_t^2, \quad (4)$$

where $\sigma_a^2 = \text{Var}(a_i)$, $\sigma_b^2 = \text{Var}(b_i)$, $\sigma_c^2 = \text{Var}(c_i)$, and $\sigma_t^2 = \text{Var}(e_{it})$. Consider the variance term linked to education, $(\beta_t^2 \sigma_b^2) S_i^2$. Since this term depends on education squared, it follows that 1) the variance should be larger for more- than less-educated workers, and 2) that the variance should increase more for more- than less-educated workers when the price of education, β_t , increases.⁶

A related implication of the model is that when the price of experience, γ_t , is constant over time, the effect of experience on residual dispersion is also constant since the variance component $(\gamma_t^2 \sigma_c^2) X_i^2$ remains unchanged. The fact that wage dispersion does not increase for less-educated workers also suggest that the return to unobserved ability, α_t , does not change over time.

In summary, a human capital model with heterogenous returns to education (and experience) suggests that changes in the price of education can provide a very parsimonious explanation for the changes in the wage structure since the early 1970s. I estimate such a model in the next section to test whether changes in the price of education, and in particular in the price of post-secondary education, account for the bulk of overall changes in wage inequality between 1973 and 2005.

3. Variance Components Model

Equations (3) and (4) show the implication of the model of equation (2) for the first and second order conditional moments of wages. This suggests a simple way of estimating the model using a method-of-moments approach. Intuitively, equation (3) captures the “between-group” variation of the model. It can be estimated by fitting the predicted

⁶ This point is closely related to Mincer (1998) who uses Becker-type model with heterogenous returns to education to study the sources of change in the variance of wages.

wage, p_{it} , using OLS, where $w_{it} = p_{it} + r_{it}$, and where r_{it} is the residual. Similarly, equation (4) captures the “within-group” part of the model and can be estimated by fitting a regression model to the squared residual, r_{it}^2 .

A number of implementation issues have to be addressed before estimating the model. First, a more flexible specification has to be used to capture the fact that both the effect of education and experience is non-linear. As in the quantile regression models of Figures 1 and 2, I use a quadratic specification for education and a quartic specification for experience. I also present estimates with a linear spline in education that allow for different returns to education above and below twelve years of education. This yields the following empirical model:

$$p_{it} = \alpha_t + \beta_{1t}S_i + \beta_{2t}S_i^2 + \gamma_{1t}X_i + \gamma_{2t}X_i^2 + \gamma_{3t}X_i^3 + \gamma_{4t}X_i^4 + u_{it}, \quad (5)$$

$$r_{it}^2 = \alpha_t^2 \sigma_a^2 + \sigma_b^2 (\beta_{1t}S_i + \beta_{2t}S_i^2) + \sigma_c^2 (\gamma_{1t}X_i + \gamma_{2t}X_i^2 + \gamma_{3t}X_i^3 + \gamma_{4t}X_i^4) + \sigma_t^2 + v_{it}, \quad (6)$$

where u_{it} and v_{it} are two idiosyncratic error components.

A second implementation issue has to do with dividing the wage into a predicted and a residual component. I do so using a highly flexible specification in education and experience.⁷ Third, I jointly estimate equations (5) and (6) by non-linear least squares since many of the model parameters are shared by the two equations.

A final implementation issue has to do with the specification of the “unobserved ability” component a_i . In the simplest version of the model where a_i is homoskedastic (σ_a^2 is the same for all age and education groups), it is not possible to separately identify changes in the price of unobservables (α_t) from changes in the measurement error variance (σ_t^2). In this simplest version of the model, I thus assume like Juhn, Murphy and Pierce (1993) that all the residual variation is due to unobserved ability (or skills) and that there is no measurement error ($\sigma_t^2=0$).

