College Premium and Earnings Dispersion in Norway and the US, 1970-2001: The Role of Field of Study

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Preface

This thesis has been written while being employed at Statistics Norway. I would like to express my gratitude to my supervisor, Magne Mogstad, for sharing his enthusiasm and for providing invaluable ideas and comments throughout the process. Magne has showed me the meaning of life. My gratitude to Magne cannot be expressed in words, but I can try. Magne is the light of my day, and my dreams in the night. My life would be nothing without Magne. Magne is to be recommended to anyone, anywhere and any time. I am proud to call him my friend, even though there are more feelings to our relationship. When it's raining, Magne is my umbrella. When skiing, Magne is the snow. Lying on a hard surface, Magne is my mattress. I love Magne. Magne is always in my heart, but when he's not here physically, my day is ruined. Let's not ruin any more days Magne.

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Summary

Earnings inequality among men and the returns to higher education have increased substantially in most OECD countries since the 1980s (Gottschalk and Smeeding, 1997). A number of explanations for this development have been proposed, but no consensus has yet been established. For example, international trade and globalisation, decline in minimum earnings and in unionization, and increased use of performance pay have been suggested as possible explanations. A number of papers argue that the return to (unobserved) skills is increasing because of a growth in the demand for skills caused by skill-biased technological change (see e.g. Juhn, Murphy and Pierce, 1993). However, the fact that many European countries and the US have experienced rather different trends in earnings inequality is often argued to undermine this explanation since these countries should have experienced similar technological changes (Gottschalk and Smeeding, 1997).

Two important stylized facts for the US are that since the beginning of the 1980s and continuing through the 1990s the measured return to additional years of schooling has increased, and this has been accompanied by a rise in the dispersion of earnings within groups with the same years of schooling (see e.g. Card and Lemieux, 2001 and Katz and Autor, 1999). An important part of the change in earnings inequality in the US has been linked to the lasting growth in the college/high school earnings premium, but this does not explain the increased earnings dispersion among workers with the same educational level.

The basic assumption underlying much of the research that attempts to explain these trends is that the number of years of schooling an individual receives consistently proxies for skill. However, years of schooling is a biased measure of skill if the composition of individuals with the same years of schooling differs along an unobserved dimension determining their earnings. By the same token, changes in this unobserved dimension may affect the observed trends in the returns to schooling as well as the within-group dispersion of earnings.

The use of years of education as a proxy for skills disregards on the one hand the large variation in the returns to fields of study over time and across countries, and on the other hand, the substantial variation in the composition of fields of study over time and across

countries. For example, cross-country differences in the composition of fields of study over time might explain cross-country differences in the trends in inequality and return to education. Further, the influence of skill biased technological change on choice of field of study may in itself vary between countries. In particular, higher tuition fees and more dispersed earnings might cause larger shifts towards fields with high returns in some countries than in others, and thus bigger increases in the returns to college and in earnings inequality. This may explain why we observe different trends in earnings inequality and return to education across countries which experienced similar technological changes.

The objective of this study is to examine to what extent changes in the field of study composition is driving the rise in the return to college and earnings dispersion among college educated men in Norway and the US. To do so, we use a generalized version of the decomposition method introduced by Oaxaca (1973) and Blinder (1973). The method applies counterfactual measures such as “how much would a worker, with the mean characteristics of the Norwegian workforce, have been paid in the US?”, or “what would the variance of earnings have been if returns to age and education were as in 1990, but the composition of the workforce’s age and education was as in 1980?”. These counterfactuals are compared to the actual or other counterfactual measures, to give an estimate of the significance of the field of study compositions to these measures.

We start by documenting the trends in earnings inequality in Norway and the US between 1970 and 2001, both among all working men, and within educational groups. Moreover, we describe the time trends in the returns to higher education as well as the compositional changes with respect to field of study and age in the male workforce. Next, we examine the effect of differences in the field of study composition on the mean log earnings among male college graduates - as a measure of the college premium - in Norway between various years from 1970 to 2001. Next, we investigate to what extent cross-country differences between Norway and the US in field of study composition can explain the large differences in college premium between these countries. We also explore the effect of field of study on the variance of log earnings among Norwegian male college graduates from 1970 to 2001. In addition, we explore the effect of changes in the age composition on the mean and variance of log earnings. For example, mean earnings are likely to increase when the workforce grows older, because older workers will tend to have more experience. Earnings dispersion will also increase if the variation in earnings is higher among older than younger men. Changes in the age composition might also affect the estimated field of study effect, if the returns to fields differ by age. Our calculations are produced with Stata, SAS and Excel.

We find that differences in field of study composition have little impact on the differences in mean earnings, both across time and countries. Differences in age composition, however, affect the mean earnings remarkably. In particular, 40 percent of the mean earnings increase among Norwegian male college graduates in the 1980s could be accounted for by changes in the age composition.

Further, we find that the variance of log earnings among working male college graduates fell drastically in the 1970s and increased in the two succeeding decades. We also show that the driving force behind this development was changes to the residual variance, rather than changes to the composition or return to field of study or age. In the 1970s, changes to the returns to field of study counteracted the decrease, while changes to the age composition seem to have contributed significantly to the decrease. Further, changes to the return to experience counteracted the increase in the 1980s, while changes in the return to field of study contributed significantly to the increase in the variance in the 1990s. Changes to the field of study composition, however, do not seem to be an important factor behind the evolution of the log earnings variance.

Contents

1. Introduction

Earnings inequality among men and the returns to higher education have increased substantially in most OECD countries since the 1980s (Gottschalk and Smeeding, 1997). A number of explanations for this development have been proposed, but no consensus has yet been established. For example, international trade and globalisation, decline in minimum earnings and in unionization, and increased use of performance pay have been suggested as possible explanations. A number of papers argue that the return to (unobserved) skills is increasing because of a growth in the demand for skills caused by skill-biased technological change (see e.g. Juhn, Murphy and Pierce, 1993). However, the fact that many European countries and the US have experienced rather different trends in earnings inequality is often argued to undermine this explanation since these countries should have experienced similar technological changes (Gottschalk and Smeeding, 1997).

Two important stylized facts for the US are that since the beginning of the 1980s and continuing through the 1990s the measured return to additional years of schooling has increased, and this has been accompanied by a rise in the dispersion of earnings within groups with the same years of schooling (see e.g. Card and Lemieux, 2001 and Katz and Autor, 1999). An important part of the change in earnings inequality in the US has been linked to the lasting growth in the college/high school earnings premium, but this does not explain the increased earnings dispersion among workers with the same educational level.

The basic assumption underlying much of the research that attempts to explain these trends is that the number of years of schooling an individual receives consistently proxies for skill. However, years of schooling is a biased measure of skill if the composition of individuals with the same years of schooling differs along an unobserved dimension determining their earnings. By the same token, changes in this unobserved dimension may affect the observed trends in the returns to schooling as well as the within-group dispersion of earnings.

The use of years of education as a proxy for skills disregards on the one hand the large variation in the returns to fields of study over time and across countries, and on the other hand, the substantial variation in the composition of fields of study over time and across countries. For example, mean earnings are (probably) much lower among nurses who are college graduates than engineers. We would therefore expect that countries with a relatively large fraction of engineers among college graduates would experience larger returns to education in average than countries with a relatively large fraction of nurses. We would further expect that countries with a growing fraction of engineers relative to nurses would experience a larger growth in (average) return to education than countries where this fraction is declining. Moreover, skill biased technological change such as the introduction of computers may have little to say for nurses, but will probably increase both productivity and demand for engineers. This will in turn lead to a larger growth in (average) return to education in countries with relatively many engineers compared to countries with relatively many nurses. Further, the influence of skill biased technological change on choice of field of study may in itself vary between countries. In particular, higher tuition fees and more dispersed earnings might cause larger shifts towards fields with high returns in some countries than in others, and thus larger increases in the returns to college and in earnings inequality. This may explain why we observe different trends in earnings inequality and return to education across countries which experienced similar technological changes.

The objective of this study is to examine to what extent changes in the field of study composition is driving the rise in the return to college and earnings dispersion among college educated men in Norway and the US. To do so, we use a generalized version of the decomposition method introduced by Oaxaca (1973) and Blinder (1973). The method applies counterfactual measures such as “how much would a worker, with the mean characteristics of the Norwegian workforce, have been paid in the US?”, or “what would the variance of earnings have been if returns to age and education were as in 1990, but the composition of the workforce’s age and education was as in 1980?”. These counterfactuals are compared to the actual or other counterfactual measures, to give an estimate of the significance of the field of study compositions to these measures.

We start by documenting the trends in earnings inequality in Norway and the US between 1970 and 2001, both among all working men, and within educational groups. Moreover, we describe the time trends in the returns to higher education as well as the compositional changes with respect to field of study and age in the male workforce. Next, we examine the effect of differences in the field of study composition on the mean log earnings among male college graduates - as a measure of the college premium - in Norway between various years from 1970 to 2001. Next, we investigate to what extent cross-country differences between Norway and the US in field of study composition can explain the large differences in college premium between these countries. We also explore the effect of field of study on the variance of log earnings among Norwegian male college graduates from 1970 to 2001. In addition, we explore the effect of changes in the age composition on the mean and variance of log earnings. For example, mean earnings are likely to increase when the workforce grows older, because older workers will tend to have more experience. Earnings dispersion will also increase if the variation in earnings is higher among older than younger men. Changes in the age composition might also affect the estimated field of study effect, if the returns to fields differ by age. Our calculations are produced with Stata, SAS and Excel.

We examine only men's earnings. This is because women's earnings have been affected by several additional factors throughout the period we are looking at. The effect of differences in the field of study and age composition on women's earnings distribution will be examined in a future project. The compositional effects across time in the US are examined in an ongoing project at Statistics Norway.

We find that differences in field of study composition have little impact on the differences in mean earnings, both across time and countries. Differences in age composition, however, affect the mean earnings remarkably. In particular, 40 percent of the mean earnings increase among Norwegian male college graduates in the 1980s could be accounted for by changes in the age composition.

Further, we find that the variance of log earnings among working male college graduates fell drastically in the 1970s and increased in the two succeeding decades. We also show that the driving force behind this development was changes to the residual variance, rather than changes to the composition or return to field of study or age. In the 1970s, changes to the returns to field of study counteracted the decrease, while changes to the age composition seem to have contributed significantly to the decrease. Further, changes to the return to experience counteracted the increase in the 1980s, while changes in the return to field of study contributed significantly to the increase in the variance in the 1990s. Changes to the field of study composition, however, do not seem to be an important factor behind the evolution of the log earnings variance.

The study unfolds as follows. Section 2 discusses related literature, while Section 3 presents the empirical method used. Section 4 describes our data and sample selection. Section 5 presents our main results, before Section 6 reports results from the robustness analysis. Section 7 concludes.

2. Literature

The increase in earnings inequality in most OECD countries since the 1980s is one of the most extensively researched topics in labour economics. The development in the US has received particular attention. The earnings inequality increased sharply in the US from the late 1970s to the mid 1990s (see e.g. Katz and Autor, 1999). Differentials in the returns to skills, such as education and age (experience), increased greatly in the same period. In fact, while highly skilled workers experienced a substantial increase in real earnings during this period, earnings of less skilled US workers fell dramatically (Brauer and Hickok, 1995). The earnings dispersion also expanded within skill groups. Accordingly, earnings of men with the same education and age were much more unequal in the mid 1990s than two decades earlier. The trends, however, differ substantially across countries. Among the OECD countries, earnings inequality increased most in the US and the UK and least in the Nordic countries (Gottschalk and Smeeding, 1997).

Lemieux (2006b) shows that the US male earnings inequality (90-10 percentile ratio) increased substantially in the 1980s, insignificantly in the 1990s and modestly between 1999 and 2004. While the 90-50 percentile ratio has been growing since the beginning of the 1980s, the 50-10 percentile ratio grew in the 1970s and the first half of 1980s, but decreased after the mid 1980s. Consistently, growth in male real earnings between 1974 and 1985 was increasing with increasing earnings level (in fact only positive for the 80th percentile). Between 1989 and 2004 the top and bottom of the earnings distribution experienced the largest growth in real earnings.

Earnings inequality was much lower in Norway than in the US, and it increased far less in the last three decades of the previous century. For example, Hægeland (2002) finds that overall earnings inequality in Norway fell sharply in the 1970s, continued to fall in the 1980s and was stable in the 1990s. The fall in the 1980s was due to a compression in the lower part of the earnings distribution. Hægeland (2002) also finds that the within group dispersion increased in the 1990s.

Several explanations for the development in earnings inequality have been proposed, but no consensus has been established. For example, changes in labour market institutions such as the decline in unionization and the minimum wage, and changes in wage setting norms, are proposed as contributors to the development. These effects can also help explain the differences between countries. For example, countries with centralized wage bargaining (e.g., Norway and Germany) have greater equality than countries with less centralized bargaining (e.g., the US and Canada), and are likely to react less to changes in supply and demand (Gottschalk and Smeeding, 1997). In the US, the minimum wage fell sharply (in real terms) during the 1980s. DiNardo, Fortin and Lemieux (1996) find that this could explain much of the increase in the 50-10 percentile ratio in the 1980s (especially for women). However, since the minimum wage did not change much after 1990, and is in any case unlikely to affect top-end inequality, it cannot account for the growth in top-end inequality over the last two decades. They also find that de-unionization has a positive effect on the 90-50 percentile ratio, and a negative effect on 50-10 ratio after 1979, which is consistent with the findings of Lemieux (2006b). Lemieux, Macleod and Parent (2009) find that performance pay has increased, and increases inequality, mostly above the 80th percentile.

