THE EVOLUTION OF

WAGE INEQUALITY

IN POST COMMUNIST ROMANIA

By

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Abstract

This study analyzes the evolution of wage inequality in Romania over the period 1950-2000. During the 1960's there is a significant increase in inequality, mainly the result of industrialization policies which relied on wage differentials to induce labor reallocation. However, at the beginning of the 1970's the inequality measures drop, and for the next twenty years they stabilize at these low levels. The next big increase in inequality is brought by the wage and price liberalization at the beginning of the transition, specifically in 1991 and 1992. Although inequality subsided afterwards, in 1996-1997, a period that coincides with the actual commencement of reforms in Romania, inequality measures went up by almost 20%. Afterwards, the trend slowly reverses so that by 2000 inequality measures were lower than in 1994. During this period, I find that the evolution of wage inequality was largely driven by changes at the upper end of the wage distribution. The decomposition of wage inequality by sub-groups shows that inequality was higher among men, private sector workers and college graduates with more years of experience.

Acknowledgements

I would like to thank Prof. John Earle and Prof. Almos Telegdy for making labor classes fascinating and fun, for getting me interested in the field and thus making the experience of writing this study a positive one. I am grateful to Anton for his invaluable assistance with STATA programming, encouragements and useful feedback. My morale wouldn't have been so high during this period hadn't it been for Irakli, Gunes and my friends who always pretended that my findings are extremely interesting. Finally and most importantly, I would like to thank my parents for making it all happen.

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1. Introduction

The restructuring of the former communist economies was expected to lead to an increase in wage inequality as wages were freed from administrative control. In Romania, prior to the current reform period, both wages and the allocation of labor were heavily regulated by the State Planning Committee. Base wages were set by the Wage Law and varied primarily by industry, occupation and experience. To be able to meet the demands of a rapidly industrializing economy, education was tightly regulated as well, strongly emphasizing engineering and vocational training relevant to the development targets set by the Committee[1]. Consistent with communist egalitarian ideals, wages were compressed to such an extent that not only Romania, but other communist Central and Eastern European (CEE) countries as well, maintained the most equal distributions of income in the world. Even the Soviet Union, although to a lesser extent, registered a relatively egalitarian income distribution (Atkinson and Micklewright, 1992).

In this study, I use data from 1950 to 2000 to study the evolution of wage inequality in Romania. The availability of such long time series gives me the unique opportunity to follow changes in the wage structure long before the fall of communism and after the turbulent changeovers in the economic system. To the best of my knowledge, such a study has not been undertaken yet for Romania, and the findings will help understand better the Romanian transition experience. The persistence of high pay differentials has important policy implications, high wage inequality can lead to political instability, growth of informal economy and lower long run rates of economic growth as a result of a potential under-investment in human capital.

There have been a few studies that started to analyze wage inequality in transition countries (see J. Rutkowski, 1996, for an early period overview) and findings point towards an

[1] See Ben Ner and Montias (1991) for a detailed discussion of these aspects

increase in inequality, and in most cases the increases are comparable to those in OECD countries. For example, Garner and Terrell (1998) show that in the Czech and Slovak republics there has been only a moderate increase in inequality in the early years of transition, a rise that was dampened by social transfers. On the other hand, Keane and Prasad (2006) conclude there was a significant increase in inequality in Poland from 1988 to 1996, with the 90-10 percentile differential rising from 96 to 112 log points during the period. Orazem and Vodopivec (1995) analyze micro data from Slovenia and report that, from 1987 to 1991, wage inequality increased strikingly, with returns to both education and experience increasing over this period. In the particular case of Romania, Andren, Earle and Sapatoru (2004) estimate the impact of schooling on monthly earnings from 1950 to 2000, and find marked increases in returns to schooling during the 1990's.

In the former Soviet countries, using a longer panel, Lukyanova (2006) documents the changes in the Russian wage structure over the 1994-2000 period and finds that overall wage inequality stayed stable in 1994-1996, and then it jumped following the 1998 crisis and remained at higher levels for three years afterwards. Ganguli and Terrell (2005) use the Ukrainian Longitudinal Monitoring Survey to determine the extent to which the introduction of markets and new institutions affected men's and women's wage inequality between 1986 and 2003. They find that wage inequality rises substantially for both men and women.

Using data from the ILO, Freeman and Oostendorp (2000) have created the new Occupational Wages around the World file, and according to their findings, overall earnings inequality and skill differentials increased in transition economies during the 1980's and 1990's.

Most explanations for the growth in inequality have been attributed to the need of economic restructuring and resource reallocation. Wage differentials were expected to increase

in order to stimulate labor reallocation from less to more productive sectors, and the extent of these increases was related to the initial distortions. Therefore, initially wage inequality was predicted to be determined by industry or firm specific factors, and later to be determined mainly by differences in worker's human capital.

Several models of transition and earnings inequality have been developed in the literature. For instance, Aghion and Commander (1999) and Commander and Tolstopiatenko (1998) present models with a state and private sector. State sector firms have a zero-profit constraint and wages set to equal average product. Private sector firms behave competitively. Initial inequality within each sector is set exogenously in the model, and the authors assume a higher inequality in the private sector. The simulation of this model predicts higher inequality in transition for the following reasons: a) workers shift from the low inequality state sector to the higher inequality private sector, and b) mean wages are higher in the private sector (due to higher productivity). In several transition countries[2], this model fails to account for several key features of the data such as lower wages in the private sector, rising inequality within both sectors over time and specifically greater increase in inequality among the more educated.

Pinto et al. (1993), Commander and Dhar (1998) and others suggest that rising inequality in the state owned enterprises (SOE's) can be explained by modifying such a model to account for the restructuring of state owned enterprises in the absence of privatization. As the fraction of firms engaged in competitive wage setting grows (both through increases in the size of the private sector and restructuring of state firms), the relative demand for high skilled will increase in the economy as a whole.

Since rising returns to skill have been predominant phenomenona in transition countries, several models have provided explanations for this empirical regularity. As transition can be

[2] See for example Keane and Prasad (2006)

interpreted as a period of technical change in the sense of reorganization of SOE to achieve greater technical efficiency, models such as those of Acemoglu (1998) or Caselli (1999) explain rising returns to skill due to higher ability of more educated workers to adapt to rapid changes in production processes. Another aspect of rising returns to skill in transition is that returns to human capital, as measured by education premiums, increased significantly while returns to experience remained small. Low returns to experience appear consistent with the notion of rapid obsolescence of firm- or industry-specific skills during a period of rapid technological change and industrial restructuring (see Svejnar, 1996).

Increases in within group inequality, especially for highly educated workers, have been discussed in Galor and Moav (2000). In their model, rising returns to education increase within group inequality among the highly educated mainly through a compositional effect. They model human capital as being a function of innate ability as well as formal education, and assume it is costlier for low-ability individuals to acquire education. Technological progress that increases returns to education without affecting the return to innate ability leads some lower-ability individuals to invest in education, thereby widening the ability dispersion among educated workers. At the same time, dispersion is narrowed among the less educated. Keane and Prasad (2006) suggested that an alternative mechanism that lowers dispersion among less educated groups would be the exit from the labor force of these low-ability groups through early retirement schemes.

I am going to look at the applicability and contribution of the most popular factors in explaining the rise in wage inequality in Romania over the transition period. In the next section, I am going to describe my data sources, sample composition and variables. Section 3 provides an overview of the main changes in overall inequality, both in the communist and the transition

periods. In Section 4, I provide further insight for the observed patterns and look at changes in real wages for specific groups of the population. Section 5.1 and 5.2 explore human capital explanations for the growth in inequality, such as returns to education, experience and occupation. In Section 5.3 I look at inter-industry differentials and their contribution in increasing wage inequality. In Section 6.1 I quantify the contribution of each source in explaining wage inequality, and Section 6.2 I analyze in depth residual inequality. The final section gives a brief conclusion.

2. Data Description

The data used in this study comes from the Romanian Integrated Household Survey (RIHS) for the years 1994-2000. Unfortunately, for the study at hand, more recent data is not available since from 2001 onwards the survey was redesigned to focus on social indicators and is lacking individual wage data. The 1994 RIHS started in April 1994 and ended in March the following year, all the subsequent surveys were organized in a similar manner up to 1997, when the RIHS started in April and ended in November. In the last three years (1998-2000) the survey was undertaken from January through December of the same year.

The structure of the questionnaire also changed throughout the sample years. One important difference for this study was the discontinuation of direct reporting of years of schooling by respondents from 1996 onwards. For this reason, I have imputed years associated with educational attainment for the years 1996-2000. Since the median is less sensitive to extreme values than the mean, I have computed the median years for each attainment category in 1994 and then I associated these medians with the corresponding categories in 1996-2000. The classification of educational categories was also changed, for consistency I have redefined the 1994-1995 classifications to match the later versions.

The sample is restricted to individuals of working age (15 to 62 years old) who reported to be employed at the time of the survey. I have excluded the self-employed or those working in agriculture due to unreliable self-reporting of earnings. In all samples, workers who reported less than the minimum wage[3] or disproportional high wages were treated as outliers and eliminated. The sample sizes exceed 20,000 observations in most years, however in 1997 and 2000 we have

[3] Minimum wages were computed as percentage of average wages from information obtained from the Romanian National Statistics Office.

fewer than 15,000 observations. Table 1 below presents sample losses due to elimination of outliers.

Table 1. Sample losses due to elimination of outliers

	1994	1995	1996	1997	1998	1999	2000
Employed Workers	27,088	25,027	25,193	16,363	22,673	20,015	18,331
Reported Net Wages	25,810	23,465	23,316	14,961	21,149	18,768	13,686
Less than Min.Wage	337	91	14	2	5	5	3
>>Top wages	48	5	5	9	2	3	5
15<Age<63	186	150	139	102	112	106	67

Note: The majority of observation loss comes from incomplete information for the calculations of net wages, and this is especially considerable for year 2000. Additional tests were performed to see if there is a selection bias between those who provide all the information necessary for calculating net wages and those who don't. I did not discover any significant differences between the two samples.

The 1994 survey contains retrospective information on starting gross wages that goes as far as the 1950's, allowing me to look at the evolution of Romanian wage inequality from the second half of the 20th century. Since this data is obtained retrospectively, questions arise concerning the accuracy of the data (recall error) and the representativeness of this cross-section. With respect to recall error, it can be argued that people may have had difficulty remembering wages as far back in time, however, wages set in the communist grid were clearly defined and did not change much over time, so I expect in particular starting wages on new jobs to be relatively easily recalled. Age bias may also be present, as workers who start jobs in earlier years (especially until the 1960's) tend to be younger than those who start later, or after 1994. Due to these limitations, I prefer to dedicate most of the analysis to the 1994-2000 period.

Following the general trend in the literature and given that most workers in Romania are salaried, the measure used for earnings is the net monthly wage, computed as the difference between gross wages and contributions in taxes, unemployment fund and pensions. However, the use of monthly wages causes some bias in the estimates to the extent to which different firms adjust to the transitional output shock by reducing both real wages and hours worked. Thus, variation in wages may hide a variation in hours worked: low wage employees may be working

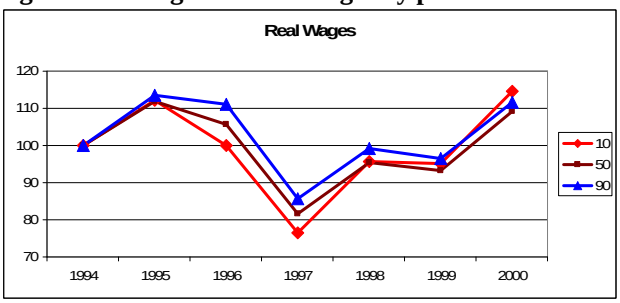
fewer hours than high wage employees. However, as mentioned before, since most workers are salaried, I expect this bias to be small. Furthermore, given that inflation was very high during the early years of transition, a within survey period nominal wage deflation is needed. As most researchers who study wages, I employ the monthly consumer price index as a deflator. Similar results were obtained under alternative approaches, such as demeaning and the inclusion of monthly trends.