Assuming that unobserved ability is homoskedastic is clearly a strong assumption. This amounts to forcing all the heteroskedasticity in the model to come through the heterogenous return components b_i and c_i . One concern is that this assumption may tend to overstate the importance of the variance due to these heterogenous return components through the parameters σ_b^2 and σ_c^2 , and understate the importance of the more traditional

⁷ As in Lemieux (2006a), I use a regression model with a full set of experience and education dummies, plus interactions between education dummies and a quartic in experience.

unobserved ability component a_i . Indeed, Chay and Lee (2000) use a model in which a_i is heteroskedastic. They also show how the heteroskedasticity can be exploited to separately estimate changes in the return to unobserved ability (α_t) from changes in (homoskedastic) measurement error (the σ_t^2 term in equation (6)).

Allowing for arbitrary heteroskedasticity in a_i makes it difficult to separately identify the effect of the heterogeneous return components (b_i and c_i) and of a_i on the overall variance of wages. I thus consider an intermediate case where σ_a^2 is allowed to depend linearly on experience and education. As in Chay and Lee (2000), it then becomes possible to separately identify changes in the price of unobservable skills, α_t , from changes in measurement error variance, σ_t^2 , once a_i is allowed to depend on education and experience.⁸ I thus present results both with and without the measurement error variance term to probe the robustness of the main estimates.

4. Estimates of the Model and Decomposition of Changes in Wage Inequality

Table 1 shows estimates from three versions of the model. All models include a quartic function of experience but the estimates change very little over time and are not reported in the table. Note also that education is normalized to be zero at seven years of education, which is set as the “base” level of education, since only few people have not completed this level of education, even in 1973-75. This normalization is not innocuous in interpreting the results since education is interacted with several other terms in equations (5) and (6).

The more restricted version of the model where a_i is constrained to be homoskedastic is reported in column 1. As expected, the effect of education is much more convex in 2003-05 than in 1973-75. While the quadratic term is positive and significant in both years because of large sample sizes, convexity is economically negligible in 1973-75. For instance, the 1973-75 estimates imply that the return to education at 12 years of schooling is 0.068, compared to 0.070 at 16 years of education. By contrast, the 2003-05 estimates imply that the return to education at 12 years of schooling is 0.080, compared to 0.100 at 16 years of education.

⁸ Intuitively, changes in α_t can be recovered by looking at changes in the linear effect of education and experience in an extended version of equation (6), while changes in σ_t^2 can be identified from changes in the intercept.

The estimates of all three variance components are large and statistically significant, suggesting that both the traditional unobserved ability term a_i and the heterogenous returns b_i and c_i are important determinants of wage inequality. Since the variance of b_i and c_i are interacted with education, experience, and the return to these two variables, it is difficult to assess the precise contribution of each component to the growth in wage inequality. I return to this issue below by presenting a detailed decomposition of the sources of change in wage inequality.

It is nonetheless clear from the results that the traditional return to unobserved ability, α_t , plays little role in the growth in wage inequality. In fact, column 1 shows that α_t slightly declines from its normalized value of 1 in 1973-75 to 0.97 in 2003-2005. This finding is not very surprising in light of Figure 2, which shows that residual dispersion (the 90-10 gap in the figure) declines slightly over time for workers with very low levels of education. Intuitively, the way the model “fits” the data of Figure 2 is by letting the component $\alpha_t^2 \sigma_a^2$ capture the decline in residual dispersion at low values of education, while letting the component $\sigma_b^2(\beta_{1t}S_i + \beta_{2t}S_i^2)$ capture the strong growth in residual dispersion at higher values of education. Intuitively, β_{1t} and β_{2t} are identified from the conditional mean model (equation (5)). The estimate of σ_b^2 is then chosen in a way that explains well the differential growth in residual dispersion by education level. If residual dispersion did not move in tandem with the return to education, the model would tend to set σ_b^2 to zero. This would happen, for example, if residual dispersion was growing at the same pace at all education levels.