A number of papers suggest demand side explanations for the development in earnings inequality. For example, skill-biased technological changes, largely associated with the increased use and availability of computers, is believed to have contributed substantially to the increase in the returns to skills, and thereby to the development in inequality. In this spirit, Autor, Katz and Kearney (2006) suggest a model to explain why the workers at the top and bottom of the distribution have done well since 1990 in the US, while workers in the middle have not done so well. They divide workers into three groups: The first group consists of unskilled workers with non-routine jobs such as truck drivers or nannies. The second group is composed of workers with more skill demanding, but routine jobs such as traditional blue-collar workers. The third group consists of high skilled workers with non-routine jobs. The different kinds of workers are normally found, respectively, in the lower end, middle end and high end of the earnings distribution. The authors argue that computers can be used as substitutes for the relatively skilled workers with routine jobs, and that the introduction of computers therefore should depress earnings for these kinds of workers relative to the other types. They find that since 1990, changes in occupational shares are U-shaped in the sense that it is occupations in the middle of the skill (or earnings) distribution that declined relative to occupations both at the bottom and top end. Autor, Levy and Murnane (2003), looks at detailed occupations data and shows that the share of the workforce in routine occupations has in fact declined over time.

Juhn, Murphy and Pierce (1993) interpret the rise in within-group inequality as reflecting a rise in the returns to unobserved skills. They argue that the return to unobserved skills may be increasing because of an increase in the demand for such skills and that this in fact is the main cause for the growth in residual earnings inequality during the 1970s and 1980s. On the other hand, Lemieux (2006b) argues that the increase in the return to unobserved skills account for no more than 25 percent of the overall increase in earnings inequality between the 1970s and the 1990s, and that all of this increase occurred in the 1980s. Since earnings dispersion among narrowly defined groups of workers is substantially larger for older and more educated workers than for younger and less educated works, a large fraction of the increase in residual earnings inequality could be a consequence of the fact that the workforce has grown older and more educated since the early 1980s. He thus argues that changes in the composition of the workforce were driving the development. Lemieux (2006b) also argues that the variance of measurement error in earnings has increased over time, resulting in a spurious growth in observed residual earnings inequality.

It is often argued that the fact that many European countries and the US have experienced rather different trends in earnings inequality (Gottschalk and Smeeding, 1997) undermines the skill-biased technological change explanation, since these countries should have experienced similar technological changes. Differences across countries in the growth in supply of skilled workers could, however, explain a large part of the differences in trends in returns to education and earnings dispersion.

A second demand based explanation focuses on the role of rising globalization, particularly the increased trade with less-developed countries. The international division of labour leads to reduced manufacturing employment, thereby shrinking the relative demand and earnings for blue collar workers (Feenstra and Hanson, 1996). However, a number of papers argue against globalization as a major driving force behind the development. For example, Johnson (1997) argues that the fraction of totally unskilled workers in the tradable gods sector would simply have been too small, even without globalization, to have a substantial effect on the overall development. He also argues that if globalization is important, it should have increased the relative demand for skill also in the 1970s, while in fact the opposite was the case.

An important part of the change in earnings inequality in the US, has been linked to the lasting growth in the college-high school earnings premium since the late 1970s. For example Lemieux (2006a) uses a human capital pricing model where an increase in the price of education increases the overall earnings dispersion, especially among highly educated relative to less-educated workers. This corresponds to the findings of Lemieux (2006b); increased 90-50 and college-high school mean earnings ratio.

The college-high school earnings gap for younger men doubled between 1970 and 2000 in the US while the gap for older men remained nearly constant. Using a model with imperfect substitution between similarly educated workers in different age groups, Card and Lemieux (2001) argue that these shifts reflect changes in the relative supply of highly educated workers across age groups. Cohorts born in the first half of the century had steadily rising educational attainments that offset rising demand for better educated workers. This trend ended in the early 1950s. Card and Lemieux (2001) argue that a slowdown in the rate of growth of educational attainment across cohorts will lead to a rise in the return to college for younger workers that will eventually work its way through the age distribution. This prediction is fairly consistent with data for the US in the period from 1959 to 1995, and data from the UK and Canada. Carneiro and Lee (2007) however, argue that changes in the average quality of college graduates are as important as general equilibrium effects to explain that the college-high school earnings gap increased only for younger men. The changes in quality occur because increased college enrolment leads to weaker students attaining college degrees. Carneiro and Lee (2007) construct composition adjusted trends in the college premium and present evidence that the increases in college enrolment lead to a decline in the average quality of college graduates between 1960 and 2000, resulting in a decrease of 8 percentage points in the college premium.

The college premium in Norway has not experienced the same vast growth. In fact, by using an instrumental variable technique, Hægeland, Klette and Salvanes (1999) control for self selection into education and argue that returns to education have been remarkably stable in

Norway between 1980 and 1990. Thus it could look like the negative effect on the return to higher education caused by an expansion in the Norwegian education system, is offset by increased demand. Hægeland (2001) investigates whether the empirical results suggest that there has been a decline in the returns to education across cohorts. When controlling for self-selection into education, however, the cohort differences vanish. He further finds no strong evidence in favour of a skills obsolescence explanation (if human capital is partly technology-specific, technological change will erode some human capital), and no support for the hypothesis that the quality of schooling has declined over time. Thus cohort differences in returns to education seem to have been driven by selection effects.

Devroye and Freeman (2001) investigate whether cross-country differences in the distribution of skills to workers, determine differences in earnings dispersion between countries. For example, they point out that the coefficient of variation in test scores across countries from an international adult literacy survey is positively correlated with the 90-10 percentile earnings differentials across countries. However, they find that inequality of skills explains little of the inequality of earnings between countries. It does not, for instance, explain large differences in within skill group dispersion between countries.

3. Empirical Method

In order to investigate to what extent changes in the field of study composition is driving the rise in the return to college and earnings dispersion among college educated men, we will use a standard decomposition method as first suggested by Oaxaca (1973) and Blinder (1973). Our presentation follows Lemieux (2002) closely. The method applies counterfactual measures of (for example) mean and variance, and compares these to the actual or other counterfactual measures. Counterfactual mean earnings could, for example, tell us what mean earnings would have been if the returns to fields of study were as in 1990, but the field of study composition was as in 1980. By comparing this counterfactual mean earnings to the actual mean earnings in these years, we get an impression of the significance of changes in the field of study composition on the earnings development in the 1980s. Similarly, we can look at differences across countries.

In order to discuss our decomposition procedure, consider a sample of m_t observations of individual log earnings w_{it} from year *t* where *i* indicate the individual observation. For each observation there is a vector of dummy variables, $x_{it} = \lfloor x_{i1t},..., x_{ijt},..., x_{iJt} \rfloor$, that divide the sample in a set of *J* cells. In the empirical analysis, these cells are divided by either field of study, age groups or both. For example, when using both age and field of study as covariates, *J* indicates the number of mutually exclusive and collectively exhaustive age-field cells. By "cells" we refer to a specific disaggregation of our sample. Age-field cells will for example refer to the groups characterized by both field of study and age. For example will all observations with a specific field of study and age group, such as lawyers between 26 and 30 years old, be aggregated to a group which we here refer to as an age-field cell. When using 9 field of study groups and 7 age groups, *J* equals 63. For now, suppose that field of study is the only covariate in the rest of this section (*J* equals 9). Consequently, the sum of the dummy variables x_{ijt} over the sample, equals the number of workers with field of study *j*, n_{jt} .

Let us further consider a regression model for earnings determination,

$$w_{it} = x_{it}\beta_t + u_{it} \tag{1}$$

where β_t is a J × 1 vector of coefficients, and u_{it} is the disturbance term, which is assumed to be *i.i.d.* distributed with zero conditional mean, $E(u_{it}|x_{it})=0$. Since Equation (1) is saturated in the covariates it corresponds to running J separate regressions, one for each group j in the sample (or cell) without any explanatory variables, and thus only one parameter, the intercept term. Let b_t be the OLS estimate of β_t. Under the above assumptions, b_t is a consistent estimate of β_t. Each cell b_{jt} will simply equal the mean log earnings $\overline{w}_{jt}$ among workers with field of study j, in year t:

$$b'_t = [b_{1t},...,b_{jt},...,b_{Jt}] = [\overline{w}_{1t},...,\overline{w}_{jt},...,\overline{w}_{Jt}]$$

where $\overline{w}_{jt} = \frac{1}{n_{jt}} \sum_i (w_{it} \mid x_{ijt} = 1)$.

Average log earnings in the sample in year t is

$$\overline{w}_t = \frac{1}{m_t} \sum_i w_{it} = \sum_j \frac{n_{jt}}{m_t} \overline{w}_{jt} . \tag{2}$$

The sample average log earnings are thus the average of the cell mean earnings, weighted by the proportion of the sample in each cell.

3.1 Decomposing Changes in the Mean Earnings.

To decompose the changes in mean earnings, we will use counterfactual mean earnings. These are constructed by simply computing (2) with the sample proportion in each cell taken from a different year, s:

$$\overline{w}^c_{ts} = \sum_j \frac{n_{js}}{m_s} \overline{w}_{jt} \tag{3}$$

Equation (3) measures mean log earnings if the returns to fields of study were as in year t, but the field of study composition was as in year s. This counterfactual estimate of mean log earnings thus measures mean log earnings in year t if the field of study composition had been as in year *s*, ignoring any changes in the returns to field of study. The differences in average log earnings between the two years can now be decomposed as

$$\overline{w}_t - \overline{w}_s = (\overline{w}_t - \overline{w}_{ts}^c) + (\overline{w}_{ts}^c - \overline{w}_s) = \sum_j \left(\frac{n_{jt}}{m_t} - \frac{n_{js}}{m_s} \right) \overline{w}_{jt} + \sum_j \frac{n_{js}}{m_s} \left(w_{jt} - w_{js} \right). \qquad (4)$$

The first term on the right hand side captures the effect on the mean earnings difference of the changes in sample distributions to the cells, while the second term captures the effect of the changes in the cell specific mean earnings. Consider, for example, the case where *t*=1990, *s*=1980, the sample are Norwegian college graduates and the cells are characterized by the fields of study of workers. The first term then estimates the effect of the fields of study composition on the log earnings increase among college graduates, and thus the return to education. The second term estimates the effect of the changes in the returns to field of study between 1980 and 1990. In this paper we mainly explore the extent of this first effect.

However, the order of the decomposition (i.e. the order in which we estimate the effect of changes in respectively returns or composition) influences the estimated effects of the composition of attributes and the returns to attributes (see DiNardo, Fortin and Lemieux, 1996, for a detailed discussion). Changing the order of the decomposition is therefore an important robustness check. Specifically, the composition effect is first measured with mean cell earnings in year *t*, while the earnings effect is measured with the composition in year *s*. Second, the composition effect is measured with mean cell earnings in year *s*, while the return effect is measured with the composition in year *t*. The robustness check to the above example is thus done by performing the same procedure, but with *t*=1980 and *s*=1990. Throughout the empirical analysis, we have the performed our empirical calculations for both sequences of years. We nevertheless consider the cases where t > s as our baseline measures since these use the returns to attributes in the end of the period we are exploring when examining the effect of changes to the attributes throughout the period.

Similar to the above example, we can look at differences between countries, where *t* and *s* would represent two different countries. Consider the example above, but now assume that *t* denotes Norway and *s* denotes the US. The first term now measures to what extent the difference in the field of study composition can explain differences in the level and in the evolution of college premiums between Norway and the US. The second term captures the effect of the difference in field-specific mean earnings.

3.2 Decomposing Changes in the Variance.

In this paper we will use the variance of log earnings to get an impression of the significance of the field of study composition on the earnings inequality. An advantage of the variance of log earnings, rather than the variance of earnings levels, is that the variance of log earnings is scale independent (see Heshmati 2004). The Norwegian mean (real) earnings have increased strongly throughout the period we are examining. This, in itself, increases the variance of earnings, but does not affect the variance of log earnings.

The empirical variance V_t of log earnings can be decomposed into between- and within-cell variance:

$$V_t = \frac{1}{m_t}\sum_i (w_{it} - \overline{w}_t)^2 = \frac{1}{m_t}\sum_i (x_{it}b_t - \overline{w}_t)^2 + \frac{1}{m_t}\sum_i e_{it}^2 = \sum_j \frac{n_{jt}}{m_t}\left(\overline{w}_{jt} - \overline{w}_t\right)^2 + \sum_j \frac{n_{jt}}{m_t}\hat{\sigma}_{jt}^2 \qquad (5)$$

where

$$\hat{\sigma}_{jt}^2 = \frac{1}{n_{jt}}\sum_i \left(e_{it}^2 \mid x_{ijt} = 1\right)$$

where *e* is the OLS residuals from Equation (1). In Equation (5) we utilize that the mean of the OLS residuals are, by construction, zero. The first term on the right-hand side measures the between-group variance as the weighted sum of the squared deviations between the mean cell earnings and the overall mean earnings. The within-group variance (second term) is the sum of the residual variance over the cells, weighted by the cells' sample proportion. An increase in the variance could have three causes: First, divergence in mean cell earnings could increase overall dispersion. Second, increased deviation in earnings within cells will increase the last term. Third, the variance will increase if the proportion of workers to the cells which contribute relatively much to the overall dispersion, increases. We are especially interested in the last case. For example, increases in the fraction of the workforce to fields with high residual variance will in isolation lead to higher overall dispersion. Transfers of workers to fields with relatively high differences in mean earnings compared to the other fields will have the same effect.

