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# Wages in the Netherlands: a Micro Approach

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**Abstract** – For many years, the Netherlands has been considered an exception to the trend of growing wage inequality that most OECD countries have experienced since the 1980s. This trend is generally explained by increasing relative demand for skilled labor due to skill biased technological progress and, to some extent, globalization. Recently, Straathof et.al. (2010) have found that Dutch top wage inequality has been rising since 2000, and conclude that the Netherlands might be following the international trend with some delay. By using microdata on the entire wage distribution from Statistics Netherlands, this paper examines trends in Dutch (real pre-tax) wage inequality between 2000 and 2005, thus extending the previous literature by covering recent years. We find that inequality, after correcting for observed worker characteristics, decreased somewhat at the lower half of the wage distribution, while increasing slightly at most of the upper half, and relatively strong at the highest few percentiles. Wage growth was also higher within already a higher initial wage level, and in the Randstad agglomerations. It is shown that changes in the wage structure are to a large extent explained by prices and quantities of worker characteristics, while changes in the residual wage distribution play a role at the highest percentiles.

## 1. Introduction

Rising wage inequality since the 1980s in the United States and other advanced economies has resulted in a vast literature describing the nature and possible causes of this phenomenon. During the 1980s and 1990s, wages of some groups on the U.S. labor market – especially blue collar workers – have fallen in real terms, whereas the wages of workers in the higher percentiles of the wage distribution have grown substantial (Lawrence, 2008). The Netherlands is often considered an exception to this general picture. Changes in wage inequality have been mild, both when compared to the substantial increase in U.S. wage inequality and when compared to trends in other European countries. For The Netherlands, Ter Weel (2003) shows that the 90–10<sup>th</sup> percentile wage differential increased by less than two percent between 1992 and 1998, after increasing by eight percent between 1986 and 1992. Atkinson and Salverda (2005) have shown that Dutch inequality has remained fairly stable during most of the 1977–1999 period.

The literature on Dutch wage inequality after the 1990s is limited. This paper aims to describe and explain trends in Dutch wage inequality during the 2000–2005 period, using microdata on wages and employee characteristics. We show that the best paid workers have gained more during this period than workers in the middle and lower tail of the distribution. The 99–90<sup>th</sup> wage differential has increased by 4.1 percent, and the 90–50<sup>th</sup> differential by 0.6 percent. At the bottom end of the wage distribution, inequality has fallen, as the 50–10<sup>th</sup> differential decreased by 1.8 percent. An important advantage of using microdata in stead of macro data is that the latter can provide insights in how changes observed in the aggregate wage distribution are related to changes

in prices and volumes of individual workers. An important insight of this paper is that changes in macro wage inequality have no single explanation, but have the net effect of diverse and complex interactions on the labor market.

We will describe levels and trends of Dutch wage inequality, and apply the framework of Juhn et al. (1993) to separate three types of effects: (i) price changes – e.g. wages – and (ii) quantitative changes of observable worker characteristics – e.g. the effect of changes in labor market composition – and (iii) residual changes that are related to unobservable worker characteristics. Additionally, we use this method to identify trends in prices and quantities of isolated components of human capital, like education, age, and gender. Well paid jobs are not uniformly distributed across professions and regions. We will therefore present our results not only for the economy as a whole, but also for different occupations and regions. This shows that in 2005 (2000), after correcting for observed human capital, managerial occupations pay a 48 (39) percent higher wage than the average occupation. Wages in the large agglomerations in the Randstad pay a 5.6 (3.8) percent premium in 2005 (2000). Overall, the paper shows that inequality of above median wages has increased over multiple dimensions.

Skill biased technological progress is generally considered the most plausible explanation for increasing wage inequality in the U.S. (Katz and Murphy, 1992; Autor et al., 1998 and 2006). Other often cited potential causes are globalization, and reduced supply of skilled labor (Nahuis and De Groot, 2003). The theories result in very similar testable hypotheses: rising skill and experience premiums. The mechanisms through which they operate are, however, very different. In the first case it is technology that is supplementary to tasks that need high skilled and experienced workers but complementary to simpler routine tasks, thus increasing relative demand for skills. In the case of globalization it is increased competition with countries housing large pools of unskilled workers that increases the skill premium. In the third case the fact that access to higher education is no longer increasing as it did during the 1970s and 1980s. It has proven difficult to empirically separate these different forces, and the debate is far from settled. Ter Weel (2003) and Nahuis and De Groot (2003) argue that the relative stability of the Dutch wage distribution is explained by the fact that educational attainment has continued to grow for a relatively long period in time. Increased demand for skilled labor (possibly caused by skill biased technological progress or globalization) was thus balanced by increased supply of skilled workers, such that the resulting price of skills showed little change. In countries where supply of skilled labor remained constant, it resulted in a higher skill premium and thereby higher wage inequality. In the Netherlands, the skill premium has increased by 7.3 percent between 2000 and 2005, which suggests that the market for skills has tightened.