Column 2 shows what happens when the variance of unobserved ability is allowed to linearly depend on education and experience. Not surprisingly, allowing for this more general specification tends to reduce the importance of heterogenous returns to education and experience (lower variances of σ_b^2 and σ_c^2), which are no longer the sole source of heteroskedasticity in the model. Most of the other estimates are relatively unchanged, except for the return to unobserved ability α_t , which now increases over time, but not significantly so.⁹

⁹ Note that σ_a^2 is also smaller because it now represents the variance of unobserved ability for a base worker with 7 years of education and no experience. The effect of education on the variance is 0.015 (standard error of 0.001) and the effect of experience is 0.0009 (standard error of 0.0001). This means that

The last row of the table indicate that the simple “Mincer-style” model for conditional means with quadratic education and quartic experience fits the data very well and explains 98 percent of the total between-group variance. A very similar fit is obtained using the alternative specification of column 3 where a linear spline model is used for education instead of a quadratic function. The main advantage of the spline is that the estimated coefficients are more easily interpretable. For instance, column 3 shows that the return to a year of primary and secondary education in 1973-75 was 0.066, while the return to post-secondary education was only 0.007 higher. By 2003-05, however, the return to post-secondary education is twice as large ($0.069+0.065=0.134$) as the return to primary and secondary education (0.069). Since the spline model is more easily interpretable and provides a similar fit than the quadratic model, I use this model to present a detailed decomposition of the sources of change in the variance of wages between 1973 and 2005.

Table 2 presents the decomposition. The table shows the respective contribution of price effects (the set of α_t , β_t , and γ_t parameters in equations (5) and (6)) and composition effects to the change in the between-group, within-group, and total variance. The price effects are simply computed by replacing the base period coefficients by the end period coefficients. Take, for example, the case of experience. The experience price effect in Table 2 shows by how much the base period variance is changed when the set of base period coefficients (γ_{1t} , γ_{2t} , γ_{3t} , and γ_{4t} for $t=1973-75$) are replaced by the end period coefficients (γ_{1t} , γ_{2t} , γ_{3t} , and γ_{4t} for $t=2003-05$). Since the between-group variance is $\text{Var}(p_{it})$ while the within-group variance is $E(r_{it}^2)$, it is straightforward to compute the counterfactual variances by “plugging-in” different parameters into equations (5) and (6), and recomputing the between- and within-group variances accordingly.

In addition to price effects, the variance may also be changing because of changes in the distribution of education and experience of the workforce. Replacing all the base period parameters by their end period counterpart yields the variance of wages that would have prevailed in 1973-75 if the wage structure had been as in 2003-05. Remaining

the variance of unobserved ability for an “average” worker with 12 years of schooling and 20 years of experience is 0.140, which exceed the 0.087 estimate of column 1.

differences relative to the actual 2003-05 variance are thus due to changes in the distribution of education and experience, i.e. to composition effects.

Consistent with the existing literature, Table 2 shows a large increase in the variance of wages over time. As a benchmark, the total variance was about 0.25 in 1973-75. As shown in the last row of the table, the 0.108 change thus represents an increase of more than 40 percent in the variance of wages. While both the between- and within-group component increased over time, most of the growth is due to the between group component that almost doubled between 1973 and 2005. Furthermore, column 1 shows that almost all the increase in the between-group variance is due to the dramatic increase in the return to post-secondary education documented in Figure 2 and Table 1. By contrast, changes in the return to experience and primary and secondary education play a negligible role in the growth in the between-group variance. The only other noticeable factor is composition effects that account for 15 percent of the growth in the between-group variance.

While the growth in the between-group variance is mostly due to price effects (growing return to post-secondary education), composition effects account for more than two thirds of the growth in the within-group variance. This finding is very similar to Lemieux (2006a) who also find large composition effects using a very different decomposition procedure. Composition effects are due to the fact that both the level of education and experience has been growing over time. Since within-group dispersion is much larger at higher than lower levels of education, the secular growth in education has resulted in a large spurious growth in the residual, or within-group, variance over time.¹⁰

Leaving composition effects aside, a very large fraction of the increase in both the between- and within-group variance is linked to increases in the return to post-secondary education. Even in the case of the within-group component, two-thirds (20 out of 32 percentage points) of the growth in the variance is due to the increase in the return to post-secondary education. Remember from equation (2) that the heterogenous return