Sample means and definitions for some of the most important variables used in the study are provided in Table A1 for the 1950-1993 period, and A2 in the Appendix for the 1994-2000 period. The stability of wages during the communist period is evident from the evolution of the mean wage, which evolved slowly until jumping up abruptly in 1990-1993, when prices and wages were liberalized. Years of schooling increase steadily (besides the drop during the 60's), and the highest growth is registered in categories such as vocational training and high school. Also the share of women in the labor force increases dramatically over the studied period, from 27% in the early 1950s to 45% in 1989.

Table A2 shows that average nominal wages increased steadily throughout the 90's, however in the light of increasing cost of living, the average real wages fell (Figure 1 below shows the drop in real wages for different percentiles). There is a steady increase in average levels of schooling from 11.42 years in 1994 to about a year more in 2000. The new cohorts entering the workforce are more likely to hold a university degree and less likely to have only an elementary or gymnasium education. This observation is in line with previous studies that document increasing returns to schooling after 1990 that influence the decision to invest in education by increasing the expected future stream of earnings (See Andren, 2004). The distribution of employment among men and women is relatively stable, as well as average years

of potential experience. The biggest shift relates to the growing share of private sector employment, from less than 10% of employment in 1994 to around 40% in 2000.

Figure 1: Changes in Real Wages by percentile



Mean wages and years of schooling are further decomposed by ownership in Table 2 below. The wages of workers employed in the State sector are consistently higher than wages of workers in the private sector. While in early transition the private sector is characterized by a more educated labor force, however the migration of lower skilled workers from state to private sector reversed and increased the education gap towards the year 2000, with the average level of education reaching almost 12.74 years in the state sector and around 12.04 years in the private sector.

Table 2.Average values by sector for selected years

	1994	1995	1996	1997	1998	1999	2000
Wages							
State	105.847	163,442	201,156	443,320	711,180	960,785	1,801,181
Private	97.226	150,841	176,211	390,438	618,972	860,888	1,582,841
Schooling							
State	11.43	11.53	11.77	11.81	12.03	12.22	12.74
Private	11.45	11.43	11.50	11.56	11.62	11.77	12.04
Observations	24,732	22,767	23,039	14,833	21,002	18,672	13,619

3. Changes in Overall Inequality

The availability of retrospective data in the 1994 survey of the RIHS gives the unique opportunity to track the evolution of inequality as measured by gross wage quintiles as far back as the 1950's. A remark must be made at this point: while before the mid 70's taxes on income were paid at the establishment level, after this period a progressive tax system was introduced, however the tax brackets were very close since the ratio of the minimum salaries to the maximum salaries was 5.5. Thus, although from 1950 to 1970's the subjects are reporting net wages and afterwards gross wages- inequality measures are more or less aligned. For comparative purposes, I report inequality measures based on gross wages for the transition period as well. Furthermore, in order to bring the pre-1994 sample more in line with the characteristics of the 1994-2000 samples, I excluded in the first stage workers employed in agriculture. However, for the analysis of the communist period I keep these observations since most of the wage inequality dynamics comes from the changing sectoral composition, specifically the migration of workers from agriculture to the industries. I look at overall inequality (percentile differentials) as well as residual inequality, especially since the two periods are not comparable in terms of workforce composition.

As seen in Figures 2 and 3 below, the trend in residual inequality (within group inequality) closely follows the trend in overall inequality as measured by the 90-10, 90-50 and the 50-10 percentile differentials. The greater part of changes in overall inequality is explained by changes in within group inequality. Since there is no information on industries before 1994, most likely the residual inequality captures part of the inter-industry differentials; however due to the compressed nature of the wage grid these differentials don't appear to be significant: the residual inequality closely follows the changes in overall inequality in a time of shifting

industrial composition and central planning targets. Both overall and residual inequalities expand dramatically by almost 100% during the early 1960's and 1990's. A diverging trend appears after 1994 when although overall inequality increases, the residual differentials remains stable. This increase in between group inequality during transition will be discussed more thoroughly in later sections. The 1994-2000 growth in inequality is brought by an increased inequality at the upper end of the distribution as measured by the 90-50 differential, while during communism it is increased inequality at the bottom that increases overall inequality.

Figure 2. Gross Wage Inequality 1950-2000

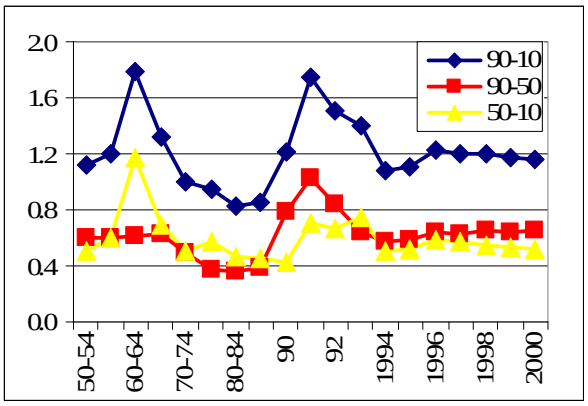
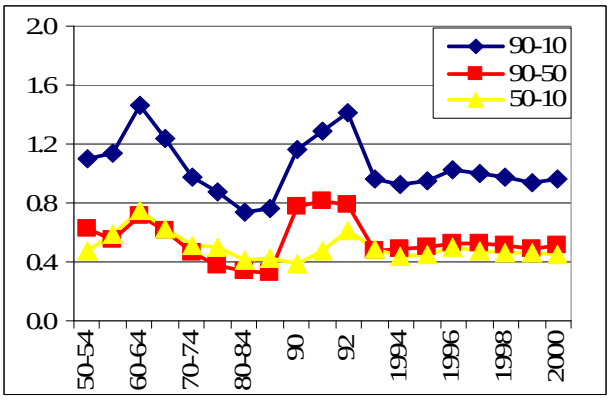


Figure 3. Residual Inequality 1950-2000



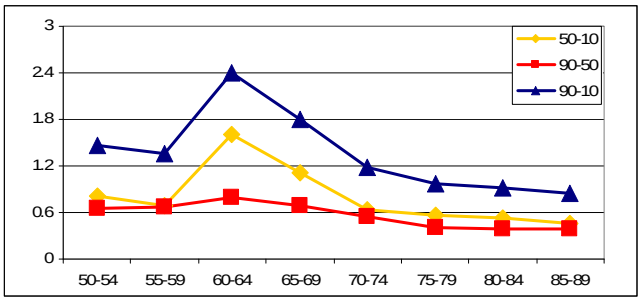
Note: Residuals are estimated from separate log gross wage regressions, with controls for education categories, experience, experience square, occupation, female and adjustments for inflation –without agricultural workers and adjusted for min wage in 1991-1993

3.1 The communist period

Turning to the analysis of the communist period, I have plotted percentile differentials for all workers. The inclusion of low-paid agricultural workers in the sample, as seen in Figure 4 below, increases significantly the 50-10 and the 90-10 percentile differentials during the first twenty years when the share of agricultural workers was comparatively much larger in the sample. The expansion of inequality in the 1960's is associated mainly with the industrialization drive that basically took off in this period and relied on wage differentials to induce worker mobility. This

surge in inequality in the early 1960's, with the 90-10 percentile differential increasing by almost 1 log points, is additionally explained by the increase in women's share in the labor force from

Figure 4. Gross Wage Inequality 1950-1989



29% in the 1950's to 47% in the early 1960's. As Romania was going through one of the most dramatic economic development during this period (12.9% annual growth in industrial output[4]), it grew its workforce also by attracting women whom at the time had significantly less education than men: in the early 1960's, 50% of the women in this sample had only an elementary education compared to 27% of men.

In Figure 5 the 90-10 wage differential is further decomposed by gender, and Figure 6 plots the 90-50 and 50-10 percentiles of log wages for men and women. For both genders inequality at the bottom half and among women is higher until the late 1980's. This fact can be easily explained by the relatively higher portion of women employed in low paying jobs[5].

Figure 5. Male-Female Differentials (90-10)

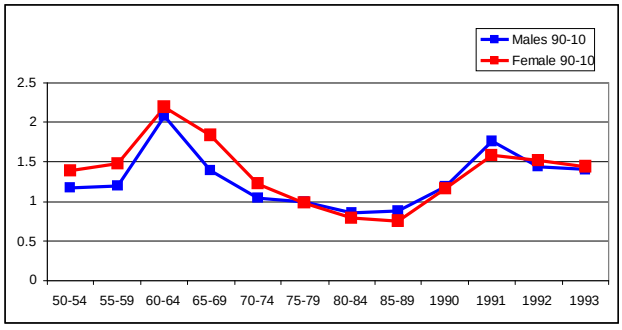
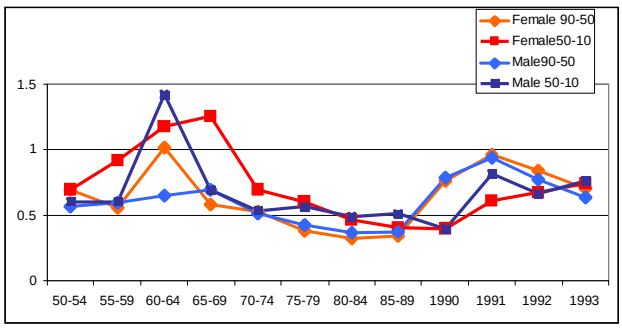


Figure 6. Male-Female Differentials (90-50& 50-10)



[4] http://countrystudies.us/romania/55.htm

[5] This fact can be explain by lower levels of education among women, as well as by the wage gap between the genders (for more info on these see Andren et al (1994))

The overall decreasing levels of inequality following the 1960's spike can be regarded as the result of Nicolae Ceausescu's industrialization policies, with the migration of peasants from low paying agriculture jobs to better paid jobs in the cities that were subject to a stricter wage grid. In the sample used here, the proportion of people employed in the agriculture sector falls from 31% in early 60's to 15% in 65-69, and to around 5% during the 80's. Although the industrialization of the Romanian workforce proceeded fast, the immediate decrease by almost 1 log points from 60-64 to 65-69 can be additionally explained by the changes in the gender composition of the Romanian workforce during the period.

The drop in women's participation rates in the late 60's from 47% to 41%, rather than a sampling error, is a result of Ceausescu's abortion policies introduced in 1966. In an attempt to boost decreasing birth rates in the autumn of 1966 Nicolae Ceausescu outlaws abortion, which was the primary form of contraception at the time, measure that meets a short term spectacular success: birth rates double within a year. A study done by Cristian Pop-Eleches (2006) finds that it was mostly more educated women who were affected by the ban- as they were more likely to resort to abortion. In this sample while male schooling trends continue to grow, average years of schooling for females drop from 8.27 in 1967 to 7.90 as soon at the ban comes into effect, and they retake their growth from 1969 onwards as alternative illegal abortion systems were set up. Thus, it is plausible that the huge drop in the female 90-50 log wage differential of .46 log points (while the 50-10 percentile differential continues to grow) may be a result of the lack of entry into the job market of more educated women due to maternity[6]. The later increasing levels of education for women and industrialization explain the reduction in wage inequality for the last twenty years of the communist period.

[6] Equality tests by classification were conducted for this period, and the difference between mean years of education in the two sample periods was significant.