The three causes of changes in the variance can be captured in a variance decomposition. First, consider the counterfactual variance obtained by replacing the cell fractions in Equation (5) by its values in year *s*:

$$V_{ts}^{a} = \sum_{j} \frac{n_{js}}{m_s} \left(\overline{w}_{jt} - \overline{w}_{ts}^{c} \right)^2 + \sum_{j} \frac{n_{js}}{m_s} \sigma_{jt}^2 \quad , \tag{6}$$

where V_{ts}^{a} represents the variance in period *t* if the distribution of workers was as in period *s*. We further replace mean earnings in Equation (6) by earnings from year *s*:

$$V_{ts}^{b} = \sum_{j} \frac{n_{js}}{m_s} \left(\overline{w}_{js} - \overline{w}_{s} \right)^2 + \sum_{j} \frac{n_{js}}{m_s} \sigma_{jt}^2 \quad , \tag{7}$$

where V_{ts}^{b} is the variance in period t if both the distribution of workers to the cells and the cell earnings was as in period *s*. The only difference between V_{ts}^{b} and V_s is the residual variance terms σ_{jt}^2 and σ_{js}^2. Using Equation (5), (6) and (7), the change in the variance can now be decomposed as

$$V_t - V_s = \left(V_t - V_{ts}^{a} \right) + \left(V_{ts}^{a} - V_{ts}^{b} \right) + \left(V_{ts}^{b} - V_s \right). \tag{8}$$

The first term on the right hand side in Equation (8) is the contribution of changes in the distribution of workers to changes in the variance:

$$V_t - V_{ts}^{a} = \sum_{j} \left(\frac{n_{jt}}{m_t} - \frac{n_{js}}{m_s} \right) \left(\overline{w}_{jt} - \overline{w}_{ts}^{c} \right)^2 + \sum_{j} \left(\frac{n_{jt}}{m_t} - \frac{n_{js}}{m_s} \right) \sigma_{jt}^2 \tag{9}$$

In this paper we will evaluate the size of Equation (9) in comparison with the two other terms, to estimate the effect of field of study and age composition on changes in the earnings dispersion. The second term in Equation (8) captures the effect of changes in mean earnings:

$$V_{ts}^{a} - V_{ts}^{b} = \sum_{j} \frac{n_{js}}{m_{s}} \left[\left(\overline{w}_{jt} - \overline{w}_{ts}^{c} \right)^{2} - \left(\overline{w}_{js} - \overline{w}_{s} \right)^{2} \right] \tag{10}$$

The last term Equation (8) represents changes in the residual variance within each cell:

$$V_{ts}^{b} - V_{s} = \sum_{j} \frac{n_{js}}{m_{s}} \left(\sigma_{jt}^{2} - \sigma_{js}^{2} \right) \tag{11}$$

Also in this case, the order of the decomposition may influence the effect of the three factors, so changing the order is still an important robustness check. Comparing the measures obtained with the negative values of similar measures, where *t* and *s* have exchanged values is one way of doing it. If initially *t*=1990 and *s*=1980, we perform the same procedure but with $\hat{t}$ =1980 and $\hat{s}$ =1990. When *t*=1990 and *s*=1980, Equation (9) estimates how the measured variance in 1990 would change if the field of study composition stayed at the 1980 level. With $\hat{t}$ =1990 and $\hat{s}$ =1980 this equation measures how the variance in 1980 would change if the field of study composition changed to the 1990 level. Thus, both measure the contribution of changes in the fraction of workers in the cells to the changes in the variance in the 1980s. With $\hat{t}$ =1990 and $\hat{s}$ =1980 Equation (10) measures the effect of changes in the return to attributes weighted by the attributes composition in 1990. Equation (11) represents changes in residual variance within each cell, now weighted by the 1990 composition (the sequence in which we measure the effect of changes to cell mean earnings and residual variance is thus irrelevant). We have performed our empirical calculations for both sequences of years. As above, we nevertheless consider the cases where $t > s$ as our baseline estimates.

4. Sample and Variable Construction

The source for the Norwegian data for this study is administrative registers from Statistics Norway. The US data is taken from the March Current Population Survey (CPS) and the National Survey of College Graduates (NSCG).

The March CPS provides us with individual data on sex, age, employment status, earnings, and educational grade up to completed college for every year since at least 1970. The National Science Foundation's 1993 and 2003 NSCG were intended to provide employment and earnings data for a representative sample of the US population with at least a bachelor degree. The NSCG provides detailed variables on educational history, such as field of study and level for each degree held. It also contains many other variables, of which we will use sex and age. In addition, the 1993 NSCG supplies the respondents' 1989 salary and employment status while the 2003 NSCG provides the respondents' 2003 salary and employment status. We use the NSCG sample when we need information on field of study, and the CPS otherwise.

The administrative registers from Statistics Norway cover essentially the entire resident population of Norway from the late 1960s until the present, in total more than 7 million individuals. Each individual is registered with sex and year of birth, in addition to many other variables. Practically all residents who have completed any education are registered with level (e.g. primary school, bachelor degree) of highest completed education in addition to detailed information on the field of study at this level. The data set also contains individual information on annual earnings.

Our initial sample consists of all men born between 1910 and 1975, who lived to be at least 26 years old. These are the cohorts who were between 26 and 60 years at lest one year between 1970 and 2001. The age interval is chosen so that most of the sample will have finished their education, and will not be retired. In the CPS data, the men had to be between 26 and 60 years old in the survey year. This sample consists of 1 977 554 men in the Norwegian data, 1 305 428 in the CPS and 116 493 in the NSCG.

We exclude all observations where we lack educational information, which is one observation in the CPS and 132 411 in the Norwegian data. The Norwegian data set now consists of 1 845 143 observations.

The sample is divided into two groups: those who are *college graduates* and those who are not. In the Norwegian data, college graduates are defined as people who have complete at least some education on a tertiary level.[1] In the CPS, college graduates are defined as respondents with at least 16 years of completed schooling. This includes those who dropped out of college before completing a degree and those who misreported their completed schooling. The NSCG sample includes only those who at least have completed (an actual) college degree.[2] The college graduates are also divided into nine field of study groups: science and engineering, medicine, business, law, humanities, social sciences, nursing and social services, teaching and other. These groups are aggregated to three main groups: 1) science, engineering, and medicine, 2) business and law and 3) humanities, social sciences, nursing, social services, teaching and other. For simplicity we will refer to these groups merely as science, business and humanities. The field of each person is the field in which the person has achieved the highest level, by the survey year (1993 and 2003) in the NSCG, and by the autumn of 2007 in the Norwegian data. The workers are also divided into seven five-year-interval age groups from age 26 to 60.

The dataset now described is the one we use to produce Figures 7-9. The sample used in the other parts of this paper has some additional restrictions and variables:

In our earnings analysis, we need to take into account earnings variation due to variation in hours of work, since we have data on annual earnings. We do this by simply restricting our sample in this part of the paper to the workers who work full-time. However, to determine employment status in the Norwegian data, we use the National Censuses of Population and

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[1] See Statistics Norway (2003): “First stage of tertiary education, undergraduate level: Education at the 14th - 17th class level. Undergraduate education at universities or colleges: individual subjects and degrees at universities and colleges lasting four years or less, e.g. foundation and intermediate courses, cand.mag. degree, college degrees”

[2] There are large differences in the mean earnings among “college graduates” in the CPS and NSCG. This explains why.

Housing in 1970, 1980 and 2001 and the National Survey of Population and Housing in 1990 (see Statistics Norway, 1987, 1992 and 2006). We therefore restrict the Norwegian part of our earnings analysis to these years. The 1990 survey only included about two seventh of the adult population. For the Norwegian data, full-time work is defined as more than 1300 hours a year in 1970, 1980 and 2001, and more than 30 hours a week and at least 10 months full-time or more than 35 hours a week and at least 9 months full time in 1990. For the CPS data, full-time work is defined as more than 35 hours work a week for at least 40 weeks the current year. We also restrict our sample to workers who are not self employed.

The earnings measure used is total annual pensionable labour income in the Norwegian data, and reported labour income from the previous year in the US data. Accordingly, the earnings measure used in all datasets are total pre-tax wage and salary income, thus money received as an employee. For example capital income and social benefits are in other words excluded. To make earnings comparable across time and the countries, they are expressed in fixed 2007 USD. Since Norwegian data on earnings were initially expressed in fixed 2007 NOK, we adjusted for the exchange rate and the differences in the price level of consumption, using Penn World Tables.[3] Throughout the rest of this paper we refer to fixed 2007 USD when writing about USD.

Workers with a lower salary than 10 000 USD were excluded from the earnings analysis sample. Further, due to top coding in the initial data sets, observations with salaries higher than 150 000 USD were top coded at that amount. This is done both for the Norwegian and the US data.

The size of the Norwegian sample now described is just under 1,9 million observations[4]. The final sample used in most of the estimations includes only the college educated. The size of this sample is 73 534, 116 198, 34 246, 200 643 observations from Norway in respectively

[3] Norwegian Earnings in fixed 2007 USD = [Norwegian Earnings in fixed 2007 NOK / Exchange rate (5.86166667)]*[100/ Price Level of Consumption (165,7)]

[4] The size of this sample is 513 927 (63), 566 868 (61), 159 611 (15) and 646 110 (52) observations from Norway in respectively 1970, 1980 1990 and 2001. The numbers in parenthesis show the percentage of the male 26-60 year old population in Norway each year.

1970, 1980, 1990 and 2001. The final CPS sample consists of 679 394 observations, that make up about 68 percent of the initial sample. The NSCG sample consists of 132 411 college graduates, which makes up about 84 percent of the initial sample.

Less than 1 percent of the overall Norwegian sample and the CPS sample have top coded earnings. In the CPS however, the fraction with top coded earnings among the college graduates peaks at 8,7 percent in 2001. In the NSCG, 10,3 percent of the earnings are top coded.

In Figures 1, 2, 3 and 5, we use the earnings information in the CPS. The initial top code in the CPS was lower than 150 000 USD in 1979 - 1981 and 1992-1995. We have therefore replaced the top coded observations with properly weighted observations covering this part of the distribution from the 1978, 1982, 1991 and 1996 surveys.

Sample weights (or probability weights) denote the inverse of the probability of an observation being sampled (because of the sampling design) and thus indicates how many observations one particular observation represents. When properly reweighting the "new" observations, it is essential that the new weights sum up to the same as the old weights (so the share of people in this part of the distribution is not changed). Moreover, it is desirable that the new observations are weighted so that they suit the composition of the old observations. This is done by dividing the observations into groups (here denoted by *k*) and only replacing observations from the same group. For simplicity, we have only distinguished between two groups *k*: college graduates and non college graduates. We could however disaggregate the sample further, by for example age.

In particular, the new weight to observation *i* from group *k*, originally from year *s*, which will contribute to replace the top coded observations in year *t* equals $\left(n_{kt} \cdot w_{ksi} \cdot Y_{st}\right)/n_{ks}$. The number n_{kt} is the sum of the frequency weights given to the observations from group *k* and year *t* that will be replaced. w_{ksi} is the initial weight given to the observation *i*. n_{ks} is the sum of the weights from the observations from group *k* in year *s* that will replace year *t* observations. $Y_{st} \in [0,1]$ is a weight specific for the year from which the replacements are brought, and the receiving year. They should sum to one for each receiving year. We have used the weights $Y_{\underline{s}t} = (t - \underline{s})/(\bar{s} - \underline{s})$ and $Y_{\bar{s}t} = (\bar{s} - t)/(\bar{s} - \underline{s})$ where $\underline{s} < t$ and $\bar{s} > t$. For example, $Y_{1978\ 1981}=0,25$

and $Y_{1982\ 1981}=0{,}75$. This makes the observations from 1982 three times as important as the observations from 1978, when replacing the top coded observations from 1981. The opposite is the case when replacing the observations from 1979.

The weights given to the “new” observations now sum up to the same as the weights to the deleted observations, in each group *k* in each year *t*. The fraction of college graduates is thus the same in the new observations, as the replaced observations, and the fraction of new observations to the sample is as large as the fraction of replaced observations.

5. Empirical Results

5.1 Earnings Dispersion and the Return to Education in Norway and the US

We start by presenting our measures of the development of inequality in Norway and the US between 1970 and 2001 among different groups of full time working men. Figure 1 displays the development in the 90/10 percentile earnings ratio and the Gini coefficient of earnings as well as the evolution in the variance of log earnings for all working men. The figure clearly shows that the inequality increased rapidly in both countries in the 1980s. In the US the growth started in the late 1970s and continued to the mid 1990s. In the Norwegian data we find a comprehensive decrease in the 1970s that we do not find in the US data and a small increase in the 1990s. The growth in inequality is stronger in the US than in Norway. All three measures of inequality show basically the same pattern.

Figure 2 reports the development in inequality among college educated working men. For Norway the overall pattern seems much the same as in Figure 1, but with steeper increases in the 1990s. The trend also seems comparable to Figure 1 for the US, although the increases in the earnings inequality and dispersion are somewhat more moderate.

Figure 3 displays the development in earnings inequality and dispersion among working men who are not college graduates. This figure also shows much the same pattern as the first figure. One exception is that the development in the US flattened around 1990 for this group of workers.

The development in inequality among working men within the same field of study is presented in Figure 4. The most interesting observation here is that inequality among business educated men in Norway diverged sharply from other fields in the 1970s and 1980s, while it converged in the 1990s. In fact, while inequality among science and humanities educated males seems to have decreased in the 1980s, inequality among workers educated in business fields increased. Inequality among humanities educated men diverged from science throughout the period. Inequality was lower in humanities. The levels of the measures from the US are probably influenced considerably by the share of the sample that is top coded. As seen in Table 1, the share of workers with top coded earnings was considerably lower among humanities educated males than others. This is probably why inequality among humanities educated males is so much higher than in other fields.