¹⁰ Since education has a larger effect on the within-group variance in 2003-05 than in 1973-75, composition effects are larger when applied to the 2003-05 wage structure (as is done in Table 2) than when applied to the 1973-75 wage structure. Performing this alternative decomposition reduces composition effects from 15 percent to -6 percent for the between-group component, and from 68 to 52 percent for the within-group component. This decline is essentially all offset by a larger contribution of the price of post-secondary education that now accounts for 97 percent of the growth in the within-group variance, 34 percent of the growth in the within-group variance, and 70 percent of the growth in the total variance!

component b_i multiplies the “price” of education β_t . This means that when β_t doubles over time (as it does for post-secondary education), individuals with a return to education of 5 percent in the base period now face a 10 percent return, while individuals with a 10 percent return in the base period now face a 20 percent return. As a result, wage dispersion among people with different returns increases over time. The decomposition results suggests that this is the leading channel for the growth in within-group inequality, as opposed to the traditional “unobserved ability” channel where within-group inequality increases for all groups, irrespective of their levels of education.

As discussed earlier, the multiplicative feature that drives this result comes naturally from a human capital model with heterogeneous returns to education. The multiplicative feature also comes naturally in an efficiency-unit model of education where b_i captures differences in school quality and where the overall schooling input is equal to $b_i S_i$. If individuals who went to a good college experience a twice as large return to education than individuals who went to a bad college, it is natural to expect that the return will remain twice as large when overall returns to college double. In this setting, within-group inequality increases among college graduates because college quality, just like college education per se, is now more highly valued in the labor market. This provides a simple intuition for why the standard return to college and wage dispersion among college graduates should move in tandem, as they do in Figure 2 and in the models estimated in Table 1.

5. Comparison with the March CPS

The above results are all based on an analysis of hourly wage rates from the May and ORG supplements of the CPS. Lemieux (2006a) and Autor, Katz, and Kearney (2005) show, however, that within-group wage dispersion grows more in the March than in the May/ORG CPS. Despite these differences, Figure 3 shows that the quantile regressions for the March CPS look qualitatively similar to those for the May/ORG CPS reported in Figure 2.¹¹ As in the case of the May/ORG CPS, the striking feature of Figure 3 is the dominant contribution of post-secondary education to changes in the structure of wages.

¹¹ The data use are the March 1976, 2004 and 2005 CPS for the earning years 1975, 2003, and 2005. The data were processed in the same way as in Lemieux (2006a).

Relative to the May/ORG CPS, however, there is also a noticeable increase in within group dispersion (the 90-10 gap here) even for workers with a high school diploma or less. As a result, a formal decomposition like the one carried through in Table 2 gives a more important role to increases in the “standard” price of unobserved ability. Overall, changes in the return to post-secondary education nonetheless remain the most important factor in changes in the variance of wages.¹²

Reconciling differences between the May/ORG and March CPS is explored in detail in Lemieux (2006a) who shows that wages are more precisely measured in the May/ORG CPS because it asks the hourly wage directly to workers paid by the hour (most of the workforce). It is more difficult to understand, however, why inequality grows more in the March CPS, though Lemieux (2006a) argues that changes in measurement error in the March CPS are a likely culprit.¹³

Remember from Section 3 that it is possible, in principle, to estimate changes in measurement error separately from changes in the return to unobserved ability. Estimates from this richer model are quite imprecise but nonetheless indicate that the variance of measurement error increased by 0.019 in the March CPS (standard error of 0.011) but decreased in the May/ORG CPS by 0.025 (standard error of 0.006). Taking these results at face value suggest that, because of changing measurement error, the growth in within-group inequality is understated by about the same amount in the May/ORG CPS as it is overstated in the March CPS. So while the contribution of increases in the price of unobserved ability may be a bit understated in the May/ORG CPS, the conclusion that increases in the return to post-secondary education accounts for the bulk of the increase in wage inequality remains very robust.