Thus, a rough comparison of the communist and transition eras reveals some interesting observations. First of all, starting with the 1970's wage inequality is much smaller during communism; the 90-10 differential is less than 1 log points, fact that can be regarded as a natural result of the wage grid. However, during the same period, inequality below the median is higher than above the median, while in transition this trend is completely reversed: we observe an expansion at the top of the wage distribution.

3.2 The transition period

Since the retrospective data poses some limitations in terms of the quality of results given the potential recall bias and sample representativeness, I will analyze more in depth the evolution of wage inequality from 1994 onwards. Given the progressive nature of the Romanian tax system and the numerous changes in tax brackets, I will use the net monthly wage in the inequality analysis since it reflects more closely the actual evolution of wage inequality among workers.

Between 1994 and 2000 wage inequality in Romania has followed a concave path. Table A3 in the Appendix summarizes a few measures of inequality, the standard deviation of log real wages and several alternative percentile differentials. Given that the distribution of wages is not exactly log normal, the standard deviation measure of wage dispersion is more sensitive than the percentile measures to outliers at the top and bottom of the distribution. However, all measures of inequality describe a similar pattern: while we see a slow growth of inequality between 1994 and 1995, the inequality grows sharply and reaches a peak in 1996 after which it decreases slowly but stays high until 1998, and in the last two years of the analyzed period it drops beyond the 1994 level.

Figure 7 and 8 plot the changes in overall inequality as captured by the different percentile measures, as well as the changes in wage differentials by gender. The increase in the

range of the wage distribution is sustained mainly by the increase in inequality among the top earners and the middle class. The changes in the middle of the wage distribution, the 75/25 differential, are somewhat insignificant, besides the spike during the years 1996-1997. Another important characteristic of the Romanian wage distribution is the compression at the lower tail: there is significantly less inequality between middle class and low income workers than at the top half. Thus, it appears that income inequality in Romania was driven by the widening of the upper end of the distribution.

Figure 7. 90-10 log wage differentials 1994-2000

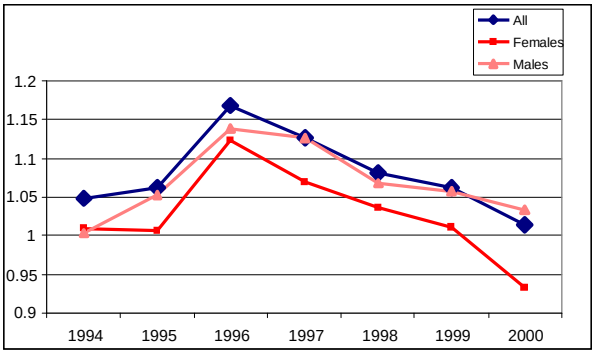
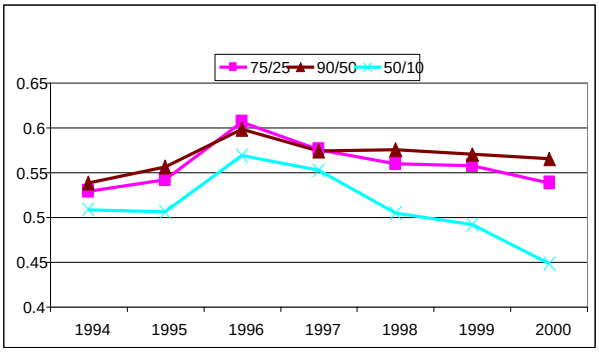
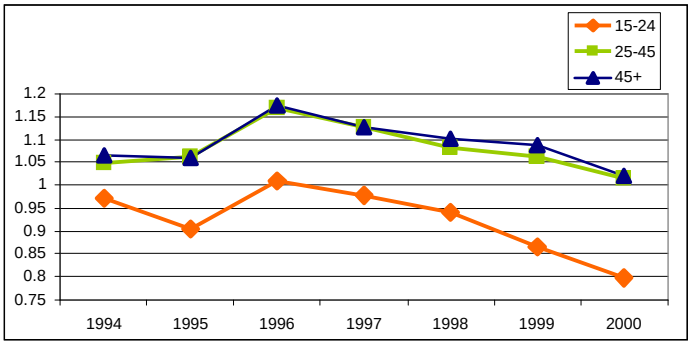


Figure 8.75-25, 90-50, 50-10 log wage differentials



The decomposition of the 90-10 log wage differential by sex reveals similar patterns of growth for both sexes, however with lower levels of inequality for women. Since for all years average wages for men were higher than those of women (with a peak in 1996) I expected to observe higher inequality among men since there are more of them at the top of the wage distribution. The sharp increase in inequality among women during 1996 is followed by a steady decrease that pulls down overall inequality after 1999. The 90/10 differentials by age groups, as plotted in Figure 9, show much greater inequality among older cohorts, while the young

Figure 9. 90-10 Differentials by Age Groups



cohorts experience a considerable drop in inequality after 1997. Given that young people are more likely to be situated at the lower tail of the distribution, this evidence is supportive of the argument made earlier that inequality in Romania was driven by the dispersion in wages of the top earners. These findings are consistent with the standard view that wage inequality rises over the life cycle due to individual specific productivity shocks as well as rising dispersion of information about worker attributes available from work histories. Of course it is impossible to separate time effects from age effects by looking at these inequality measures based on broadly defined age categories; however the fact that all groups experience increases in inequality during the same period is suggestive of important time effects.

The next two figures show the evolution of inequality by education groups. Figure 10 plots a dramatic increase in overall inequality among college graduates, with the 90-10 percentile differential rising by .15 log points from 1994 to 1997, and more moderate increases among professional and High School graduates. The increasing shares of more educated workers in the overall composition coupled with increasing inequality within these groups helps explain the pattern observed in overall inequality. The inequality for less educated groups, Figure 11, after the transitory spike in 1996 and 1997, drops beyond 1994 levels from 1997 onwards and matches the shrinking at the low end of the distribution. For example, the 90-10 differential for gymnasium graduates drops by .23 points from 1994 to 2000, which is about twice as much as the drop for workers with a vocational education.

Figure 10. 90-10 differential for more educated

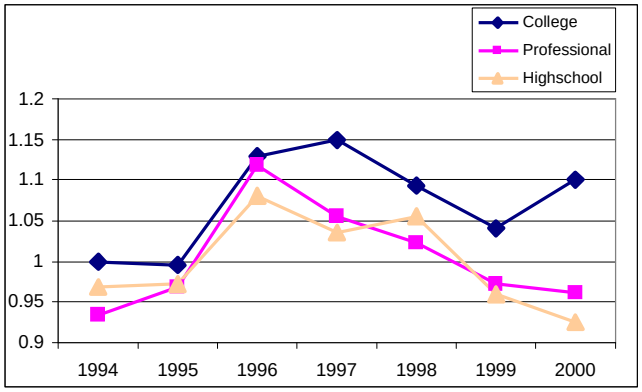
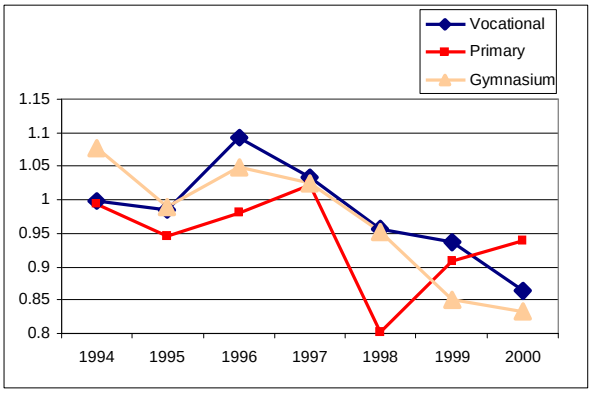


Figure 11. 90-10 differential for less educated



The striking change in ownership composition motivates a sectoral analysis of wage inequality. Figure 12 reveals much higher levels of overall inequality in the private sector, although by 2000 the inequality falls below the state level. A decomposition of the change in inequality in the private sector below and above the median in Figure 13 shows that much of the decrease in the 90-10 differential is due to the contraction of inequality at the lower half of the distribution. The 90/50 differential has a similar evolution in both sectors; however it is obvious that it is the large drop in the 50/10 differential in the private sector that reduces the overall observed inequality towards 2000.

Figure 12. 90-10 Differentials by Sector

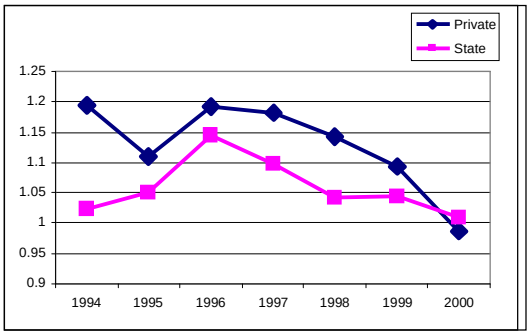
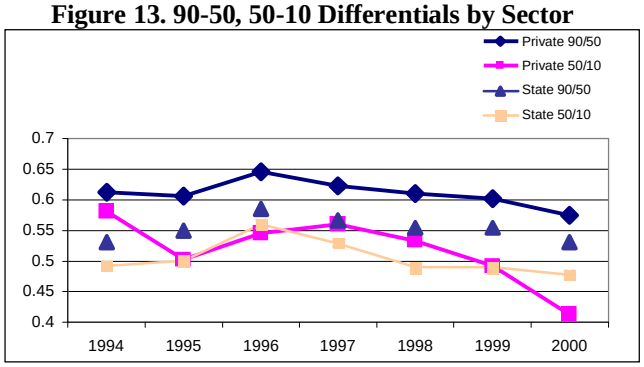


Figure 13. 90-50, 50-10 Differentials by Sector



At a first glance it is somewhat surprising that the private sector exhibits a higher inequality given that it is characterized by a less educated workforce (which has on average lower levels of inequality). It is clear that the analysis of inequality based on percentile differentials can give limited insights into the sources that drive the inequality. A possible

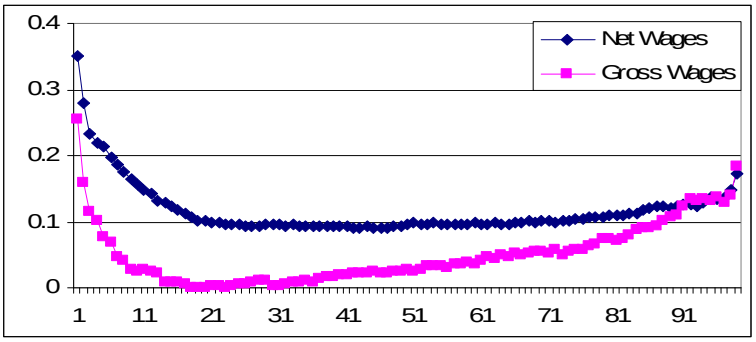
explanation would be higher returns to schooling of highly educated workers in the private sector that shifted the 90-50 differential outward. A study of the wage effects of schooling in Romania (see Andren et.al. 2004) finds evidence of organizational and institutional changes that increase the value of education in the private sector. Their interpretation of the results is that the adoption of new organizational practices, especially the higher rewards for individual initiative, increases the value of education within the private sector. As later my regression results will confirm, while returns to schooling up to a Professional degree are very similar in magnitude in both sectors, returns to college education remain particularly high in the private sector, although there is a trend towards closing the gap as the state sector undergoes changes within its own organizational practices.

To sum up, the basic pattern of changes in the wage distribution is robust across the inequality measures employed in this section. Both the standard deviation and the percentile differentials portray increasing levels of inequality during 1996-1997 and the further reduction until 2000. The increase in overall inequality seems to be driven by the greater dispersion at the top of the distribution and the increase of the private sector share. Within group inequality rose significantly for college educated workers, males and private sector workers.