The contents of the remainder of this paper are as follows. The next section will present the microdata used in this paper. Section 3 presents descriptive statistics on (trends in) Dutch wage inequality between 2000 and 2005. Section 4 discusses the methodology that we have used to decompose trends in inequality in different components, and present the results of this exercise.

Section 5 adds to this by presenting data on trends in wages and wage inequality for different occupation categories, while Section 6 discusses the regional dimension of wage inequality. Section 7 concludes.

## 2. Data

The results that are presented in this paper are obtained using employee microdata from Statistics Netherlands (CBS). Data on worker characteristics are drawn from different cross-sections of the annual labor market survey (EBB, *Enquête Beroepsbevolking*), 2000–2005. For wages, we rely on tax data reported by employers, available through the CBS social statistics database (SSB, *Sociaal Statistisch Bestand*). For workers with multiple jobs, we include each job as a separate observation. We have used the CBS consumer prices deflator (CPI, *Consumenten Prijs Index*) to deflate annual earnings. Throughout our analyses, we rely on log hourly wages, defined as the natural logarithm of the deflated pre-tax wage divided by the number of hours worked.

To make sure that only workers with a sufficiently strong attachment to the labor market are included, we have dropped some observations. Workers must be aged 18–65, and work at least 12 hours per week<sup>1</sup>. We have dropped all observations with a hourly wage less than 10 percent of the median wage in each year. These observations are unlikely to be regular wages, as they are below the minimum wage. To avoid high standard deviation of the wages of top earners (there are, for example, only a few workers with an income above one million Euros in each cross-section), we have also dropped all workers earning more than 10 times the median wage. We use age as a proxy for experience, which captures different sources of human capital, including – but not limited to – present and previous occupations. We measure education as the nominal years of schooling that is needed to achieve the highest level of education that a worker has successfully graduated from. Other worker characteristics that are included are country of birth (a binary variable that indicates whether a worker is born in the Netherlands or not), gender, and whether a worker is employed part-time or full-time.

Table 1 presents some descriptive statistics concerning the variables that have been introduced in this section. These are the quantities discussed in the introduction. Net real wages have increased by 5.4 percent between 2000 and 2005, though for most years after 2001 wage growth is barely enough to keep up with inflation. Even though the period of observation is limited, some pronounced changes have occurred. Workers in 2005 are on average 0.53 years higher educated than workers in 2000, and are 2.46 years older. The share of females has increased by 3.2 percent points, while the share of part-time jobs increased by 4.7 percent points to almost half of total jobs. As part-

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<sup>1</sup> Statistics Netherlands defines workers with a working week of at least 12 hours as employed, workers with a working week of at least 36 hours are considered full-time employees. Jobs occupied by teenagers are often sideline jobs, that would be outliers in our dataset.

time workers and females tend to be overrepresented at the lower percentiles of the wage distribution, and older and higher educated workers at the higher percentiles, this could have resulted in increasing wage inequality. If, however, changes in worker characteristics are evenly distributed (e.g. if the higher average age is not the result of something like increased labor market participation of older workers, but only a level effect), inequality would have remained unchanged. The use of microdata gives the possibility to determine what forces are dominant, and how they interact.