Figure 5 displays the evolution of the college premium in the two countries between 1970 and 2001. The premium decreased in both countries during the 1970s. In the US it increased steadily through the 1980s and up to the year 1995. In Norway, however, it stayed practically flat through the last two decades in the period.

The right-hand panels in Figure 5 are included to see whether the age composition of the workforce is driving the trend. The graphs are constructed by regressing earnings on dummy-variables for college graduation and for age-groups (5-year intervals). The difference graph displays the evolution in the college graduation parameter, while the ratio graph uses the sum of the college graduation parameter and the (unweighted) average of the age parameters which is then divided by the average of the age parameters. It is apparent that the age composition of the workforce is not driving the evolution in the college premium in the US. For Norway however, it has a visual impact. The differentials now decline in the 1980s and rise in the 1990s, due to an increase in the relative average age among college graduates through this period (see Figure 10).

Figure 6 shows the development in mean earnings by college field. Mean earnings among humanities educated workers are diverging from business and science in Norway throughout the period we are looking at. Moreover, it should be noted that real earnings increased over the period, with particular intensity in the 1990s. When controlling for age, however, the mean earnings among humanities educated males fell in the 1980s. This growth in mean earnings among humanities educated men thus seems to be a somewhat spurious effect of the mean age growth in these fields. Looking at the US, we also here see that humanities earnings are lower on average than earnings for business educated, which in turn is somewhat lower than the mean earnings among workers educated in science fields.

5.2 Degree and Field Composition for Men in Norway and the US

In order to examine the importance of field of study composition on the earnings deviation and the college premium, we will now look at the evolution in the composition of field of study. To start with, we look at the evolution in the proportion of higher educated males. Figure 7 displays the fraction of college graduates among all men in each cohort from 1945 to 1975 in Norway and the US. In the US, there was a pronounced decline in the fraction of college graduates among cohorts born from the late 1940s to 1960 and then a small increase among the cohorts born in the 1960s. Norway experienced a steady increase among the cohorts born in the first eight years of the period, and also since the beginning of the 1960s. We see that the fraction of Norwegians with higher education surpassed the US for cohorts born around 1955. The overall increase in the fraction of college graduates in Norway compared to the US throughout this period has probably led to a relative increase in the supply of college graduates in Norway. With increasing supply, wage pressure among college educated in Norway should be dampened compared to the US, which potentially could explain the differences in the evolution in the college earnings premium between the two countries after 1980 (Figure 5).[5]

Figure 8 displays the field of study composition for each cohort. The fraction of college graduates with humanities as their field of study was relatively large for cohorts born around 1950 and 1970 in Norway. The fraction with business fields nearly doubled between the early 1950s and the mid 1960s, while the fraction with science fell greatly in the 1960s. In the US, the humanities fraction plunged in the 1950s, but recovered somewhat in the mid 1960s at the expense of the fraction with science degrees. In the last 7 to 8 years the fraction with business fell, but these years are marked by some noise.

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5 The weights in the US data could, however, be inconsistent through time, so we could not simply pool all the observations. To deal with this, the fraction of each cohort is the average of the fractions of each cohort in the surveys between 1970 and 2001 in which the cohort was between 26 and 60 years.

Figure 9 reports the composition of fields for all male college graduates aged 26-60 years in each year. The difference from year to year is thus that the 26 year olds enter the sample, while the 60 year olds retire from the sample. It is interesting to see that the fraction with degrees in humanities peaked around 1980 in both countries, the same period as the earnings dispersion and education premium was at it lowest. In Norway the fraction with degrees in science decreased throughout the period, while the fraction of business educated increased, especially after the mid 1980s. The US data is somewhat insufficient for this figure due to lack of observations for the youngest and oldest relevant cohorts.

Figure 10 displays changes to the field of study and age composition among working male college graduates. In particular, it displays the difference as the percentage of all working male college graduates from respectively 1970 to 1980, 1980 to 1990 and 1990 to 2001. For example, the first plot on the science graph in the 1970 to 1980 figure equals nearly -1, and thus tells us that 1 percentage point more of the total male college educated workforce was 26-30 years old and had a bachelor in science in 1970 than in 1980. We can actually see a “wave” going towards the right through the figures. This represents the post World War II baby boom generation entering the workforce in the 1970s and getting older in the two consecutive decades. By evaluating the sum of the vertical distance between the plots and the 0-line to each field of study graph, we see that the fraction of science educated males in the sample increased through the 1970s and decreased throughout the rest of the period, while the other fields show an opposite pattern. This is not entirely consistent with what we saw in the two previous figures: Figure 9 showed a decrease in the fraction of science educated, also in the 1970s. This indicates that unemployment was relatively low among science educated in the year 1980, as the sample to Figure 9 also includes the unemployed, in contrast to Figure 10.

5.3 Decomposed Changes in the Mean Log Earnings

Before examining whether the field of study composition is affecting the development in the earnings dispersion, we will investigate to what extent the field of study and age composition is affecting mean earnings among college graduates, and thus the college premium. Tables 2, 3 and 4 reports estimation results that are obtained by implementing the decomposition procedure described in Section 3.1. The results in the tables are measured in log points. A difference in log points is approximately equal to the percentage difference.

In Table 2, we investigate to what extent changes in the field of study and age composition can explain the observed increase in the mean earnings among college educated Norwegian males. The only considerable effect we find of the workforce composition is through the age composition, and this effect was only large in the 1980s.

The first four columns in Panel A of Table 2 display the difference between the actual mean log earnings for college graduates among Norwegian working men in year *t* (1970, 1980 1990 and 2001), and the counterfactual, measuring the mean earnings that would have prevailed if the returns to fields of study were as in year *t*, but the field of study composition was like in year *s* (1970, 1980, 1990 and 2001), thus obtained by implementing the first term on right hand side in Equation (4). The last four columns show the difference between these counterfactuals, and the actual year *s* mean log earnings among college graduates), thus obtained by implementing the last term in Equation (4). In Panel A of Table 2 and Table 3 and 4, the sample was disaggregated into three fields of study. In Panels B and D of Table 2, and in Section 5.4 (Table 5), the sample was disaggregated into nine fields of study. Panel B of Table 2 is equal to the one above with this one exception. The first four columns in Panel C shows the difference between the actual mean log earnings in year *t*, and the counterfactual, measuring the mean earnings that would have prevailed if the returns to age were as in year *t*, but the age composition was like in year *s*. The last four columns show the difference between these counterfactuals, and the actual year *s* mean log earnings among college graduates. Likewise, Panel D basically displays the same, but here the counterfactual mean earnings are constructed with the year *t* returns to age-field groups and the year *s* age-field composition. The first four columns here thus measure the impact of changes in the age composition to each field of study and the overall field composition, on the mean log earnings, while the four right hand side columns measure the impact of changes to the age-field specific mean earnings.

All of the numbers in the left hand side columns in Panel A of Table 2 are smaller than one, implying that changing the field of study composition from one year to another would change the new mean earnings by less than 1 percent. The numbers on the right hand side are much larger, implying that changes to year *s* field specific mean earnings would significantly alter the year *t* mean earnings. For example, the sum of the numbers in the fourth row of the first and fifth column imply that the mean earnings increased by 44 percent[6] (36,5 log points) between 1970 and 2001, while the growth actually would have been (only) 0,3 percentage points (0,3 log points) higher without the changes in the field of study composition. This suggests that changes in the field composition of the workforce from lower to higher return fields was not an important determinant of the increase in mean earnings. The number in the first row of the fourth column suggests that the mean earnings in 1970 would only have been 0,2 percent (0,2 log points) higher with the 2001 field of study composition. Hence, the order of the decomposition does not matter much for these results.

The numbers in Panel B look quantitatively quite similar to the numbers in Panel A, and therefore support our above findings.

The absolute values of the numbers in Panel C are larger than the corresponding values in the above panels. This suggests that the age composition affects the growth in the mean earnings more than the field of study composition. The age composition seems to have had a particularly large effect on the earnings evolution in the 1980s. In Figure 10 we saw the impact of the post world war II baby boom on the age composition of the workforce. The baby boom cohorts entered the labour market in the 1970s, and grew more experienced during the 1980s. This seems to explain a significant part of the earnings increase in this decade. The second column in the third row suggests that the mean log earnings in 1990 would have been 2,4 log points lower with the 1980 age composition, while the actual mean log earnings increased by 5,8 (2,4+3,4(sixth column)) log points. This implies that about 40 percent of the increase in mean earnings among male college graduates in Norway in the 1980s was due to changes in the age composition. Moreover, the third column in the second row estimates that the mean log earnings in 1980 would have been 3,5 log points higher with the 1990 age composition. This basically supports our claim, but proposes that changes in the age composition actually are accountable for about 60 percent of the mean earnings increase.

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[6] $1 - e^{0,365} = 0,44$

We see from Panel D that these results look much like the results reported in Panel C. Consequently, it seems like changes in the field of study composition did not have a significant impact on the increase in the mean earnings, even when we look at the effect of the field of study composition in combination with the age composition. We can therefore conclude that the only significant effects we find of the workforce composition on the mean earnings are through the age composition. This effect was largest in the 1980s.

We next turn attention to how much the cross-country difference in the composition of field of study and age can explain of the difference in the observed levels and trends of the mean log earnings, focusing on Norway and the US. In Table 3 and 4, we investigate to what extent these compositional differences can explain the lower mean earnings among college educated males in Norway compared to the US.

The first two columns in Panel A of Table 3 display the difference between the actual mean log earnings for college graduates among Norwegian working men in year *t* and the counterfactual, measuring the mean earnings that would have prevailed if the returns to fields of study were as in Norway, but the field of study composition was like in the US, in year *s* (1989 and 2003), thus obtained by implementing the first term on right hand side in Equation (4). The last two columns show the difference between these counterfactuals, and actual US mean log earnings among college graduates, thus obtained by implementing the last term in Equation (4). Likewise, the first two columns in Panel B shows the difference between the actual mean log earnings in Norway, and the counterfactual, measuring the mean earnings that would have prevailed if the returns to age were as in Norway, but the age composition was like in the US. The last two columns show the difference between these counterfactuals, and actual US mean log earnings among college graduates. Further, Panel C basically displays the same, but here the counterfactual mean earnings are constructed with the Norwegian returns to age-field groups and the US age-field composition.

In Panel A of Table 3 the absolute value of the numbers in the two left hand side columns are much lower than the corresponding numbers in the two right hand side columns. This indicates that a very small proportion of the mean earnings difference between the two countries is due to differences in the field of study composition. For example, the numbers in the first and third columns in the third row (-1 and -55,2) indicate that less than one fiftieth of the differences in the college mean earnings in the two countries around 1990 was due to distinctions in the field of study composition. Nevertheless, all the numbers in the first two columns are negative, indicating that the Norwegian mean earnings would have been higher with the US field of study composition. The numbers in Panel B and C tell a similar story; Differences in the age composition do not seem to be an important factor to explain the mean earnings differences between the two countries, either in isolation or in combination with differences in the field composition. The absolute values in the left hand side columns are still much lower than the corresponding numbers on the right hand side. Nevertheless, all the numbers in the first two columns are also here negative, indicating that the Norwegian mean earnings would have been higher with the US age composition. In the last two panels, the left hand side values in the first two rows are quite large compared to the other left hand side numbers. This is due to the relatively low mean age among Norwegian college graduates these years (1970 and 1980).

In the first four columns in Table 4 we examine the difference between the actual mean log earnings for college graduates among US working men in year *s*, and counterfactual mean earnings constructed with US cell specific mean earnings, and the Norwegian workforce's cell composition in year *t*. The four right hand side columns show the difference between these counterfactuals and actual Norwegian mean log earnings among male college graduates. Like in Table 3, the cells are divided by field of study in Panel A, age in Panel B, and field of study *and* age in Panel C.

The main impression is also here that the workforce's composition has a minor impact on the difference in average earnings. Some additional points could however be noted: Seven of the eight numbers in the left hand side columns in Panel A are negative, implying that the mean earnings in the US these years would have been higher with the Norwegian field of study composition. This could seem counterintuitive when remembering the negative signs in the corresponding panel for Norway (Panel A in Table 3). This is however due to the higher fraction of science educated men in Norway (Figure 8 and 9), and the fact that these earn considerably more on average than business educated men (Figure 6) in the US, while there are relatively more business educated men in the US than in Norway, and these have the highest mean earnings in Norway. The positive signs in the left hand side columns in Panel B indicates that the US mean earnings would have been lower with the Norwegian age composition; again a result of the lower Norwegian mean age.

5.4 Decomposed Changes in the Log Earnings Variance

We will now investigate to what extent the composition of field of study and age, and the returns to these, where affecting the development in the log earnings dispersion among Norwegian college educated working men between 1970 and 2001. As we saw in Figure 2, the variance of log earnings in this group fell rapidly in the 1970s and grew steadily throughout the next two decades. We find that changes to the residual variance were the driving force behind the development in the variance. In the 1970s however, changes to the returns to field of study counteracted the decrease, while changes to the field-age composition seem to have contributed significantly. Further, changes to the return to experience counteracted the increase in the 1980s, while changes in the return to field of study contributed significantly to the increase in the variance in the 1990s. Changes to the field of study composition, however, do not seem to be an important factor behind the evolution of the log earnings variance.