4. Changes in Real Wages

The analysis of real wage changes between different subgroups of the population gives further insight into the nature of wage inequality growth in Romania during 1994 and 2000. A snapshot of the changes in gross and net real wages during this period is given in Figure 14. For the whole sample, workers at the low and top end of the net wage distribution gain more than workers at the middle, an incremental 0.2 log points for workers below the 10th percentile and 0.1 log points for those above the 90th percentile. The log gross wage growth displays a similar pattern; however the apparent gain for most workers above the 30th percentile is removed by the progressive nature of the tax code.

Figure 14. Changes in Real Wages 1994-2000



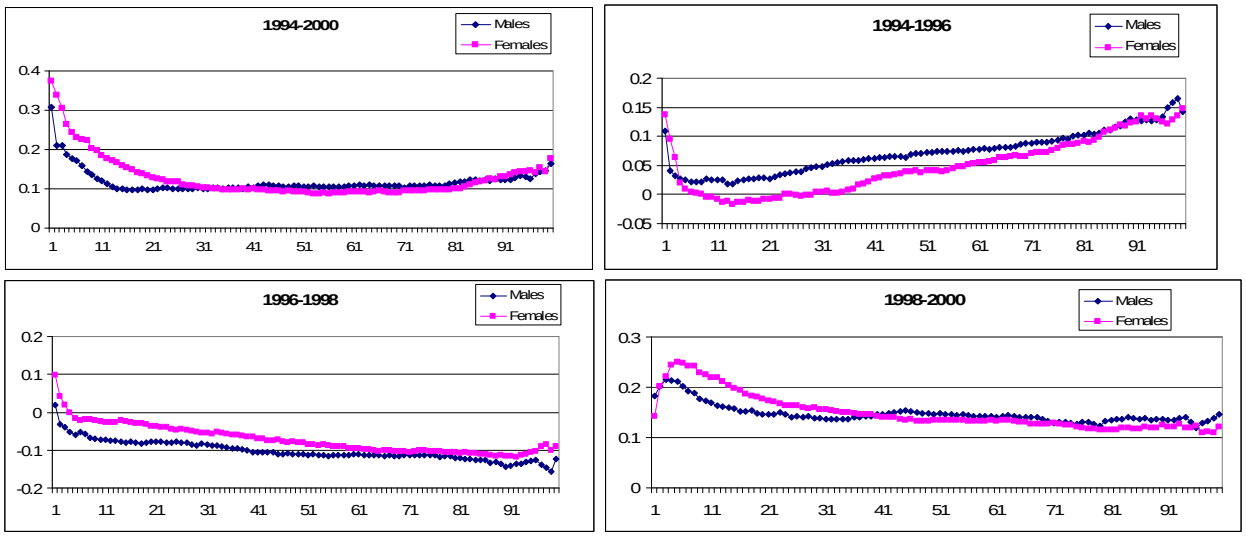
4.1 Gender Differentials

Figure 15a below plots the changes in real log net wages for males and females for the entire period. As mentioned above, while at all percentiles workers have gained in real terms around 0.1 log points, the males at the lower end of the wage distribution gained about twice as much and females three times more. Thus, the evidence found earlier of a shrinking inequality at the low end of the wage distribution can be explained partly through an increased appreciation of real wages for the less skilled workers.

The sub-period analysis reveals the same pattern of real wage appreciation for the lower percentiles in all Figures 15b-15d. However, the evolution of wage changes is very different in

each sub-period. Between 1994 and 1996 real wages appreciate for males, with males at the 10th percentile gaining about 0.025 log points, while those at the 90th percentile gaining around 0.15 log points. Wage growth for females follow a similar pattern, however there is a slight depreciation of wages for females situated below the 30th percentile. The real wage appreciation at the upper percentiles explains the surge in the 90-50 inequality measure. The less significant gain for women situated below the median account for the smaller increase in the 50-10 differential in Figure 8 (0.06 log points compared to 0.08 for the 90-50 differential).

Figure 15a-d. Changes in real wages by gender



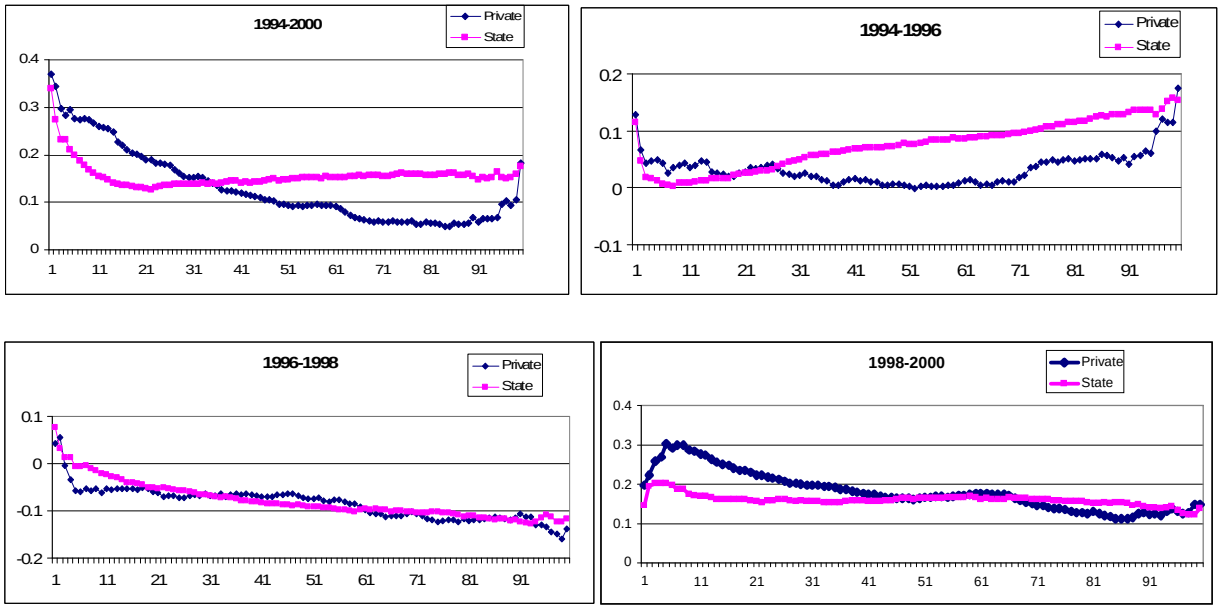
From 1996 to 1998 real wages dropped for all subjects (Figure 15c), with males experiencing greater losses at all percentiles. The workers at the top of the distribution experience a relatively greater depreciation, and this effect contributes to the drop in the 90-50 inequality measure observed in this period. Below the median as presented in Fig.8 there was a drastic decrease in inequality and this is again accounted for by the relative drop in wages around the median compared to the 10th percentile. The last period (Figure 15d) is characterized by increasing real wages, and workers at the lowest end of the wage distribution gain substantially more, an average of 0.2 log points compared with 0.13 at the 90th percentile. Inequality as

measured by the 50-10 and 90-50 percentiles declined further during this period (see Figure 8), and the bigger drop in the 50-10 measure is accounted for the relative greater appreciation of the wages at the low tail of the distribution.

4.2 Private and State Sector Differentials

The private and state sector already showed two very distinct patterns of inequality growth and for that reason I am going to look at the changes in real log wages in these two sectors. Figure 16a-d plot the changes by percentile for the whole period and then by sub-period. The changes for the whole period show a steady wage gain in the state sector at all percentiles, with the already documented bigger relative gain for the less skilled. However, in the private sector the workers below the median gain more than the workers above the median both within the sector and between the two sectors.

Figure 16a-d. Changes in real wages by sector



The years 1994-1996 are characterized by higher inequality in the private sector (see Fig.11 and Fig.16b). This is driven mainly by the relatively higher wage gain of the workers situated at the 90th percentile employed in the private sector compared to those at the 50th

percentile: the 90-50 wage gain in the state sector is only 0.07 log points compared to the almost 0.2 in the private sector. Figure 16b also reveals that wage gains in the state sector were higher at all percentiles besides the lowest 10^{th}. Thus, in this period, the nature of between sector inequality is the comparative incapability of the private sector to secure wage growth for workers at the median of the wage distribution. The wage setting practices were thus very different in the two sectors between these two years.

The last two Figures, 16c and 16d, show a more aligned wage growth in the two sectors. The documented drop in the 50-10 differential is driven by the comparative wage gain at the low end of the distribution: 0.3 in the private sector compared to 0.17 log points in the state sector. Thus we can see that the higher wage growth in the private sector at the low end of the distribution in the last period accounts for the private-state differential noticed in Figure 16a.

4.3 Education-Experience Group Differentials

In the first section of this study I documented the large increase in inequality among highly educated workers, in particular among college educated workers. I return now to the study of changes in log real net wages within these education groups which are further divided by experience categories. As was shown in Figure 9 there are important age effects that influence wage inequality, and for this reason I want to control for different experience levels. I define four categories: D1 from 0 to 10 years of experience, D2 from 11 to 20, D3 from 21 to 30, and D4 for more than 31 years of experience. While I am aware that there is an important skill gap between a worker with ten years of experience and another with only one year, a selection with smaller experience intervals did not alter the conclusions and so, for ease of exposition the present classification was chosen.

Figure 17 plots the changes in real wages by percentiles for college educated workers from 1994 to 2000. It is obvious that even within these narrowly defined groups, wage growth is quite different across experience cells. Although at higher percentiles all experience subgroups gain about 0.2 log points, below the median the trends diverge. Below the 25th percentile college workers with fewer than ten years of experience undergo real wage losses during the studied period. However, groups with more years of experience gain between 0.1 and 0.25 log points at the lowest percentiles. Overall, college graduates with more experience gain more and the significant gains experienced by workers with a college degree, in particular at the top of the distribution, help explain the high 90-50 differential.

Figure 17. Real Wage Changes for College Graduates

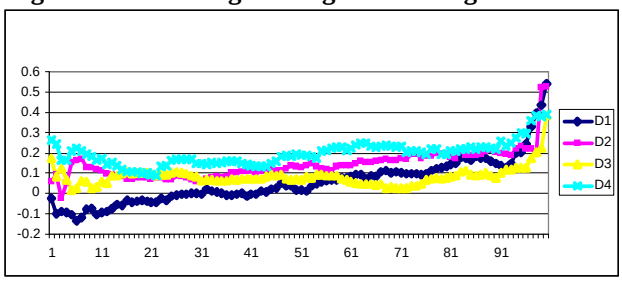
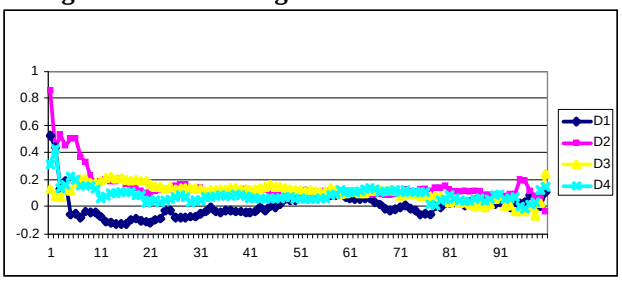


Figure18. Real Changes for Professional Graduates



Professional school graduates (Figure 18), a group that has share of 10% out of the working population, also experience real wage gains of about 0.1 log points on average, however, gains at the bottom of the distribution are significantly greater than those at higher percentiles. In this group as well, young workers experience wage losses below the 40th percentile. The differences across higher experience groups are not so significant.