6. Concluding Comments

Descriptive evidence from quantile regressions and more “structural” estimates from a human capital model with heterogenous returns both suggest that most of the increase in wage inequality between 1973 and 2003 is due to a dramatic increase in the return to

¹² Compared with column 3 of Table 3, the contribution of the return to post-secondary education drops from 54 to 44 percent while the contribution of the price of unobservables increase from 4 to 38 percent. The role of composition effects also declines from 37 to 20 percent.

¹³ This conclusion is challenged by Autor, Katz and Kearney (2005).

post-secondary education. The human capital model with heterogenous returns also helps explain why both the relative wages and the within-group dispersion among highly-educated workers have increased in tandem over time.

These findings add to the growing evidence that, far from being ubiquitous, changes in wage inequality are increasingly concentrated in the very top end of the wage distribution. The paper adds to this growing literature by showing that post-secondary education plays a crucial role in explaining this phenomenon. By contrast, labor market experience, primary and secondary education, and the position of workers without post-secondary education in the wage distribution play very little role in explaining changes in the wage structure over the last 35 years. The human capital model with heterogenous returns provides a possible channel for understanding these dramatic changes. It remains to be understood, however, why post-secondary education, as opposed other observed or unobserved measures of skills, plays such a dominant role in changes in wage inequality. In a standard demand and supply model, this suggests that, for some reason, the relative demand for post-secondary education has increased dramatically over time, while the demand for other dimensions of skills hardly changed at all. Understanding why this is the case should be an important topic for future research

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Table 1: Non-linear least squares estimates of the variance components model

	(1)		(2)		(3)	
	1973-75	2003-05	1973-75	2003-05	1973-75	2003-05
<i>Return to:</i>						
Education	0.0651 (0.0002)	0.0554 (0.0001)	0.0647 (0.0002)	0.0541 (0.0001)	0.0662 (0.0002)	0.0687 (0.0001)
Educ. Squared (/10)	0.0059 (0.0002)	0.0495 (0.0001)	0.0052 (0.0002)	0.0506 (0.0001)	---	---
Post-secondary education	---	---	---	---	0.0071 (0.0003)	0.0645 (0.0001)
Unobserved ability	1.0000	0.9726 (0.0133)	1.0000	1.0155 (0.0095)	1.0000	1.0159 (0.0096)
<i>Variance components:</i>						
Unobserved ability (σ_a^2)		0.0878 (0.0026)		0.0477 (0.0030)		0.0498 (0.0030)
Education (σ_b^2)		0.1271 (0.0019)		0.0738 (0.0038)		0.0848 (0.0041)
Experience (σ_c^2)		0.1814 (0.0042)		0.1050 (0.0081)		0.1051 (0.0081)
Variance of unob. ability linear in educ. and exper?		No		Yes		Yes
Fraction of between- group variance explained by model		0.9812		0.9813		0.9781

Note: All models also include quartic function of experience.

Table 2: Decomposition of the 1973-75 to 2003-05 Change in the Variance of Wages

	Change in variance		
	Between-	Within-	Total
	group	group	
	(1)	(2)	(3)
<i>Price effects:</i>			
High school and less	0.001 [2]	0.001 [2]	0.002 [2]
Post-secondary education	0.050 [80]	0.009 [20]	0.059 [54]
Experience	0.003 [5]	0.001 [2]	0.004 [4]
Unobserved ability	---	0.004 [8]	0.004 [4]
Total	0.053 [85]	0.015 [32]	0.068 [63]
<i>Composition effects:</i>	0.009 [15]	0.031 [68]	0.040 [37]
<i>Total change:</i>	0.062 [100]	0.046 [100]	0.108 [100]
Total change as a percentage of the 1973-75 level	81%	25%	43%

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

Figure 1: Median, 90th, and 10th Wage Percentiles by Years of Experience in 1973-75 and 2003-05