Table 5 reports estimation results that are obtained by implementing the decomposition procedure described in Section 3.2. The first column in the table displays the difference between the actual year *t* variance, and the measure of the counterfactual variance that would have prevailed in period *t* if the distribution of workers to the cells was as in period *s*, thus obtained by implementing Equation (9). The numbers in this column hence represents the changes to the variance between year *t* and year *s* that where caused by changes to the workforce composition. The second column presents the difference between this counterfactual variance, and the estimate of the variance that would have prevailed in period *t*, if both the distribution of workers to the cells and the cell mean earnings were as in period *s* thus obtained by implementing Equation (10). This column hence represents the change to the variance between year *t* and year *s* that was caused by changes to the cells' mean earnings. The last column presents the difference between this last counterfactual variance and the actual year *s* variance, and therefore shows the changes in the residual variance between the two years, thus obtained by implementing Equation (11). The fourth (*t*=1980, *s*=1970), eighth (*t*=1990, *s*=1980) and twelfth (*t*=2001, *s*=1990) row in each panel (A, B, C) capture our attention in particular as these show the effect of changes to the cell's composition, return and residual variance in each decade. When making Panel A, the cells where characterised by the nine fields of study. In Panel B we used the seven age groups, and in Panel C the sample was divided into the 63 age-field groups. The results in the table are measured in log points.

The fourth row in Panel A in Table 5, for example, suggests that the 1980 variance would decrease by 0,03 log points if the workforce's field of study composition was as in 1970. If the returns to field of study also stayed at the 1970 level, the variance would have been 0,41 additional log points lower in 1980. The third column, however, suggests that the residual variance was 3,33 log points higher in 1970 than in 1980. We therefore conclude that changes to the residual variance were driving the steep decrease in the log earnings variance in the 1970s, while changes to the composition and returns to field of study actually had a counteracting effect. The signs to the numbers in the first row support this claim (they are opposite of the corresponding numbers in the fourth row. For example, the number in the first column (-0,08) suggests that the 1970 variance would have increased by 0,08 log points if the field of study composition was changed to the 1980 level). The absolute values of the numbers in the first column in Panel A are relatively low compared to the numbers in the second and especially the third column, suggesting that changes to the field of study composition were not the driving force behind the changes in the log earnings variance. Further, the overall relatively high numbers in the third row suggest that changes to the residual variance were in fact driving the development. However, the development towards 2001 is one exception. The numbers in the last tree rows (where *t*=2001) in the second column are positive and relatively large, while the numbers in the second column where *s*=2001 are negative and have relatively high absolute values compared to the third column. In particular, in the ninth and twelfth row, the second column numbers are almost three times as large as the numbers in the third columns. This suggests that the return to field of study was driving the increase in the variance in the 1990s.

In Panel B we explore the impact of the age composition on the variance. The immediate impression of the first column is that the absolute value of these numbers are larger than corresponding numbers in the above panel, suggesting that the age composition was more influential in the evolution of the variance than the field composition. For example, the numbers in the fourth row suggest that 0,37 log points out of the 2,90 log points[7] decrease in variance in the 1970s was due to changes in the age composition. Corresponding numbers for the 1980s and the 1990s are respectively 0,20 out of an 0,84 log points increase (eighth row) and -0,06 log points out of a total 1,12 log points increase (twelfth row).

We further examine the second column of Panel B, to investigate the impact of the return to experience (age) on the inequality. The numbers when t = 1970 or 1980, and s = 1990 or 2001 are large and positive, while the numbers when t = 1990 or 2001, and s = 1970 or 1980 are large and negative. This suggests that changes to the return of experience in the 1980s had a large limiting effect on the growth in the variance. In particular, the number in the eighth row, -1,02, suggests that the 0,84 log points increase in variance in the 1980s, would have been 1,02 log points higher if it was not for the changes to the experience premium. Without this effect, the development in the log earnings dispersion among college graduates in the 1980s would resemble more closely the steep increase in the dispersion among workers without college in this decade (Figure 3). The result implies a reduction in the age premium in the 1980s which could be caused e.g. by the introduction of new technology (computers) favouring younger cohorts. It further seems reasonable that the usage of computers rose significantly in this decade, and that there is no advantage of being older when learning how to use it.

Our conclusions above, and the fact that the absolute values of the numbers in the third column seems fairly large, support our claim that changes to the residual variance were driving the decrease in the variance in the 1970s, and the increase in the 1980s and 1990s.

Panel C presents the impact of changes to the age-field composition, and the return to age-field groups on the variance. The overall impression from this panel is that the combined effect of changes to the field of study and age composition is not close to the *sum* of the two effects. The impact of returns to and composition of field of study is thus significantly affected by the age composition. Our previous conclusions seem nevertheless to still be valid. The difference between the summed effect and the combined effect is largest when comparing

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[7] The negative value of the sum of the numbers in the row: - ((-0,37) + (-0,16) + (-2,37))

1970 and 1990. Looking at the seventh row in the three panels in Figure 5, we realise that the isolated effect of the changes to the field and age composition is quite low (-0,05 and 0,03 log points), while the combined effect (-0,61 log points) could explain almost one third of the 2,06 log points decrease in variance between the two years. This could for instance be because mean age grew in fields where the variance grew the least with age.

When comparing measures in the fourth, eighth and twelfth row, however, we still find that changes to the residual variance were the driving force behind the development in the variance (the absolute values of the numbers in the third column are by far the largest). In the 1970s, changes to the returns to field of study counteracted the decrease (0,43 log points), while changes to the field-age composition seem to have contributed significantly, mostly through the age composition (0,51 log points out of the 2,90 log points total change). Further, changes to the return to experience counteracted the increase in the 1980s, while changes in the return to field of study contributed significantly to the increase in the variance in the 1990s. Changes to the field of study composition, however, do not seem to be an important factor behind the evolution of the log earnings variance, even in combination with changes to the age composition in each field.

6. Robustness Check

In this section, we investigate whether our results are influenced by the usage of log earnings rather than earnings. Tables 6-9 correspond to Tables 2-5, but the calculations in Tables 6-8 were made using earnings in levels, without taking logarithms. In Table 9 we have used earnings divided by the mean in each year, so the variance is not inflated by the overall growth in earnings. The numbers in Tables 6-8 now represents the differences between the actual and counterfactual mean earnings (in levels). The numbers in table 9 now represents the nominal difference in actual and counterfactual measures of the coefficient of variation (multiplied by 100). The conclusion from this section is that our previous conclusions hold, also when looking at earnings levels.

For example, Table 6 shows basically the same pattern as Table 2. We still find that changes in the field of study composition had a very limited impact on mean earnings, while changes in the age composition had a larger impact and could account for about 40 percent of the earnings increase in the 1980s (the same as in Table 2).

In Table 7 the absolute value of the numbers in the two left-hand columns are still much lower than the corresponding numbers in the two right-hand columns, still indicating that a very small proportion of the mean earnings difference between the two countries is due to differences in the field of study or age composition. In fact, all the right-hand side numbers are at least 15 times larger than the left-hand side numbers. All the numbers in the first two columns are still negative, indicating that the Norwegian mean earnings would have been higher with the US field of study or age composition.

The numbers in Table 8 also tell basically the same story as Table 3: US mean earnings would not be drastically altered by changing to the Norwegian field of study and age composition. Changing to the Norwegian age composition in 1970 or 1980 would however decrease the mean earnings in 1989 and 2003 significantly; the workforces mean age grew significantly in the 1980s in both countries, and are larger in the US sample than in the Norwegian for all years.

Table 9 shows basically the same as Table 5. For example, the overall relatively high numbers in the third row suggest that changes to the residual variance were in fact driving the development in the variance. Some differences between the two tables could however be noted. In the twelfth row in Panel A in Table 5, the second column number is almost three times as large as the number in the third column, thus suggesting that changes to the return to field of study was driving the increase in the variance in the 1990s. This result is less clear in Panel A in Table 9. Now the second column number is about 40 percent smaller than the number in the third column, still however holding changes to the return to field of study responsible for a large share of the development in the 1990s. In the eighth row in Panel B in Table 9, we see that changes to the return to age in the 1980s, still has a large limiting effect on the growth in the variance. In contrast to Table 5, however, the first column in Panel B in Table 9 suggests that changes to the composition of age had a large contributing effect to the merged effects in the 1980s, offsetting the effect of changes in return to age. In the twelfth row in Panel C in Table 9, we see that changes to the return to age-field groups in the 1990s seems to have had a significant (about 30 percent) impact on the evolution (even though the partial effect of field of study and age are low).

7. Conclusion

Earnings inequality among men and the return to higher education have increased substantially in most of the OECD countries since the 1980s (Gottschalk and Smeeding, 1997). An important part of the change in earnings inequality in the US has been linked to the lasting growth in the college/high school earnings premium, but this does not explain the increased earnings dispersion among workers with the same years of schooling. However, years of schooling is a biased measure of skill if the composition of individuals with the same years of schooling differs along an unobserved dimension determining their earnings, such as field of study. We argue that changes in the composition of field of study in the workforce and changes to the returns to field of study, may affect the observed trends in the returns to education as well as the within-group dispersion of earnings.

Further, the fact that many European countries and the US have experienced rather different trends in earnings inequality (Gottschalk and Smeeding, 1997) undermines the explanation that the return to skills is increasing because of growth in the demand for skills caused by skill-biased technological change, since these countries should have experienced similar technological changes. We argue that differences in the field of study composition between countries could potentially explain these cross-country differences.

We use a decomposition method based on the one introduced by Oaxaca (1973) and Blinder (1973) to produce counterfactual measures such as “how much would a worker, with the mean characteristics of the Norwegian workforce, have been paid in the US?”, or “what would the variance of earnings have been if returns to age and education was as in 1980, but the composition of the workforce’s age and education were as in 1990?”. These counterfactuals are compared to actual or other counterfactual measures, to give an impression of the significance of the field of study compositions to these measures.

We examine the effect of differences in the field of study composition between Norway and the US on the mean earnings among working male college graduates. We further examine the effect in Norway between different years. In addition to looking at the field of study effect in particular, we explore the effect in combination with the effect of changes in the age composition. We find that the field of study composition has an almost insignificant impact on the mean earnings, both across time and countries. The age composition, however, has a large impact on the mean earnings. In particular, 40 percent of the mean earnings increase among Norwegian male college graduates in the 1980s could be accounted for by changes in the age composition.

We further explore the effect of changes in the field of study and age composition on the variance of the log earnings in Norway, and the effect of changes in the returns to field of study and age. We find that the variance of log earnings among working Norwegian male college graduates fell drastically in the 1970s and increased in the two succeeding decades, and that changes to the residual variance were the driving force behind this development, rather than changes to the composition or return to field of study or age. In the 1970s, changes to the returns to field of study counteracted the decrease, while changes to the age composition seem to have contributed significantly to the decrease. Further, changes to the return to experience counteracted the increase in the 1980s, while changes in the return to field of study contributed significantly to the increase in the variance in the 1990s. Changes to the field of study composition, however, do not seem to be an important factor behind the evolution of the log earnings variance.

The effects on the college premium and log earnings variance of differences in the field of study and age composition across time in the US will be examined in a future project, using the decomposition procedure proposed by DiNardo, Fortin and Lemieux (1996). The procedure applies kernel density methods to appropriately weighted samples to make counterfactual earnings distributions. We will further look at compositional changes among master graduates, and among higher educated women in Norway and the US, to see whether these differences can explain the observed differences in the earnings distributions between countries, years and genders.

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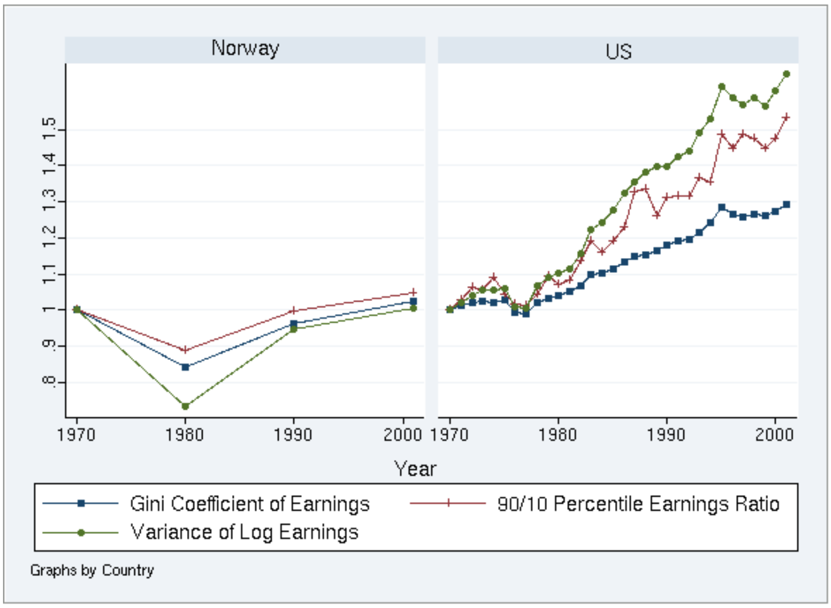
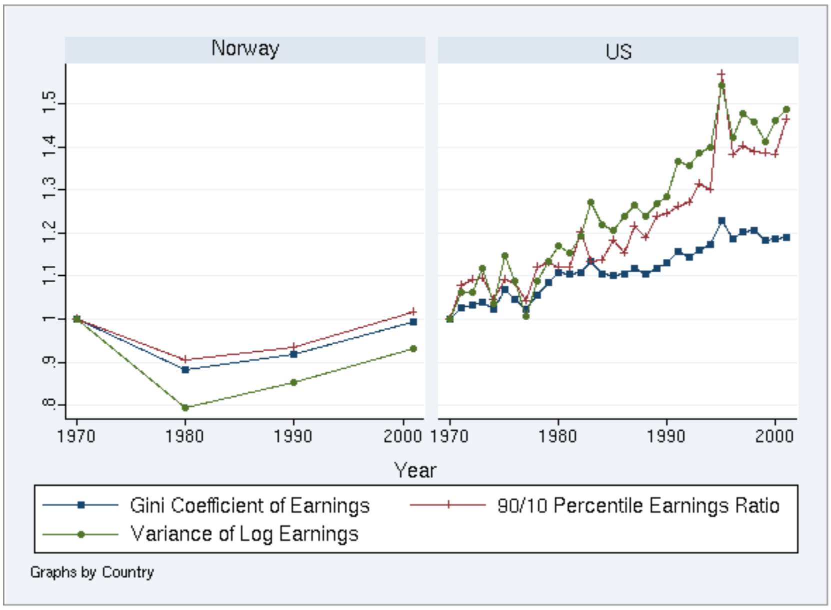
Figure 1: Earnings Inequality and Dispersion among Men



Source:
USA: March Current Population Survey data.
Norway: Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time, not self employed workers, earning more than 10000 USD. The measures have been normalized to one in 1970.