For the other three groups, real wage gains have been more significant for those with ten to thirty years of experience, the results (not reported here) show a 0.10 log points gain for high school graduates and 0.025 for those with a vocational education and below the median. Workers with a vocational education and above the median experience wage losses, with higher losses

among the young workers. For those with an elementary& gymnasium education there is no significant change in real wages, besides a drop in wages at higher percentiles.

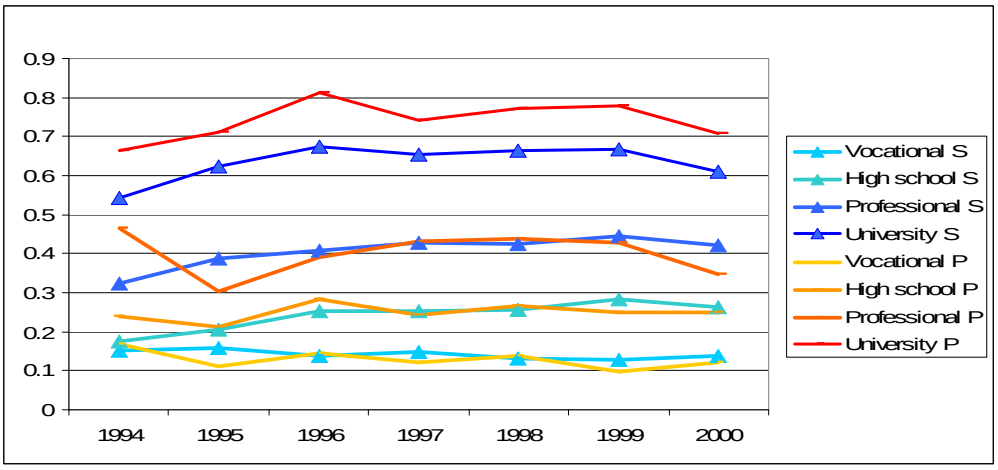
5. Sources of Growth in Inequality

5.1 Returns to Education and Experience

As was seen in the previous sections, inequality is much higher at the top of the wage distribution and in the private sector. One potential explanation for this is the increasing returns to schooling as the Communist wage grid was abolished. I have estimated by OLS an extended Mincerian equation for all transition years in order to observe the effects that may be shifting over time. Estimating such an equation has many shortcomings, such as several biases coming from mismeasurement of wages, omitted variables or selection problems. It is beyond the scope of this study to account or correct for these, however since I am mainly interested in the comparison between the private and state sector dynamics, I expect these biases to be consistent across sectors and thus not to influence the validity of my conclusions.

Most of the estimates in Tables A4.1 and A4.2 in the Appendix are economically and statistically significant. Returns to education have increased over the 1994-2000 period in most education categories, and college workers have experienced the largest increases (see Figure 19 below). The coefficients on education variables in the private sector are larger in magnitude than in the state sector, thus supporting the evidence of higher dispersion of wages in the private sector. For example, the college degree coefficient in the private sector increased from 32.4% in 1994 to 49.1% in 1996 and reached a magnitude of 42.6% in 2000; overall throughout the period an increase of 10.2 percentage points. In the state sector the growth is less spectacular overall, the wage premium of college educated workers increases only by 1.5 percentage points from 1994 to 2000, but increases by 10 percentage points in the first two years. As it can be observed in Figure 19, there was a widening of the college-high school premium in Romania as well.

Figure 19. Returns to Education



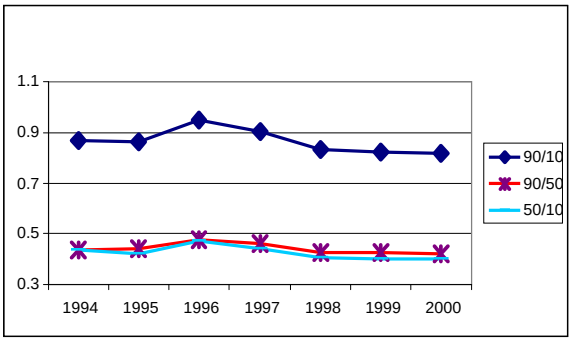
An additional evidence for the higher inequality in the private sector is the wage premia associated with highly skilled occupations, such as top officials or brain workers. These premia are larger in the private sector throughout the most of the period, however as with the educational premia the gap between the sectors is closing towards the end of the period. The inclusion of industry dummies in the earnings regressions changes only insignificantly the magnitude of the estimated coefficients for the private sector, and increases moderately the coefficients for the state sector. I will analyze more in depth the changes in occupation and industry structure of earnings and employment in the next sections.

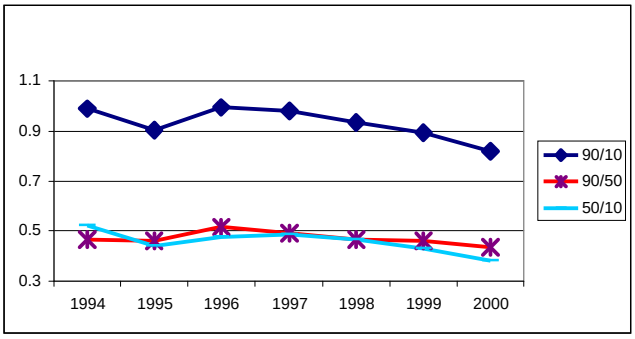
While education and skills seem to be more valued in the private sector, one factor that reduces inequality between sectors is that wage returns to potential experience are higher in the state sector after 1996, which may be evidence of a greater prevalence of seniority pay scales. Towards 2000 the gap between returns to potential experience in state and private sector respectively, increased to 18%. These results are similar to those obtained in similar studies on transition economies, but indeed returns to experience are much smaller than those typically

found in Western data sets. The gender wage gap is *ceteris paribus* higher in the private sector than in the state sector, however it is declining towards the end of the period.

The residual variance graphs obtained from these regressions (see Figures 20a-b below) reveal the same pattern of inequality dynamics as those representing overall inequality. As expected, the changes in residual inequality are much smoother, especially those at the upper part of the wage distribution since it has been controlled for increasing returns to education. Looking at the magnitude of the residual inequality it becomes quite clear that most of the inequality is accounted for by the unobservables. In the last section I will use decomposition methods to determine exactly how much.

Figure 20 a-b. Residual Inequality by Sector





5.2 Changes in the Occupation Structure

Figure 8 from the second section displayed the 90-50 and 50-10 log monthly wage differentials for all workers from 1994 to 2000. It showed increases in the upper half and a diverging trend for the lower half which exhibits a contraction of .60 log points. Diverging lower and upper tail inequality are observed for females and males separately as well. The analysis of real wage changes showed that wage growth has polarized since 1994, with the fastest growth in the lowest and highest quartiles compared to the middle range. The residual wage inequality, as will be seen in later sections, follows a similar pattern.

I will investigate the connection between wage polarization and potential employment polarization to see whether there are demand shift explanations concerning the changing Romanian wage structure. Models such as Autor et. al (2003) predict that technological changes- such as computerization- have displacing effects of middle-skilled jobs, such as bookkeeping and repetitive production work. They contend that if routine tasks are more complementary to high-skilled abstract tasks than to "non-routine manual" tasks (such as those of truck drivers), the computerization of routine work can generate labor market polarization. Thus, this model predicts that wage polarization should be accompanied by employment polarization.

I sort occupations (10 ISCO categories, since the 3digit codes are available only for the first two years of the survey) into percentiles by mean years of schooling in 1994, and by two other alternative "skill definitions"- median hourly wage in an occupation and skill level in 1994. I then look at employment growth in these skill cells, measured as the change in an occupation's share of employment from 1994 to 2000. All three classifications depict a similar story (see Figure 22 below): declining employment at the bottom of the distribution, and increasing shares

for high skilled jobs. At the middle of the distribution (as ranked by schooling and skill level) there seem to be more moderate changes. Thus the pattern of job growth (and possible labor

Figure 21. Changes in Returns to Occupation

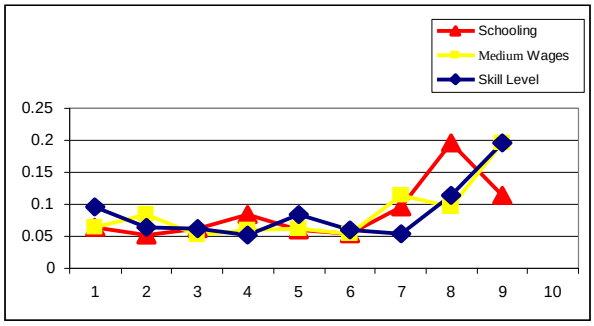
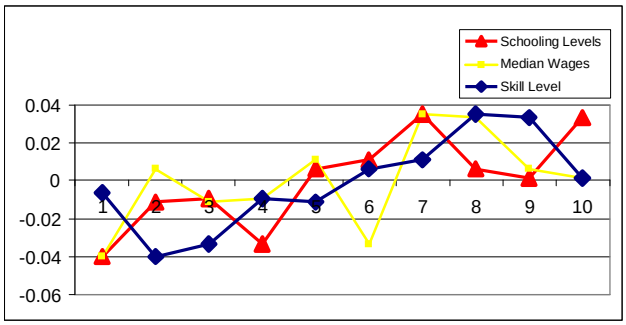


Figure 22. Changes in Occupational Shares



demand shifts) does not correspond to the U shaped wage structure changes observed in Romania. While it seems that labor demand shifts have favored the high skilled workers, the declining shares of employment in low skilled occupations do not corroborate the job polarization hypothesis. However, as seen in Figure 21, returns to occupation[7] have increased for the highly skilled relatively more than they did for the middle skilled, and apparently the low skilled also gain more than the middle skilled. Thus, the relative increase in returns to low skills can serve as a reason for rising real wages at the bottom of the distribution. Other institutional explanations for rising low wages also do not apply to the Romanian inequality dynamics. Minimum wages declined as percentage of average wages throughout the studied period, and union coverage in Romania[8] declined significantly as well.

Given that growth in wages at low percentiles was concentrated in the private sector towards the end of the period might be suggestive of potential alignment of marginal products with wages. The study of the productivity effects of privatization in Romania by Brown et. al (2006) finds a substantial positive effect of privatization on productivity in the range of 15 to

[7] Estimates are obtained from log wage regressions, with controls for education, experience, gender, industry and ownership. Workers in agriculture are the omitted category

[8] http://www.eurofound.europa.eu/eiro/2003/07/feature/ro0307101f.html

50%. Thus, it is plausible that the shift of low skilled workers from an unproductive state sector to a more productive private sector could have given rise to the observed growth.

5.3 Industry Structure of Earnings and Inequality

Although residual inequality seems to drive most of the wage inequality dynamics, many studies of wage inequality in transition countries find increasing inter-industry wage differentials as a principal cause of increases in wage inequality (i.e. Newell 2001). In this section I am going to look more in depth at changes in the industry structure of wages, and the allocation of workers of different skill types across industries from 1994 to 2000. To start with, I am going to look at the wage premiums associated with each industry, estimates obtained from the regression equation employed in the previous section, as well as their employment shares. Table 3 below presents the results for three selected years.