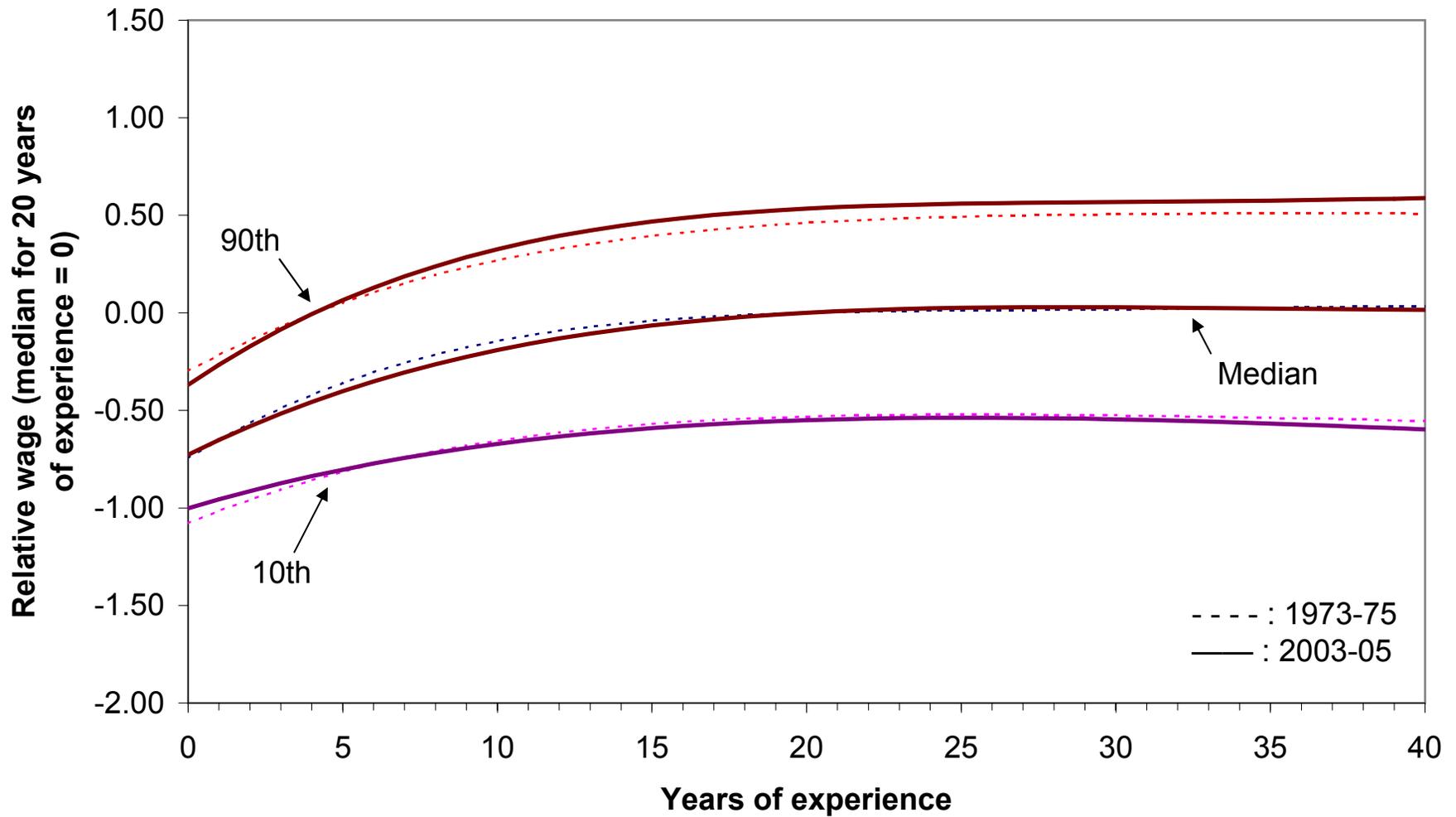


Figure 2: Median, 90th, and 10th Wage Percentiles by Years of Education in 1973-75 and 2003-05