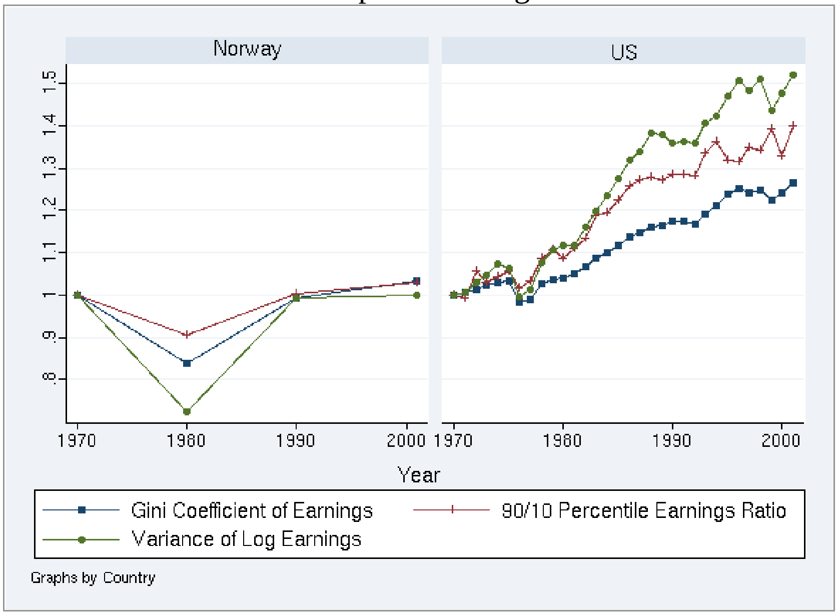
Figure 2: Within Group Earnings Inequality and Dispersion among Male College Graduates



Source:
USA: March Current Population Survey data.
Norway: Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed college graduates, earning more than 10000 USD. The measures have been normalized to one in 1970.

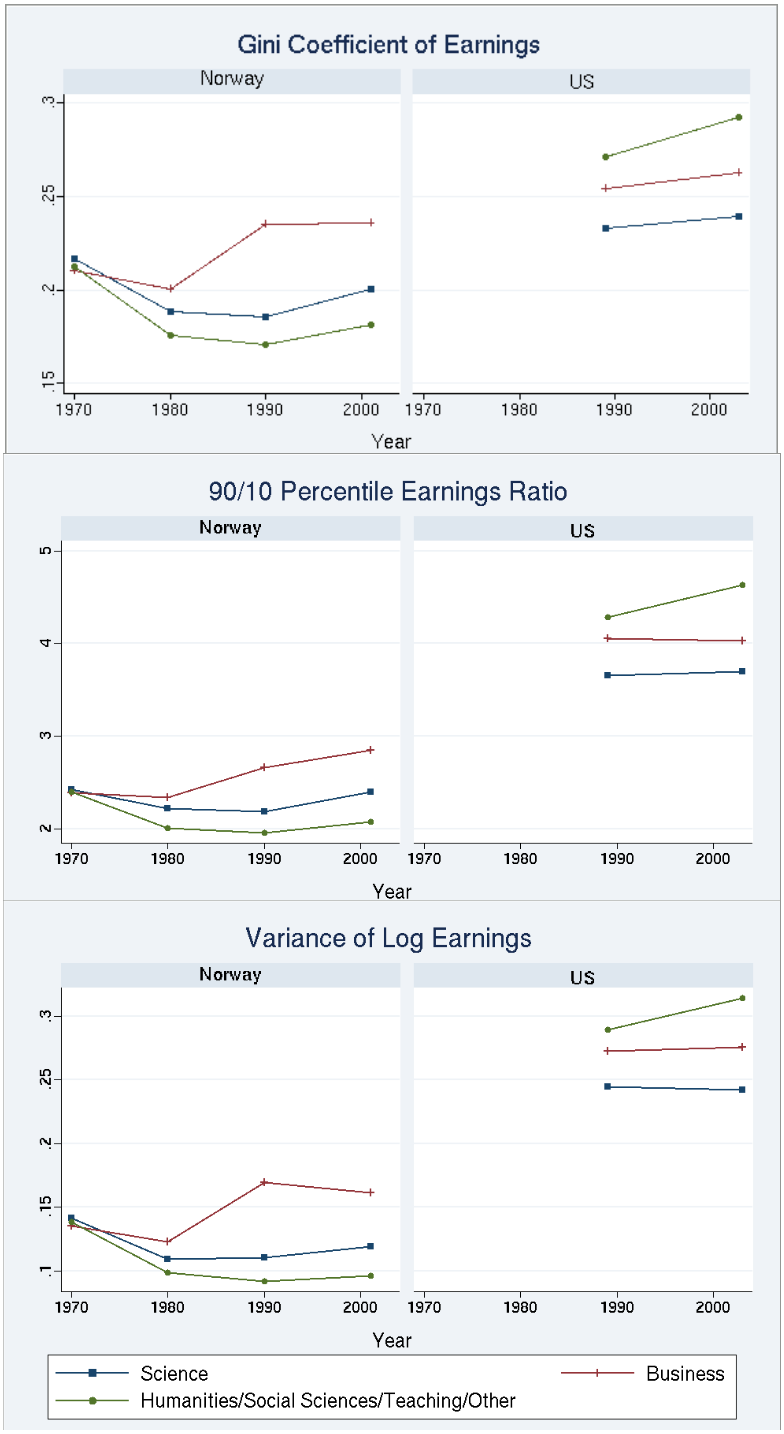
Figure 3: Within Group Earnings Inequality and Dispersion among Men without Completed College



Source:
USA: March Current Population Survey data.
Norway: Administrative registers from Statistics Norway.

Note: Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time, not self employed workers who have not completed college, earning more than 10000 USD. The measures have been normalized to one in 1970.

Figure 4: Earnings Inequality and Dispersion by College Fields of Study, among Men.

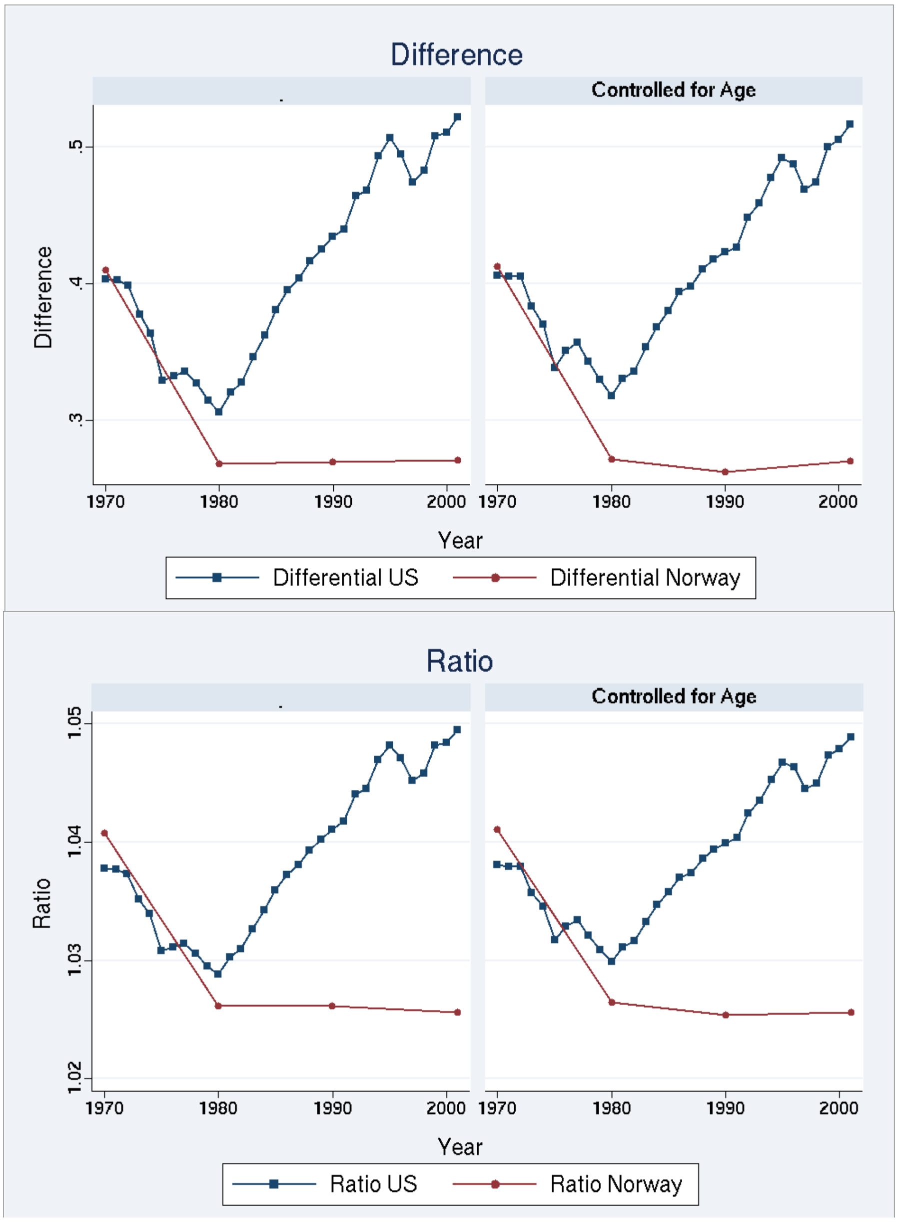


Source:
USA: National Survey of College Graduates.
Norway: Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed college graduates, earning more than 10000 USD.

The field for each person is the field in which the person have achieved the highest grade, by the survey year (1993 and 2003) in the US data, and by the fall of 2007 in the Norwegian data. The science fields also include engineering and medicine, the humanities fields also include law.

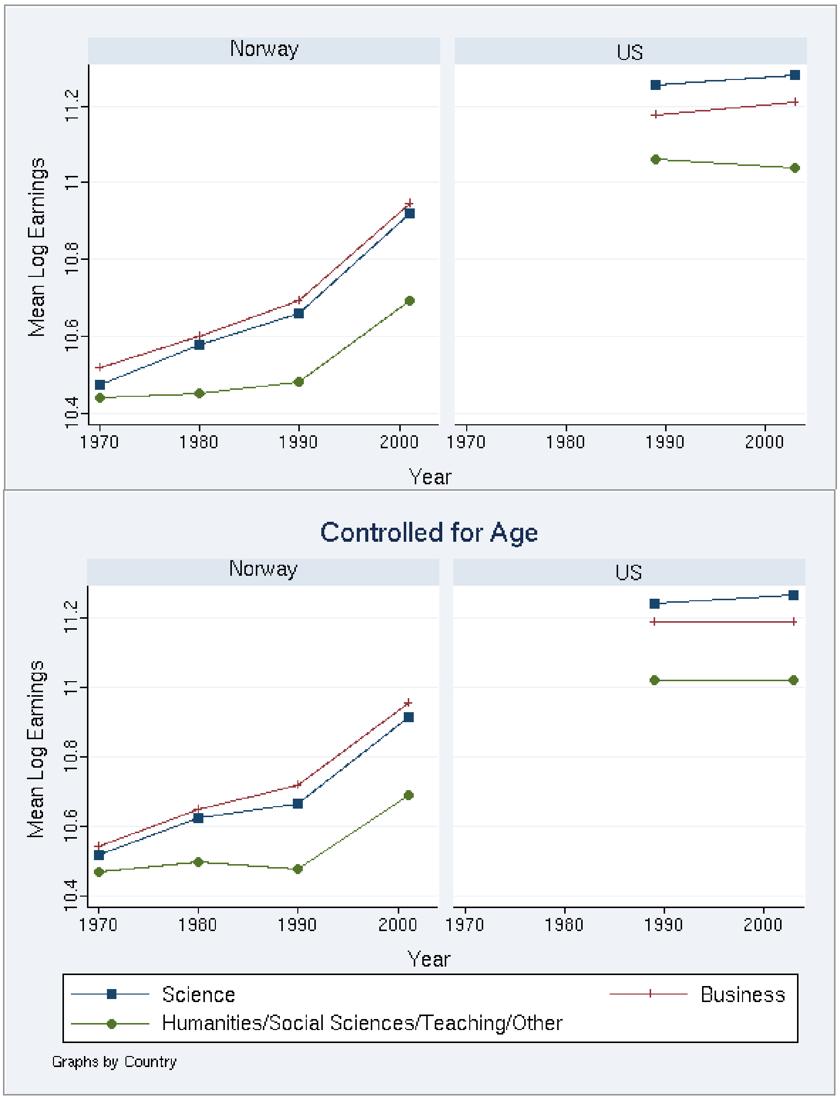
Figure 5: Log Earnings Differentials between Men with and without Completed College



Source:
USA: March Current Population Survey data.
Norway: Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time, not self employed workers, earning more than 10000 USD.