Table 3. Industry Wage Differentials and Employment Shares

Industry:	1994		1997		2000	
	Earnings	Share	Earnings	Share	Earnings	Share
Agriculture, Forestry, Fishing, Hunting	-	8.54	-	6.68	-	3.97
Extracting	0.454	4.65	0.413	4.2	0.392	3.36
Processing	0.112	36.35	**0.191**	36.5	0.131	34.79
Electric and Thermic Energy, Gas, Water	0.329	3.78	**0.358**	3.66	0.298	**4.39**
Construction	0.135	6.82	**0.176**	6.07	0.118	5.64
Retail and Wholesales, Hotels, Restaurants	0.057	8.22	0.053	10.11	0.053	9.9
Transportation and Communications	0.207	9.32	**0.249**	9	0.203	9.19
Finance, Banking, Insurance	0.190	1.83	**0.239**	1.96	0.237	**2.17**
Real Estate	0.001	0.53	**0.197**	0.61	0.151	**0.76**
Public administration	0.121	5.24	0.096	5.62	0.161	**7.12**
Education	-0.076	6.28	-0.067	6.32	-0.024	**7.94**
Health and Social Security	0.040	4.34	-0.038	5	0.047	**5.95**
Other Services	0.017	3.92	0.020	4.12	0.054	**4.74**
Activities of household personnel	0.003	0.12	-0.168	0.09	0.172	0.04
International institutions and Organizations	0.273	0.06	0.352	0.07	0.138	0.04

The bold figures for 1997 represent industries that had higher wage differentials than their 2000 level. The bold figures in 2000 represent industries that expanded throughout the period.

Even after controlling for human capital characteristics, such as education and occupation, wage differentials across industries remain significant. Most industries have a large positive differential compared to agriculture, with the highest premiums in Extracting and Utilities. Between 1994 and 1997, earnings differentials changed substantially, especially in white collar/high skill industries such as Finance, Banking and Insurance or Real Estate, where

premiums overshoot their eventual 2000 level (see the bold figures in Table 3). Towards 2000 inter-industry wage differentials decrease, however in expanding industries such as Education, Health and Social Security or Finance they remain high. Overall, employment shares increase in White collar industries mainly.

Next, I examine education premia (by sector) from the log wage equations with and without industry controls. The coefficients with industry dummies are reproduced from Tables A4 in the Appendix. Education coefficients seem to be unchanged with industry controls for lower levels of education in the private sector. In the State sector, especially for workers with a Vocational education, education premium increases when industry is controlled for. This result could be driven by the wage premium in industries such as Extracting, which are mainly state owned and employ mostly low educated workers. Towards the end of the period, in both sectors, the gap between with and without industry controls for highly educated workers closes, fact which provides evidence of the reallocation of educated workers from blue collar industries towards high paying/ white collar industries. In the state sector, the contribution to the R squared from including industry dummies remains significant throughout the transition period.

Table 4. Education coefficients with and without industry dummies

State	1994		1996		1998		2000	
Vocational	0.100	0.090	0.088	0.085	0.066	0.057	0.073	0.050
High school	0.101	0.098	0.166	0.168	0.135	0.142	0.155	0.146
Professional	0.186	0.191	0.265	0.281	0.244	0.257	0.255	0.245
University	0.363	0.386	0.435	0.456	0.413	0.433	0.378	0.379
Industry	Yes	No	Yes	No	Yes	No	Yes	No
R^sq	.272	.211	.318	.250	.382	.303	.345	.283
Observations	21,440		17,601		13,210		5,856	

Private	1994		1996		1998		2000	
Vocational	0.107	0.110	0.109	0.109	0.104	0.100	0.091	0.095
High school	0.147	0.150	0.200	0.200	0.179	0.177	0.181	0.183
Professional	0.277	0.270	0.259	0.267	0.278	0.284	0.250	0.256
University	0.324	0.340	0.491	0.483	0.450	0.465	0.426	0.437
Industry	Yes	No	Yes	No	Yes	No	Yes	No
R^sq	.340	.320	.360	.337	.349	.337	.338	.327
Observations	2,393		3,989		5,464		5,324	

Given the changing shares of industries and the general increase in the levels of education since 1994, I am going to look more in depth at the sorting of workers (by education level) across industries. For ease of exposition I group industries[9] into three categories. Group 1 is comprised of industries which are typically considered to be blue collar, such as Agriculture, Extracting, Processing, Construction and Household Personnel. Industries from Group 2 are medium skilled industries; it includes Transportation, Real Estate, Retail and Wholesale, Hotels and Restaurants and Other Services. The last group is comprised of industries that are typically high skilled, Finance, Banking and Insurance, Education, Health and Social Security and Public Administration and Utilities.

In Table 5 panel A I report the allocation of workers, by education level, across these three industry groups in 1994 and 2000. The predominance of low skilled in Group1, with more than 60% of total workers who completed at most a vocational education, and the large shares of highly educated workers clustered in Group 3, reinforce and are consistent with the industry classification chosen.

What is an interesting pattern is the migration of the highly educated workers out of Group 1 industries. The percentage of college educated workers employed in group 1 drops from 38.3% in 1994 to 30.2 % in 2000, which is by far the largest drop in this group. Workers of all types exit group 1, the fraction of all workers employed in this group falls from 56.4% to 47.7%. Group 3 industries expand the most during this period, by almost 30%. Even with this expansion, the proportion of college educated workers employed in Group 3 grows by 2 percentage points. Group 2 industries also increase their share of high skilled workers, by 6 percentage points.

[9] For a similar approach see Keane and Prasad (2006)

Table 5
A. The allocation of education groups across industries

	Group1		Group2		Group3	
	1994	2000	1994	2000	1994	2000
College	38.3	30.2	15.7	21.8	45.9	47.9
Professional	26.7	32.3	22.3	19.8	50.8	47.8
High School	50.1	41.3	26.7	30.2	23.0	28.6
Vocational	68.5	66.9	20.2	21.7	11.2	11.2
Gymnasium	65.9	59.1	20.8	21.6	13.1	19.2
Elementary	66.4	59.3	18.3	23.0	15.1	17.5
All	56.4	47.7	22.0	24.6	21.4	27.5

B. Employment Distribution across industries by education level

	Group1		Group2		Group3	
	1994	2000	1994	2000	1994	2000
College	7.9	10.5	8.3	14.7	25.0	28.9
Professional	2.0	6.4	4.3	7.6	10.04	16.5
High School	29.9	31.05	40.9	44.08	36.1	37.13
Vocational	34.3	43.60	25.91	27.48	14.85	12.70
Gymnasium	21.70	7.5	17.59	5.33	11.40	4.23
Elementary	4.08	0.08	2.89	0.06	2.45	0.04

Industry groups are:
Group 1- Agriculture, Extracting, Processing, Construction and Household Personnel
Group 2- Transportation, Real Estate, Retail and Wholesale, Hotels and Restaurants and Other Services
Group 3- F,B&I, Education, Health and Social Security, Public Administration and Utilities.

In panel B of Table 5, I describe the composition of industries by education level. In all industry groups the percentage of workers with an elementary or gymnasium education falls dramatically. At the same time, in all industry groups the share of college educated or professional school graduates increases. In group 1 for example, the proportion of college workers increases from 7.9% to 10.5%, in Group 2 it increases from 8.3% to 14.7% and finally in Group 3 a less dramatic increases from 25% to 28.9%. Similar increases are experienced in the professional school graduates group. Thus, the skill upgrading pattern is significant and consistent across industries. As was presented in the data description chapter, one of the causes for this pattern is due to cohort effects, as average levels of education increased from 1994 to 2000. Another potential factor would be the selection of low skill/low wage workers out of the labor market as generous early retirement programs were offered.

Industrial employment shifts since 1994 have favored industries that more intensively utilize college graduates to less educated workers, a pattern that is similar to the changes in the occupational distribution. The preponderant growth of white collar industries was associated with shifts in relative wages that favored these industries. The main result of this dynamics was the reallocation of workers out of blue collar industries such as Agriculture, Extracting or Processing and into higher skilled industries, such as Finance, Banking and Insurance, Public Administration or Education.

The wage differentials boost experienced during 1997 is relatively evened out in 2000, with the exception of high skilled industries. Also, the explanatory power of industry dummies is greatly reduced towards 2000, especially in the private sector, suggesting a realignment of industry relative wages. It appears that part of the surge in inequality experienced in 1997 can be attributed to rising inter-industry wage differentials. The growth of the high skilled industries and the wage premiums associated with these industries, could have contributed to the sustained 90-50 differential observed throughout the period. However, the extent to which industry differentials can explain overall inequality will be the subject of the next section.

6. Decomposition analysis

6.1 Fields Decomposition

Dividing the sample according to human capital characteristics or ownership categories, proves useful in the analysis of wage inequality within these broadly defined groups; regression analysis helps identify sources for increased wage inequality, however none of these methods helps isolating the contribution of each characteristic towards inequality. A more useful method was proposed by Fields (2002), a method which considers simultaneously the impact of several given explanatory factors if accounting for levels of wage inequality at a point in time.

Starting from the extended Mincerian regression in which log wages were regressed on a set of explanatory variables, the estimated coefficients will capture the impact of various individual characteristics on inequality. The contribution of each characteristic is given by the relative variances and covariances of the explanatory variables:

$$S_k = \frac{Cov(\beta_k X_k, Y)}{\sigma^2(Y)} = \frac{\beta_k \sigma(X_k) Corr(X_k, Y)}{\sigma(Y)},$$

Where S_k is the proportion of inequality which is due to the *k*-th explanatory variable and β_k is the estimated coefficient of the *k*-th explanatory variable. Table 6 below presents the results for the 1994-2000 period.

Table 6. Fields Decomposition %

	1994	1995	1996	1997	1998	1999	2000
Vocational	-0.84	-0.79	-0.75	-0.8	-0.68	-0.59	-0.67
High School	-0.71	-0.91	-1.13	-1.14	-1.03	-1.13	-1.08
Professional	1.09	1.23	1.46	1.61	1.44	1.49	1.4
College	8.41	9.09	10.27	10.63	9.8	10.43	8.96
Experience	2.84	3.01	3.36	3.62	3.27	3.34	3.35
Occupation	6.01	6.44	7	6.22	6.95	6.85	7.02
Total HC	**16.8**	**18.07**	**20.21**	**20.08**	**19.75**	**20.39**	**18.98**
Female	3.09	3.22	3.38	2.99	3.06	3.18	3.45
Industry	5.45	5.69	5.88	5.68	6.06	4.94	5.01
Ownership	0.53	0.73	0.8	0.8	-0.7	0.3	0.35
Residual	74.13	72.29	69.73	70.42	70.44	71.16	72.22

The Fields decomposition shows that the wage equation itself explains only about 30% of variance in wages, and the largest contribution is that of the residual term, i.e. within group inequality. Among the explanatory variables the largest proportion of wage dispersion (from 17% to 20%) is explained by human capital characteristics[10], such as education, experience and occupation. The impact of education follows the changes in the education premium, and as expected, high education has the biggest impact. Low levels of education, such as vocational and High School, act towards reducing inequality. Their increasing contribution matches the decline in the 50-10 differential. Occupation explains in 2000 one percentage point more than it did in 1994. The shift from low to high skill occupations, with higher wage premiums, explains this pattern.

Industry and Ownership explain about 6% of inequality. The contribution of industry to inequality follows roughly the concave shape of wage differentials that was discussed in the previous section: during increasing wage premiums the industry contribution increases as well. Towards 2000, as wages were more or less realigned, industry explains as little as 5% of total inequality. The ownership category has overall a surprisingly small impact on inequality. However, this is mainly the result of opposing signs (that cancel each other out) of the state and the private sector contributions. The state sector has mainly a negative sign that acts toward reducing inequality, while the private sector contributes positively to inequality. The magnitudes of these contributions do not exceed 2%.