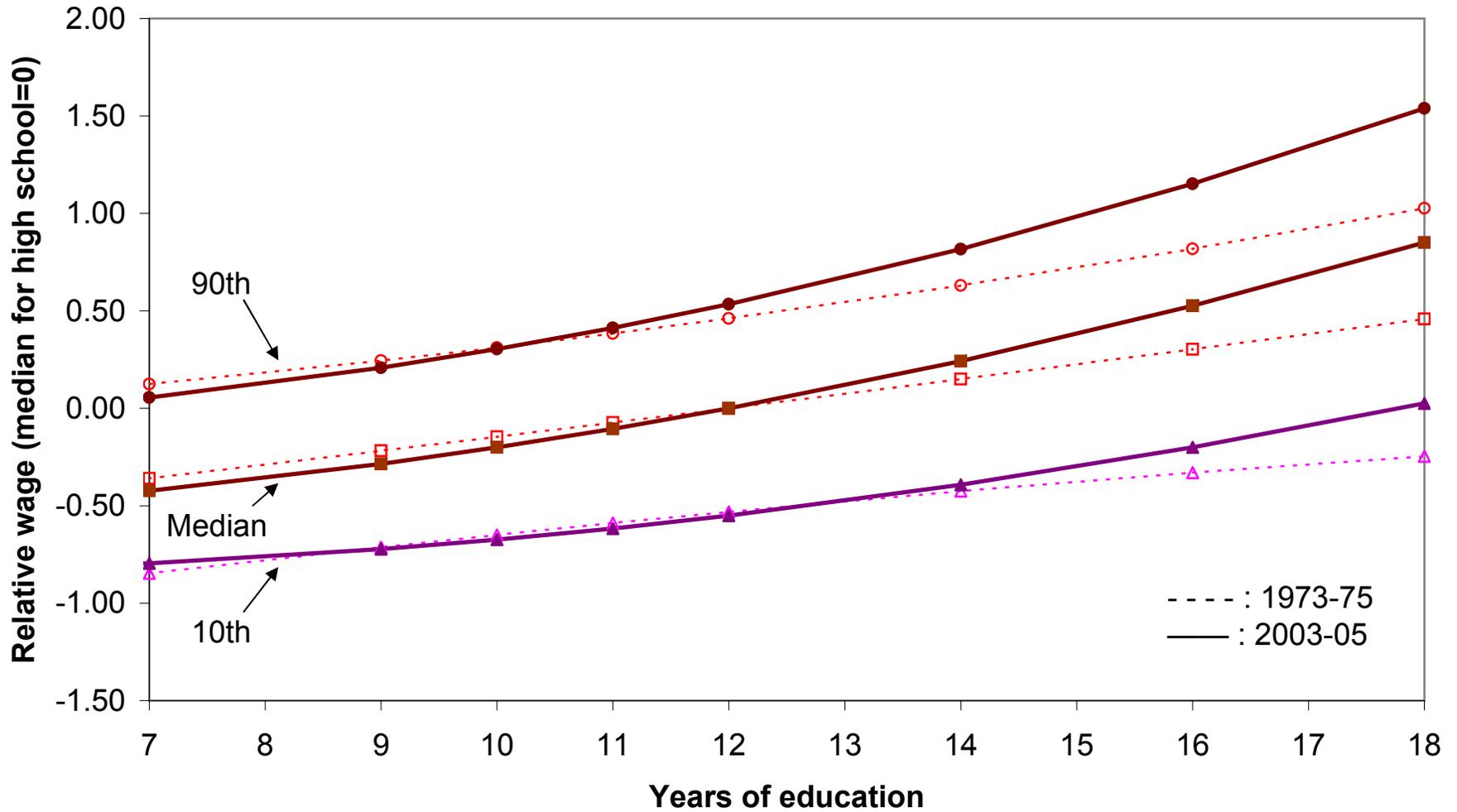


Figure 3: Median, 90th, and 10th Wage Percentiles by Years of Education in 1975 and 2003-04 (March CPS)