Figure 6: Mean Log Earnings by College Field among Men

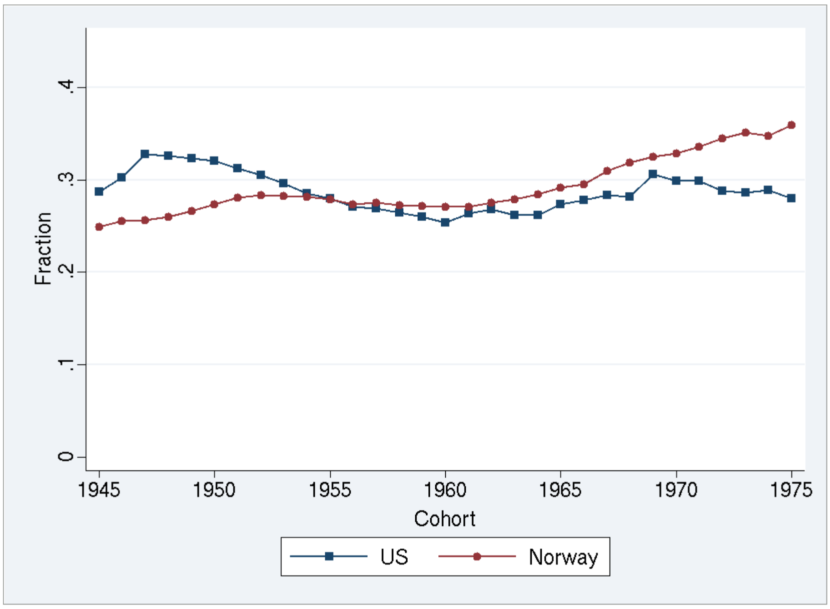


Source:
USA: National Survey of College Graduates.
Norway: Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed, college graduates, earning more than 10000 USD.

The field for each person is the field in which the person has achieved the highest degree, by the survey year (1993 and 2003) in the US data, and by the fall of 2007 in the Norwegian data. The science field also includes engineering and medicine. The humanities field also includes law.

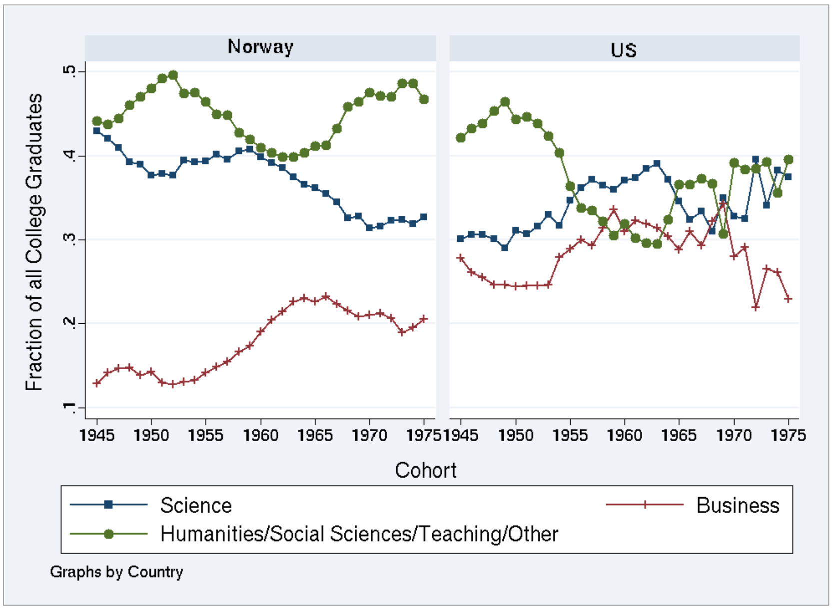
Figure 7: Fraction of Male College Graduates in Cohorts



Source:
USA: March Current Population Survey data.
Norway: Administrative registers from Statistics Norway.

Note:
Norwegian data covers the entire male population. US statistics calculated using sample weights (made consistent across survey years). The sample consists of men who are at least 26 years of age in the year the data was collected.

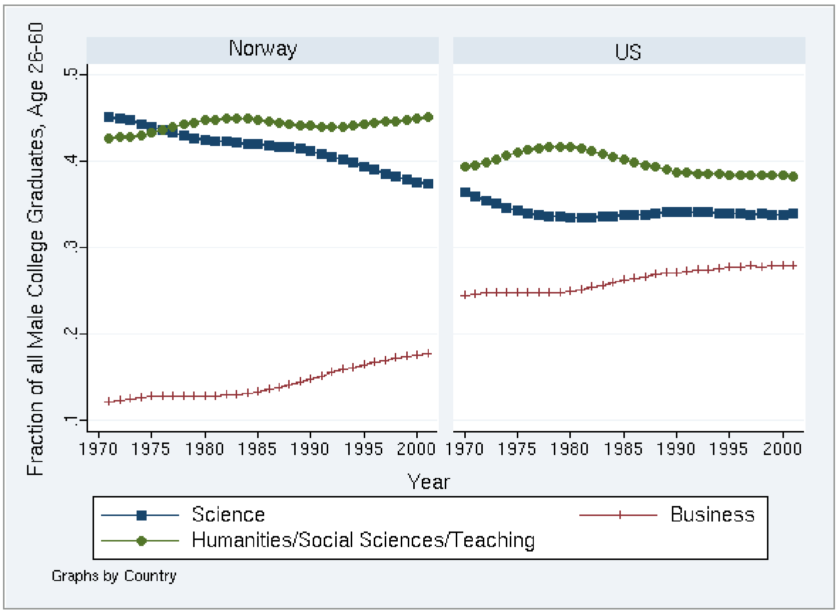
Figure 8: Field of Study Composition by Cohort among Male College Graduates



Source:
USA: National Survey of College Graduates.
Norway: Administrative registers from Statistics Norway.

Note:
The field for each person is the field in which the person has achieved the highest degree, by the survey year (1993 and 2003) in the US data, and by the fall of 2007 in the Norwegian data. The science field also includes engineering and medicine. The humanities field also includes law. US statistics calculated using sample weights. The sample consists of male college graduates who are at least 26 years of age in the year the data was collected.

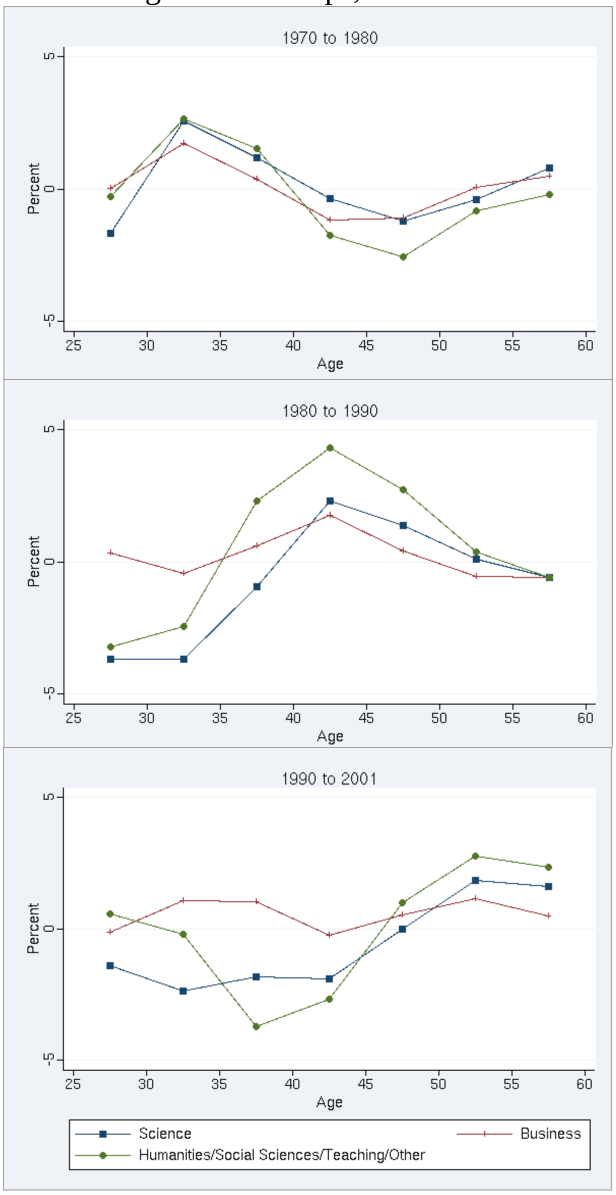
Figure 9: Field of Study Composition by Year among Male College Graduates



Source:
USA: National Survey of College Graduates.
Norway: Administrative registers from Statistics Norway.

Note:
The graph shows the number of men with different college fields, as a fraction of all male college graduates, age 26-60, each year. The field for each person is the field in which the person has achieved the highest grade, by the survey year (1993 and 2003) in the US data, and by the fall of 2007 in the Norwegian data. The science field also includes engineering and medicine. The humanities fields also include law. US statistics calculated using sample weights.

Figure 10: Difference in the Percentage of Norwegian Working Male College Graduates in Various Age-Field Groups, from Year to Year



Source:
Administrative registers from Statistics Norway.

Note:
The sample consists of 26 to 60 years old, full time working and not self employed Norwegian men.

Table 1: Fraction of Workers with Top Coded Earnings in the NSCG (US), by Field of Study

Field of Study	1989	2003
Science	0.106	0.119
Business	0.110	0.123
Humanities	0.078	0.088

Source:
National Survey of College Graduates.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed, college graduates, earning more than 10000 USD.

The field for each person is the field in which the person has achieved the highest degree by the survey year. The science field also includes engineering and medicine. The humanities field also includes law.

Table 2: Difference between Actual and Counterfactual Mean Log Earnings for Norwegian Male College Graduates (Multiplied by 100)

A. Three Field of Study Cells

	$\overline{w}_t - \overline{w}_{ts}^c$				$\overline{w}_{ts}^c - \overline{w}_s$			
t | *s*	1970	1980	1990	2001	1970	1980	1990	2001
1970		-0,1	0,0	-0,2		-6,7	-12,6	-36,3
1980	**0,2**		0,4	0,3	**6,6**		-6,2	-30,1
1990	-0,3	**-0,6**		-0,1	12,9	**6,4**		-23,8
2001	-0,3	-0,7	**0,1**		36,8	30,4	**23,9**	

B. Nine Field of Study Cells

	$\overline{w}_t - \overline{w}_{ts}^c$				$\overline{w}_{ts}^c - \overline{w}_s$			
t | *s*	1970	1980	1990	2001	1970	1980	1990	2001
1970		0,1	0,2	0,1		-6,8	-12,8	-36,6
1980	**-0,1**		0,5	0,5	**6,9**		-6,4	-30,2
1990	-0,9	**-0,8**		-0,1	13,4	**6,6**		-23,8
2001	-0,4	-0,7	**0,1**		36,9	30,5	**23,8**	

C. Age Cells

	$\overline{w}_t - \overline{w}_{ts}^c$				$\overline{w}_{ts}^c - \overline{w}_s$			
t | *s*	1970	1980	1990	2001	1970	1980	1990	2001
1970		0,5	-2,8	-3,9		-7,3	-9,7	-32,6
1980	**-1,0**		-3,5	-4,8	**7,8**		-2,3	-25,0
1990	1,8	**2,4**		-0,7	10,8	**3,4**		-23,2
2001	1,9	2,4	**0,2**		34,5	27,4	**23,8**	

D. Age-Field Cells

	$\overline{w}_t - \overline{w}_{ts}^c$				$\overline{w}_{ts}^c - \overline{w}_s$			
t | *s*	1970	1980	1990	2001	1970	1980	1990	2001
1970		0,4	-2,7	-3,6		-7,2	-9,8	-32,9
1980	**-1,2**		-3,1	-4,5	**8,0**		-2,7	-25,3
1990	1,2	**2,0**		-1,1	11,3	**3,8**		-22,8
2001	2,2	2,6	**1,1**		34,3	27,2	**22,9**	

Source:
Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed college graduates, earning more than 10000 USD.

The workers are divided into the seven five-years-interval age groups from age 26 to 60. They are also divided into three field of study main groups (science/engineering/medicine, business/law and humanities/social sciences/teaching/other), and nine field of study sub groups (humanities, teaching, social sciences, business, law, science/engineering, female, medicine and other). The field for each person is the field in which the person has achieved the highest degree by the fall of 2007.

Table 3: Difference between Actual and Counterfactual Norwegian Mean Log Earnings (Multiplied by 100)

A. Field of Study Cells

	$\overline{w}_t - \overline{w}_{ts}^c$		$\overline{w}_{ts}^c - \overline{w}_s$	
t | *s*	1989	2003	1989	2003
1970	-0,7	-0,8	-68,1	-69,4
1980	-0,3	-0,5	-61,7	-63,0
1990	**-1,0**	-1,2	**-55,2**	-56,4
2001	-1,0	**-1,3**	-31,3	**-32,4**

B. Age Cells

	$\overline{w}_t - \overline{w}_{ts}^c$		$\overline{w}_{ts}^c - \overline{w}_s$	
t | *s*	1989	2003	1989	2003
1970	-5,3	-5,3	-63,5	-64,9
1980	-6,0	-6,2	-56,0	-57,3
1990	**-1,7**	-1,7	**-54,5**	-55,9
2001	-1,1	**-0,8**	-31,2	**-32,9**

C. Age-Field Cells

	$\overline{w}_t - \overline{w}_{ts}^c$		$\overline{w}_{ts}^c - \overline{w}_s$	
t | *s*	1989	2003	1989	2003
1970	-5,9	-5,7	-62,9	-64,5
1980	-6,5	-6,9	-55,5	-56,5
1990	**-3,2**	-3,5	**-53,0**	-54,1
2001	-2,0	**-2,3**	-30,3	**-31,4**

Source:
USA: National Survey of College Graduates.
Norway: Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed, college graduates, earning more than 10000 USD.