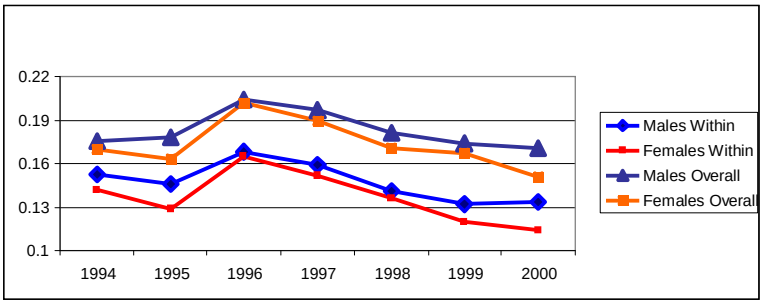
[10] I have done the decomposition including these variables for the 1950-1993 period as well. Education had a significantly diminished contribution, in line with the lower returns to schooling; out of occupations it was only agricultural employment that had a significant contribution, of at least 5%, towards inequality. Without being able to control for industry, the residual explained on average more than 90% of inequality.

6.2 Lemieux Residual Decomposition

Wage inequality in Romania seems to have been driven, as the results from the previous sections point out, by increasing returns to human capital and the increasing share of highly educated workers in the workforce. The increase in inequality during the 1996-1997 period can be additionally explained by the overshooting of inter-industry wage differentials in several white collar industries. Among factors that reduce inequality are the growth in real wages at the bottom of the distribution, overall skill upgrading, and a certain slow down in the increase of the college premium.

However, about two thirds of wage inequality is explained by residual inequality- wage dispersion among workers with the same education and experience profile[11]. Figure 23 below plots the within and between group variance for men and women- the pattern is almost identical for both measures: within group inequality is following the same concave shape, with a spike in 1996 and decreasing levels towards 2000. Thus, at a first glance, we could argue that returns to unobserved skills grow over time, but the dispersion of unobserved skills falls towards the end of the period, perhaps due to composition effects, ultimately decreasing within group variance. In this section I am going to look at the sources of decline in residual wage inequality.

Figure 23. Within and Overall Group Variance



[11] Since relatively little contribution is brought by variables such as industry, occupation or ownership per se, I am going to concentrate from now on only on pure "measures" of skill.

Following Lemieux (2002), changes in residual wage inequality can be interpreted as evidence of changing skill prices only when the distribution of unobserved skills and the variance of measurement error are constant over time. In this study I am going to abstract from the analysis of the changes in the variance of measurement error, and I will instead consider only the contribution of rising skill prices and composition effects (and their impact on within group variance) to the dynamics of the residual variance.

Starting from the residual of a Mincer-type wage equation, we can write the residual variance as follows (leaving aside measurement error):

$$Var(\varepsilon_{it}) = p_t^2 Var(e_{it}) \quad (1)$$

Observed skills, x_{it}, are divided into a finite number of cells j. Thus, the unconditional variance of unobserved skills, $Var(e_{it})$, is linked to the conditional variance, σ^2_{jt} by the formula:

$$Var(e_{it}) = \sum_j \theta_{jt} \sigma^2_{jt}, \quad (2)$$

where $\sigma^2_{jt} = Var(e_{it} \mid x_{it} \in j)$, and θ_{jt} is the share of workers in cell j. Thus, changing the shares will result in changes in the unconditional variance $Var(e_{it})$.

Furthermore, there is evidence that the variance of wages generally grows with education and experience (heteroskedasticity). Since the conditional variance in wages, V_{jt}, is linked to the conditional variance of unobserved skills by the equation

$$V_{jt} = p_t^2 \sigma^2_{jt}, \quad (3)$$

this suggests that σ^2_{jt} also increases as a function of experience and education. For example, with the general increase in the education levels of the Romanian workforce this can result in significant composition effects.

Assuming, the distribution of unobserved skills is stable within a cell, the residual variance of wages can be written as:

$$Var(e_{it}) = p^2{}_t \sum_j \theta_{jt}\sigma_j^2, \quad (4)$$

Thus, a decrease in residual variance can be interpreted as a decrease in skill prices only when the skill composition is held constant.

Lemieux proceeds to construct counterfactual values of the shares, $\theta *_{jt}$, as a way to keep the composition of the workforce constant. Thus, the counterfactual residual variance V_t^* is

$$V_t^* = \sum_j \theta_j^* V_{jt}, \ \ where\ V_{jt} = p_t^2 \sigma_j^2 \quad (5)$$

Having these in mind, the overall change in residual variance can be decomposed into two terms:

$$V_t - V_s = \sum_j (\theta_{jt} V_{jt} - \theta_{js} V_{js}) = \sum_j \theta_{js}(V_{jt} - V_{js}) + \sum_j (\theta_{jt} - \theta_{js}) V_{jt} \quad (6)$$

The first term in equation (6) is a weighted average of changes in the within group variance, this represents the change in the counterfactual variance when the counterfactual weights are set at their base period level. The second term in equation (6) captures composition effects. Composition effects result in a spurious growth in the residual variance when changes in the weights are positively correlated with the within group variances.

At last, finer experience-education were constructed using estimates from a logit model to reweight the data in a way that keeps the distribution of skills constant over time.

I divide the workers in 20 skill groups based on five education categories (elementary and gymnasium, vocational, high school, professional and college) and four experience categories (1-10, 11-20, 21-30, and 30+ years of potential experience). Table A5 shows the within group

variance for each of the education-experience cells in 1994 and 2000 respectively, as well as changes in the composition of the workforce in each cell.

Table A5.1 reports the changes in within group variance in column 3. For all college graduates and high school graduates with 11-20 years of experience the changes in residual variance are large and positive. For the 15 other education-experience cells, residual variance falls, both for young and old professional and the rest of the high school graduates falling less than the overall change in residual variance (-0.031).

There are other clear patterns that emerge from Table A5.1. Variance grows as a function of experience only for college graduates, while it falls for the low skilled groups such as gymnasium and vocational school graduates. This pattern is somewhat expected in post communist countries where experience accumulated before transition is more or less irrelevant for less skilled workers. On the other side, it is clear that within group variance grows as a function of education. For example, the average in the college group is .197 in 2000 compared to .128 for high school graduates and professional school graduates in the same year. The pattern holds for 1994 as well, however the difference is smaller. This finding suggests that returns to unobserved skills increased among the highly skilled over the studied period, however I expect composition effects to be quite significant given that the shares of these large variance groups increased as well.

The results for women in Table A5.2 are quite similar to those of men, with the exception of professional school graduates for which changes in variance are large and positive as well (just like in the case of men, the bold figures represent positive changes in the variance). For groups with less than a high school education the drop in variance is quite significant, and it seems that for women within group variance grows as a function of experience as well.

Columns 4 and 5 show the share of each skill group in the workforce in 1994 and 2000 respectively, with the last column presenting the change in shares over time. For both men and women there is a large decline in the share of workers with at most a gymnasium education and high school graduates with at most 10 years of experience. The largest declines have been recorded in these groups for those with many years of experience, suggesting the influence of early retirement schemes. On the other side, there are significant increases in the share of workers with a college degree with up to 30 years of experience.

The lower panels of Tables A5.1 and A5.2 show the magnitudes of composition effects. The first row shows the weighted average of the within group variances when the weights used are the actual shares in the corresponding year. The 1994 shares are used to weight the 1994 variances, and the 2000 shares are used to weight the 2000 variances. Thus, they correspond to the unadjusted residual variance for the two years. For men, residual variance falls by 0.031 percentage points, while for women it decreases by 0.037 percentage points.

The second row of panel B shows that the change in residual variance is much smaller when shares are held at their 1994 levels. For both men and women, only about 15% of the change in variance is due to the decrease in the within group variance. The remaining part, is explained by compositional effects. When shares are held at their 2000 levels, residual variance actually increases. This result is expected since using the 2000 shares puts more weight on college graduates who experience an increase in their within group variance. Thus, compositional effects play a much larger role in residual dynamics than increasing returns to unobserved skills.

7. Conclusion

This paper investigated the evolution of wage inequality in Romania over the last half a century, with particular emphasis on the transition period. Inequality in communist Romania was extremely low starting with the 70's, the growth in inequality experienced during the 60's being mainly the result of industrialization policies. Starting with 1990, once wages and prices were liberalized, inequality measures almost doubled. Although inequality subsided afterwards, in 1996, a period that coincides with the actual commencement of reforms in Romania, inequality measures went up again by almost 20%. Towards the end of the studied period the trend slowly reversed again so that by 2000 inequality measures based on net wages were lower than in 1994.

Pre-transition inequality was driven mainly by higher inequality at the low end of the distribution, while during transition the changes at the upper half are more important in explaining the increase in inequality. The sharp contraction below the median after 1997, a period of economic growth, explains the overall drop in inequality towards the end of the period.

The decomposition of wage inequality by sub-groups shows that inequality was higher among men, private sector workers and college graduates with more years of experience. The regression analysis revealed increasing returns to education, in particular to college education. The higher education premia in the private sector contribute to a higher inequality in the private sector. However, towards the end of the period the gap between sectors is closing as wage setting practices become more aligned and low income workers in the private sector experience a large growth in real wages. The occupational shift from low-skill to high skill occupations in a period of rising returns to skill suggest the importance of demand side adjustment in explaining wage inequality in Romania. Overall, human capital characteristics explain up to 20% of inequality.

Further, I find that the industry wage structure changed quite significantly during the studied period. Industrial employment shifts since 1994 have favored industries that more intensively utilize college graduates to less educated workers, pattern that is similar to the changes in the occupational distribution. The effect of reforms starting with 1996-1997 is seen by higher inter-industry wage differentials that facilitated worker reallocation. The preponderant growth of white collar industries was associated with shifts in relative wages that favored these industries. Thus, the main result of this dynamics was the reallocation of workers out of blue collar industries such as Agriculture, Extracting or Processing and into higher skilled industries such as Finance, Banking and Insurance, Public Administration or Education. Inter-industry differentials explain about 5% of wage inequality.

The decomposition analysis suggests that more than two thirds of wage inequality is explained by unobservables. I further decompose residual inequality into "price" and composition effects, and find that only 15% is accounted by increases in returns to unobserved ability and the rest is the effect of composition effects. Over the transition period the share of low skilled workers falls, particularly in the last age group, suggesting the effect of early retirement policies in reducing inequality. At the same time, the share of high variance groups, such as highly educated workers, increases significantly.

The implications of my analysis should be viewed in the light of the limitations that such a study may pose. First of all, there are associates measurement problems with the recording of wages. Unfortunately, there is no information on non-monetary benefits and since it is expected that non-monetary benefits increase in wages, the measures of inequality presented here potentially understate real inequality of labor income. Second, the lack of information on hours worked may have led to the inclusion in the sample of workers with different hour loads and thus

variation in wages may hide some variation in working hours. Third, the reliability of retrospective data could be questioned, and thus my pre-transition analysis should be regarded with extra care. However, the stability of inequality measures suggests that mistakes in answering these questions are not leading to systematic biases.

At last, I do not control for the selection of women (or men of that matter) into and out of the workforce. My previous research in the area suggests that it is mainly less educated women who opt out of the labor market and thus it would be an interesting exercise to see whether the dynamics in participation rates have a big impact on the compression at the low end of the wage distribution.

Appendix

Table A 1. Sample means for the retrospective data

	50-54	**55-59**	**60-64**	**65-69**	**70-74**	**75-79**	**80-84**	**85-89**	**1990**	**1991**	**1992**	**1993**
GW	529	582	557	850	1195	1445	1742	1969	3099	10731	25990	52982
	(342)	(323)	(417)	(494)	(538)	(553)	(594)	(652)	(1873)	(7837)	(15680)	(24...)
LW	6.12	6.22	5.99	6.56	6.98	7.19	7.39	7.53	7.9	9.09	10.01	10.77
	(0.54)	(0.53)	(0.88)	(0.64)	(0.48)	(0.42)	(0.37)	(0.34)	(0.49)	(0.56)	(0.53)	(0.44)
S	8.55	8.86	7.14	8.12	9.01	9.79	10.50	10.86	10.93	11.22	11.43	11.21
	(3.61)	(3.9)	(3.39)	(3.42)	(3.41)	(3.27)	(3.25)	(2.77)	(2.66)	(2.50)	(2.36)	(2.36)
E	.25	.25	.43	.28	.19	.13	.10	.06	.05	.02	.03	.03
G	.32	.30	.34	.36	.35	.31	.24	.20	.21	.21	.13	.17
V	.21	.15	.10	.19	.23	.25	.25	.29	.27	.25	.30	.28
H	.12	.15	.06	.10	.16	.21	.30	.36	.39	.42	.45	.41
P	.03	.05	.02	.01	.03	.03	.03	.02	.01	.02	.02	.05
C	.05	.07	.03	.04	.03	.05	.07	.06	.05	.06	.06	.05
X	4.83	7.07	12.68	12.75	12.52	12.11	11.2	10.08	9.7	9.33	8.98	10.53
	(4.11)	(5.75)	(7)	(8.52)	(9.94)	(11.08)	(11.42)	(11.56)	(11.07)	(10.3)	(10.05)	(9.61)
F	.29	.39	.47	.41	.44	.47	.45	.46	.45	.48	.41	.38
N	518	728	1426	998	1401	1469	1811	2760	559	276	240	166

Note: GW is the gross wage. LW is the natural log of GW, S is years of schooling and E stands for Elementary, G for Gymnasium, V for vocational, H for High School, P for Professional School and U for University. X is potential experience, F is a dummy for female and N is the number of observations. Standard deviations are shown in parentheses.

Table A 2. Sample means for the transition period

	1994	1995	1996	1997	1998	1999	2000
NW	123,212	180,051	265,785	482,680	817,227	1,150,222	1,994,008
LNW	11.62	12.00	12.37	12.97	13.50	13.85	14.40
S	11.42	11.50	11.69	11.72	11.86	12.06	12.44
E	0.03	0.03	0.024	0.019	0.015	0.013	0.006
G	0.18	0.17	0.12	0.112	0.097	0.090	0.060
V	0.28	0.29	0.34	0.347	0.345	0.333	0.311
H	0.33	0.34	0.32	0.318	0.332	0.344	0.359
P	0.04	0.04	0.09	0.084	0.082	0.081	0.095
C	0.11	0.12	0.11	0.117	0.127	0.136	0.166
X	20	20.41	20.32	20.75	20.49	20.51	20.70
F	0.42	0.41	0.42	0.42	0.43	0.44	0.436
Pr	0.09	0.14	0.17	0.21	0.26	0.33	0.39
N	24,732	22,767	23,039	14,833	21,002	18,672	13,619

Note: NW is the nominal net wage. LW is the natural log of NW, S is years of schooling and E stands for Elementary, G for Gymnasium, V for vocational, H for High School, P for Professional School and U for University. X is potential experience, F is a dummy for female, Pr is a dummy for private and N is the number of observations. Standard deviations are shown in parentheses.

Table A 3. Measures of wage inequality for net monthly wages

	SD of log wage	Percentile of log wage distribution			
		90/10	90/50	50/10	75/25
All sample					
1994	.427	1.048	.538	.509	.53
1995	.425	1.062	.556	.506	.542
1996	.463	1.168	.599	.569	.606
1997	.452	1.126	.574	.552	.576
1998	.43	1.081	.576	.505	.56
1999	.423	1.062	.57	.492	.558
2000	.413	1.014	.565	.449	.539
Females					
1994	.413	1.009	.497	.503	.507
1995	.404	1.007	.526	.481	.515
1996	.449	1.124	.581	.543	.585
1997	.436	1.07	.545	.525	.547
1998	.414	1.036	.55	.486	.529
1999	.409	1.011	.545	.466	.537
2000	.388	.933	.537	.396	.489
Males					
1994	.420	1.003	.533	.5	.532
1995	.422	1.053	.556	.497	.545
1996	.451	1.138	.590	.547	.586
1997	.444	1.126	.584	.542	.563
1998	.426	1.068	.621	.447	.553
1999	.417	1.058	.562	.496	.554
2000	.414	1.033	.552	.481	.539

Table A 4.1 Regression Estimates for the State Sector

lnwage	1994	1995	1996	1997	1998	1999	2000
Vocational	0.100	0.091	0.088	0.088	0.066	0.071	0.073
	(0.007)	(0.008)	(0.010)	(0.012)	(0.011)	(0.013)	(0.021)
High school	0.101	0.112	0.166	0.156	0.135	0.172	0.155
	(0.008)	(0.008)	(0.010)	(0.013)	(0.011)	(0.013)	(0.020)
Professional	0.186	0.221	0.265	0.272	0.244	0.277	0.255
	(0.014)	(0.014)	(0.013)	(0.016)	(0.013)	(0.016)	(0.023)
College	0.363	0.403	0.435	0.461	0.413	0.462	0.378
	(0.018)	(0.020)	(0.021)	(0.027)	(0.022)	(0.025)	(0.032)
Experience	0.020	0.024	0.023	0.026	0.024	0.025	0.027
	(0.0009)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Experience2	-0.0003	-0.0004	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004
	(0.00002)	(0.00002)	(0.00002)	(0.00003)	(0.00002)	(0.00003)	(0.00004)
Female	-0.121	-0.150	-0.134	-0.122	-0.109	-0.120	-0.136
	(0.005)	(0.005)	(0.006)	(0.008)	(0.006)	(0.007)	(0.009)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^sq	**.248**	**.289**	**.292**	**.300**	**.347**	**.353**	**.322**
Observations	21,440	18,556	17,601	10,631	13,210	9,079	5,856

Note: These are estimates obtained from OLS log wage regressions, all the coefficients are significant and the dummy variables are jointly significant.

Table A 4.2 Regression Estimates for the Private Sector

lnwage	1994	1995	1996	1997	1998	1999	2000
Vocational	.107	0.106	0.109	0.086	0.104	0.054	0.091
	(0.025)	(0.020)	(0.021)	(0.025)	(0.018)	(0.016)	(0.019)
High school	0.147	0.161	0.200	0.162	0.179	0.163	0.181
	(0.024)	(0.019)	(0.022)	(0.026)	(0.019)	(0.017)	(0.020)
Professional	0.277	0.251	0.259	0.293	0.278	0.276	0.250
	(0.056)	(0.050)	(0.039)	(0.038)	(0.029)	(0.027)	(0.028)
College	0.324	0.451	0.491	0.427	0.450	0.483	0.426
	(0.051)	(0.046)	(0.045)	(0.049)	(0.023)	(0.034)	(0.023)
Experience	0.021	0.022	0.026	0.025	0.019	0.022	0.023
	(0.002)	(0.002)	(0.002)	(0.0025)	(0.001)	(0.001)	(0.001)
Experience2	-0.0004	-0.0005	-0.0004	-0.0004	-0.0003	-0.0004	-0.0004
	(0.00007)	(0.00005)	(0.00005)	(0.00006)	(0.0004)	(0.00004)	(0.00004)
Female	-0.178	-0.162	-0.163	-0.128	-0.157	-0.145	-0.143
	(0.018)	(0.0146)	(0.013)	(0.015)	(0.010)	(0.009)	(0.010)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^sq	**.285**	**.321**	**.328**	**.316**	**.303**	**.342**	**.302**
Observations	2,393	3,165	3,989	3,153	5,464	6,297	5,324

Note: These are estimates obtained from OLS log wage regressions, all the coefficients are significant and the dummy variables are jointly significant.

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Table A 5.1 Within Group Variance of wages by Experience-Education Cell for Men, 1994-2000

	Within-group variance			Work-force share		
	1994 (1)	2000 (2)	Change (3)	1994 (4)	2000 (5)	Change (6)
A. By Education -Experience						
Gymnasium& Elementary						
1-10	0.198	0.052	-0.147*	0.078	0.035	-0.043
11-20	0.186	0.147	-0.039	0.099	0.043	-0.056
21-30	0.160	0.120	-0.039	0.147	0.045	-0.103
30+	0.151	0.111	-0.041*	0.201	0.101	-0.100
Vocational						
1-10	0.157	0.103	-0.054*	0.063	0.071	0.009
11-20	0.172	0.131	-0.041*	0.070	0.109	0.039
21-30	0.141	0.109	-0.031*	0.076	0.120	0.044
30+	0.138	0.110	-0.027*	0.025	0.061	0.036
High School						
1-10	0.142	0.116	-0.026*	0.083	0.079	-0.004
11-20	0.144	0.145	**0.001**	0.062	0.111	0.049
21-30	0.145	0.131	-0.014	0.027	0.062	0.035
30+	0.138	0.122	-0.016	0.007	0.020	0.013
Professional						
1-10	0.166	0.150	-0.016	0.002	0.006	0.004
11-20	0.206	0.119	-0.087*	0.002	0.007	0.005
21-30	0.160	0.125	-0.035	0.002	0.012	0.010
30+	0.128	0.120	-0.009	0.001	0.005	0.004
College						
1-10	0.132	0.209	**0.076***	0.016	0.035	0.019
11-20	0.157	0.208	**0.051***	0.021	0.029	0.007
21-30	0.172	0.181	**0.009**	0.013	0.038	0.026
30+	0.158	0.191	**0.033**	0.005	0.012	0.007
B. Weighted Average(alternative shares)						
Actual Shares	0.159	0.128	-0.031			
1994 Shares	0.159	0.154	-0.005			
2000 Shares	0.120	0.128	0.008			

Note: Standard Errors range from 0.009 to 0.035 (the significant changes are starred).

Table A 5.2-Within Group Variance of wages by Experience-Education Cell for Women, 1994-2000

	Within-group variance			Work-force share		
	1994 (1)	2000 (2)	Change (3)	1994 (4)	2000 (5)	Change (6)
A. By Education -Experience						
Gymnasium& Elementary						
1-10	0.110	0.112	**0.002**	0.068	0.027	-0.042
11-20	0.151	0.064	-0.087*	0.105	0.025	-0.080
21-30	0.164	0.089	-0.074*	0.217	0.076	-0.141
30+	0.151	0.089	-0.062*	0.133	0.100	-0.033
Vocational						
1-10	0.165	0.056	-0.109*	0.026	0.028	0.002
11-20	0.144	0.099	-0.045*	0.041	0.065	0.024
21-30	0.141	0.096	-0.045*	0.029	0.071	0.042
30+	0.147	0.104	-0.042	0.005	0.013	0.008
High School						
1-10	0.133	0.101	-0.032*	0.114	0.096	-0.018
11-20	0.149	0.126	-0.022*	0.108	0.164	0.056
21-30	0.136	0.106	-0.030*	0.057	0.119	0.062
30+	0.124	0.120	-0.004	0.008	0.028	0.020
Professional						
1-10	0.091	0.099	**0.008**	0.005	0.020	0.014
11-20	0.129	0.131	**0.003**	0.007	0.014	0.007
21-30	0.115	0.104	-0.011	0.012	0.021	0.010
30+	0.097	0.123	**0.026**	0.002	0.007	0.005
College						
1-10	0.147	0.153	**0.006**	0.019	0.043	0.024
11-20	0.135	0.135	**0.000**	0.025	0.039	0.014
21-30	0.159	0.167	**0.007**	0.015	0.038	0.023
30+	0.076	0.168	**0.092***	0.002	0.006	0.004
B. Weighted Average (alternative shares)						
Actual Shares	0.146	0.109	-0.037			
1994 Shares	0.146	0.142	-0.004			
2000 Shares	0.099	0.109	0.010			

Note: Standard Errors range from 0.006 to 0.033 (the significant changes are starred).

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