The workers are divided into the seven five-years-interval age groups from age 26 to 60, and three (science/engineering/medicine, business/law and humanities/social sciences/teaching/other) field of study groups. The field for each person is the field in which the person has achieved the highest degree, by the survey year (1993 and 2003) in the US data, and by the fall of 2007 in the Norwegian data.

Table 4: Difference between Actual and Counterfactual US Mean Log Earnings (Multiplied by 100)

A. Field of Study Cells

	$\overline{w}_s - \overline{w}^c_{st}$				$\overline{w}^c_{st} - \overline{w}_t$			
s | t	1970	1980	1990	2001	1970	1980	1990	2001
1989	-1,5	-1,7	**-0,9**	-0,6	70,2	63,7	**57,1**	32,9
2003	-0,8	-1,1	-0,2	**0,1**	71,0	64,6	57,8	**33,5**

B. Age Cells

	$\overline{w}_s - \overline{w}^c_{st}$				$\overline{w}^c_{st} - \overline{w}_t$			
s | t	1970	1980	1990	2001	1970	1980	1990	2001
1989	7,8	9,2	**3,6**	0,9	61,0	52,8	**52,6**	31,4
2003	4,3	4,8	1,2	**1,0**	65,9	58,6	56,4	**32,7**

C. Age-Field Cells

	$\overline{w}_s - \overline{w}^c_{st}$				$\overline{w}^c_{st} - \overline{w}_t$			
s | t	1970	1980	1990	2001	1970	1980	1990	2001
1989	2,6	2,8	**0,1**	-0,1	66,1	59,2	**56,1**	32,4
2003	9,0	10,4	5,2	**2,6**	61,2	53,1	52,4	**31,1**

Source:
USA: National Survey of College Graduates.
Norway: Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed, college graduates, earning more than 10000 USD.

The workers are divided into the seven five-years-interval age groups from age 26 to 60, and three (science/engineering/medicine, business/law and humanities/social sciences/teaching/other) field of study groups. The field for each person is the field in which the person has achieved the highest degree, by the survey year (1993 and 2003) in the US data, and by the fall of 2007 in the Norwegian data.

Table 5: Differences between various measures of Actual and Counterfactual Variances of log Earnings among Norwegian Male College Graduates (Multiplied by 100)

A. Field of Study Cells

t	s	$V_t - V_{ts}^a$	$V_{ts}^a - V_{ts}^b$	$V_{ts}^b - V_s$
1970	1980	-0,08	-0,46	3,44
	1990	-0,08	-0,40	2,54
	2001	0,00	-1,06	2,00
1980	1970	**0,03**	**0,41**	**-3,33**
	1990	-0,04	0,07	-0,87
	2001	-0,08	-0,66	-1,21
1990	1970	-0,05	0,35	-2,36
	1980	**-0,01**	**-0,10**	**0,95**
	2001	-0,27	-0,63	-0,21
2001	1970	0,12	1,11	-2,17
	1980	0,08	0,63	1,24
	1990	**0,07**	**0,75**	**0,29**

B. Age Cells

t	s	$V_t - V_{ts}^a$	$V_{ts}^a - V_{ts}^b$	$V_{ts}^b - V_s$
1970	1980	0,17	0,16	2,56
	1990	0,45	0,90	0,71
	2001	0,35	1,15	-0,55
1980	1970	**-0,37**	**-0,16**	**-2,37**
	1990	0,03	0,87	-1,73
	2001	-0,16	1,14	-2,93
1990	1970	0,03	-1,27	-0,82
	1980	**0,20**	**-1,02**	**1,66**
	2001	0,02	0,24	-1,38
2001	1970	0,28	-1,60	0,37
	1980	0,51	-1,29	2,73
	1990	**-0,06**	**-0,21**	**1,39**

C. Age-Field Cells

t	s	$V_t - V_{ts}^a$	$V_{ts}^a - V_{ts}^b$	$V_{ts}^b - V_s$
1970	1980	0,17	-0,44	3,17
	1990	0,62	-0,13	1,57
	2001	0,65	-0,47	0,76
1980	1970	**-0,51**	**0,43**	**-2,81**
	1990	0,20	0,51	-1,55
	2001	-0,05	0,06	-1,97
	1970	-0,61	-0,17	-1,28

1990	1980	**-0,17**	**-0,63**	**1,64**
	2001	-0,26	-0,30	-0,55
	1970	0,12	-0,07	-0,99
2001	1980	0,41	-0,40	1,95
	1990	**0,10**	**0,39**	**0,62**

Source:
Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed college graduates, earning more than 10000 USD.

The workers are divided into the seven five-years-interval age groups from age 26 to 60, and nine (humanities, teaching, social sciences, business, law, science/engineering, female, medicine and other) field of study groups. The field for each person is the field in which the person has achieved the highest degree by the fall of 2007.

Table 6: Difference between Actual and Counterfactual Mean Earnings for Norwegian Male College Graduates (Multiplied by 100)

A. Three Field of Study Cells

	$\overline{w}_t - \overline{w}_{ts}^c$				$\overline{w}_{ts}^c - \overline{w}_s$			
t | s	1970	1980	1990	2001	1970	1980	1990	2001
1970		-26	-3	-62		-1953	-4541	-16387
1980	**80**		160	116	**1899**		-2726	-14587
1990	-95	**-217**		-109	4640	**2783**		-11796
2001	-91	-280	**101**		16540	14751	**11803**	

B. Nine Field of Study Cells

	$\overline{w}_t - \overline{w}_{ts}^c$				$\overline{w}_{ts}^c - \overline{w}_s$			
t | s	1970	1980	1990	2001	1970	1980	1990	2001
1970		6	77	49		-1984	-4622	-16498
1980	**-59**		199	152	**2038**		-2765	-14622
1990	-384	**-339**		-108	4928	**2905**		-11797
2001	-196	-344	**105**		16645	14815	**11799**	

C. Age Cells

	$\overline{w}_t - \overline{w}_{ts}^c$				$\overline{w}_{ts}^c - \overline{w}_s$			
t | s	1970	1980	1990	2001	1970	1980	1990	2001
1970		231	-1 007	-1 450		-2210	-3538	-14999
1980	**-488**		-1 414	-1 984	**2467**		-1152	-12486
1990	774	**1 043**		-306	3771	**1523**		-11599
2001	1 127	1 415	**78**		15323	13056	**11826**	

D. Age-Field Cells

	$\overline{w}_t - \overline{w}_{ts}^c$				$\overline{w}_{ts}^c - \overline{w}_s$			
t | s	1970	1980	1990	2001	1970	1980	1990	2001
1970		196	-930	-1 255		-2 175	-3 615	-15 194
1980	**-606**		-1 213	-1 834	**2 585**		-1 353	-12 636
1990	380	**816**		-544	4 165	**1 750**		-11 361
2001	1 205	1 525	**607**		15 244	12 946	**11 298**	

Source:
Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed college graduates, earning more than 10000 USD.

The workers are divided into the seven five-years-interval age groups from age 26 to 60. They are also divided into three field of study main groups (science/engineering/medicine, business/law and humanities/social sciences/teaching/other), and nine field of study sub groups (humanities, teaching, social sciences, business, law, science/engineering, female, medicine and other). The field for each person is the field in which the person has achieved the highest degree by the fall of 2007.

Table 7: Difference between Actual and Counterfactual Norwegian Mean Earnings

A. Field of Study Cells

	$\overline{w}_t - \overline{w}^c_{ts}$		$\overline{w}^c_{ts} - \overline{w}_s$	
t | *s*	1989	2003	1989	2003
1970	-253	-282	-41 157	-42 565
1980	-173	-254	-39 258	-40 614
1990	**-643**	-768	**-36 224**	-37 535
2001	-680	**-871**	-24 281	**-25 527**

B. Age Cells

	$\overline{w}_t - \overline{w}^c_{ts}$		$\overline{w}^c_{ts} - \overline{w}_s$	
t | *s*	1989	2003	1989	2003
1970	-1 919	-1 957	-39 491	-40 889
1980	-2 449	-2 557	-36 982	-38 311
1990	**-737**	-715	**-36 130**	-37 588
2001	-654	**-467**	-24 307	**-25 931**

C. Age-Field Cells

	$\overline{w}_t - \overline{w}^c_{ts}$		$\overline{w}^c_{ts} - \overline{w}_s$	
t | *s*	1989	2003	1989	2003
1970	-2 131	-2 104	-39 279	-40 743
1980	-2 695	-2 957	-36 736	-37 911
1990	**-1 617**	-1 792	**-35 249**	-36 512
2001	-1 296	**-1 499**	-23 664	**-24 899**

Source:
USA: National Survey of College Graduates.
Norway: Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed, college graduates, earning more than 10000 USD.

The workers are divided into the seven five-years-interval age groups from age 26 to 60, and three (science/engineering/medicine, business/law and humanities/social sciences/teaching/other) field of study groups. The field for each person is the field in which the person has achieved the highest degree, by the survey year (1993 and 2003) in the US data, and by the fall of 2007 in the Norwegian data.

Table 8: Difference between Actual and Counterfactual US Mean Earnings

A. Field of Study Cells

	$\overline{w}_s - \overline{w}_{st}^c$				$\overline{w}_{st}^c - \overline{w}_t$			
s | *t*	1970	1980	1990	2001	1970	1980	1990	2001
1989	-814	-979	**-446**	-232	42 224	40 410	**37 313**	25 193
2003	-448	-658	-26	**174**	43 295	41 526	38 329	**26 223**

B. Age Cells

	$\overline{w}_s - \overline{w}_{st}^c$				$\overline{w}_{st}^c - \overline{w}_t$			
s | *t*	1970	1980	1990	2001	1970	1980	1990	2001
1989	5 188	6 392	**2 691**	475	36 222	33 039	**34 175**	24 486
2003	3 412	3 868	1 229	**863**	39 434	37 000	37 075	**25 535**

C. Age-Field Cells

	$\overline{w}_s - \overline{w}_{st}^c$				$\overline{w}_{st}^c - \overline{w}_t$			
s | *t*	1970	1980	1990	2001	1970	1980	1990	2001
1989	5 028	6 107	**2 781**	609	36 382	33 324	**34 086**	24 352
2003	3 336	3 529	1 470	**1 085**	39 510	37 339	36 834	**25 313**

Source:
USA: National Survey of College Graduates.
Norway: Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed, college graduates, earning more than 10000 USD.

The workers are divided into the seven five-years-interval age groups from age 26 to 60, and three (science/engineering/medicine, business/law and humanities/social sciences/teaching/other) field of study groups. The field for each person is the field in which the person has achieved the highest degree, by the survey year (1993 and 2003) in the US data, and by the fall of 2007 in the Norwegian data.

Table 9: Differences between various measures of Actual and Counterfactual Variances Earnings (Divided by the Yearly Mean) among Norwegian Male College Graduates (Multiplied by 100)

A. Field of Study Cells

t	s	$V_t - V_{ts}^a$	$V_{ts}^a - V_{ts}^b$	$V_{ts}^b - V_s$
1970	1980	-0,06	-0,83	6,07
	1990	0,08	-0,66	5,08
	2001	0,23	-1,26	3,49
1980	1970	**-0,13**	**0,78**	**-5,83**
	1990	-0,02	0,17	-0,83
	2001	-0,32	-0,56	-1,84
1990	1970	-0,48	0,63	-4,66
	1980	**-0,18**	**-0,22**	**1,08**
	2001	-0,60	-0,54	-0,89
2001	1970	0,22	1,30	-3,97
	1980	0,15	0,46	2,10
	1990	**0,24**	**0,69**	**1,11**

B. Age Cells

t	s	$V_t - V_{ts}^a$	$V_{ts}^a - V_{ts}^b$	$V_{ts}^b - V_s$
1970	1980	0,34	-0,01	4,85
	1990	-0,51	0,76	4,25
	2001	-0,92	0,96	2,42
1980	1970	**-0,77**	**0,04**	**-4,44**
	1990	-0,86	0,89	-0,71
	2001	-1,62	1,11	-2,22
1990	1970	0,61	-1,06	-4,05
	1980	**1,00**	**-1,02**	**0,70**
	2001	-0,21	0,17	-2,01
2001	1970	0,99	-1,29	-2,16
	1980	1,48	-1,19	2,43
	1990	**0,09**	**-0,13**	**2,08**

C. Age-Field Cells

t	s	$V_t - V_{ts}^a$	$V_{ts}^a - V_{ts}^b$	$V_{ts}^b - V_s$
1970	1980	0,34	-1,03	5,87
	1990	-0,20	-0,51	5,21
	2001	-0,23	-0,82	3,51
1980	1970	**-1,20**	**1,11**	**-5,09**
	1990	-0,66	0,79	-0,81
	2001	-1,60	0,29	-1,42
1990	1970	-0,63	0,35	-4,22
	1980	**0,57**	**-0,90**	**1,01**

	2001	-0,79	-0,24	-1,01
	1970	1,02	0,27	-3,75
2001	1980	1,72	-0,73	1,73
	1990	**0,64**	**0,31**	**1,09**

Source:
Administrative registers from Statistics Norway.

Note:
Annual earnings are in 2007 USD. The earnings are top coded at 150000 USD. Statistics calculated using sample weights. The sample consists of 26 to 60 years old, full time working, not self employed college graduates, earning more than 10000 USD. Earnings divided by the yearly mean

The workers are divided into the seven five-years-interval age groups from age 26 to 60, and nine (humanities, teaching, social sciences, business, law, science/engineering, female, medicine and other) field of study groups. The field for each person is the field in which the person has achieved the highest degree by the fall of 2007.