**Table 1. Descriptive statistics, 2000–2005**

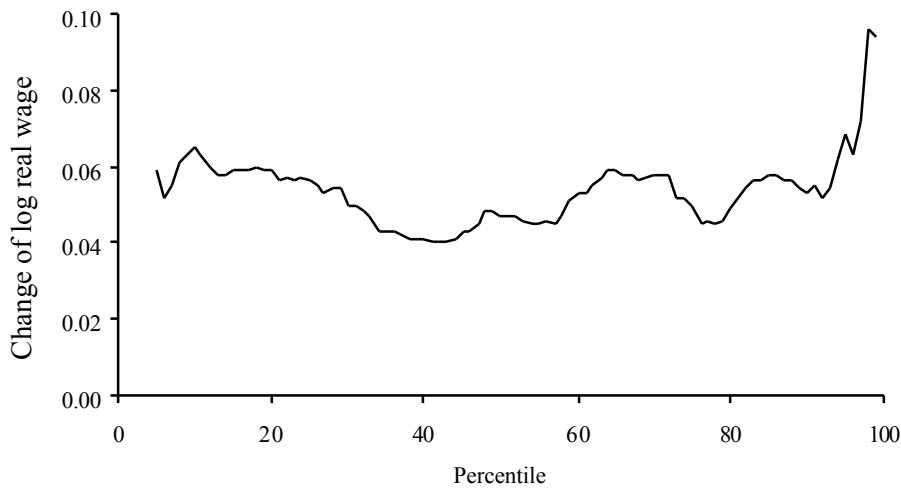
	<b>2000</b>	<b>2001</b>	<b>2002</b>	<b>2003</b>	<b>2004</b>	<b>2005</b>
Log real hourly wage	2.844 (0.434)	2.880 (0.424)	2.895 (0.426)	2.896 (0.428)	2.886 (0.453)	2.898 (0.438)
Age	39.13 (10.71)	40.06 (10.57)	40.61 (10.68)	40.92 (10.73)	41.10 (10.84)	41.59 (10.79)
Education (years)	14.63 (3.110)	14.68 (3.106)	14.80 (3.141)	14.86 (3.110)	15.04 (3.135)	15.16 (3.129)
Females	0.483 (0.500)	0.483 (0.500)	0.496 (0.500)	0.500 (0.500)	0.511 (0.500)	0.515 (0.500)
Part-time	0.438 (0.496)	0.429 (0.495)	0.448 (0.497)	0.460 (0.498)	0.473 (0.499)	0.485 (0.500)
Foreign born	0.077 (0.267)	0.074 (0.262)	0.072 (0.259)	0.067 (0.251)	0.068 (0.252)	0.070 (0.256)

Note: standard deviations are between parentheses

### 3. Trends in inequality

Figure 1 shows recent trends in Dutch wage inequality, as measured by percentile changes of log hourly wages between 2000 and 2005, for each percentile of the wage distribution. The median wage has increased by 4.7 percent. The negative slope for the bottom half of the wage distribution implies that wages have become somewhat more equal for the lower incomes. For above median wages, the pattern is diverged, though most of the higher percentiles experienced above median wage growth. At the highest percentiles, there has been substantial diversion. Workers at the 90<sup>th</sup> percentile have gained 7.4 percent and workers at the 99<sup>th</sup> percentile as much as 9.4 percent. It seems thus that “the rich” have gained the most. It is important to note that wages in Figure 1 have not been corrected for a changing composition of the labor market. It could be that the people that are rich in 2005 have different characteristics than those in 2000.

**Figure 1. Trends in wage inequality, 2000–2005<sup>2</sup>**



The four panels in Figure 2 compare wage changes by percentiles for different subgroups on the labor market. Differences in average wage growth are related to between group inequality (e.g. if one curve is above another on average, average wage growth was higher in that group), while differences in the shape of the distributions are the result of changing within group inequality. Similar to Figure 1, it compares aggregated change in real log wages between 2000 and 2005. Panel A compares workers with different levels of education. We start by discussing level effects. Wages of workers with only primary education have increased by 0.9 percent on average, wages of workers with secondary education by 2.1 percent and wages of workers with tertiary education by 2.7 percent. Between group inequality has thus increased (as the highest growth rate was experienced by the group with the highest average wage in 2000). For workers with only primary education, wages around the median have decreased in real terms, while wages at the lower percentiles have increased. For workers with secondary education, wages have increased somewhat faster at the lower than at the higher percentiles, thus decreasing within group inequality. Compensation of workers with tertiary education has increased more at the higher percentiles than at the rest of the distribution, resulting in higher inequality. At first sight, the fact that wages increased by 5.4 percent on average seems incompatible with the finding that wage growth was lower than 5.4 percent at each individual level of education. This is, however, the result of the increased share of higher educated workers. As they are vastly overrepresented in the higher percentiles, this change in labor marked composition results in higher wages at higher percentiles of the aggregate wage distribution, even when inequality within education groups would not have changed at all.

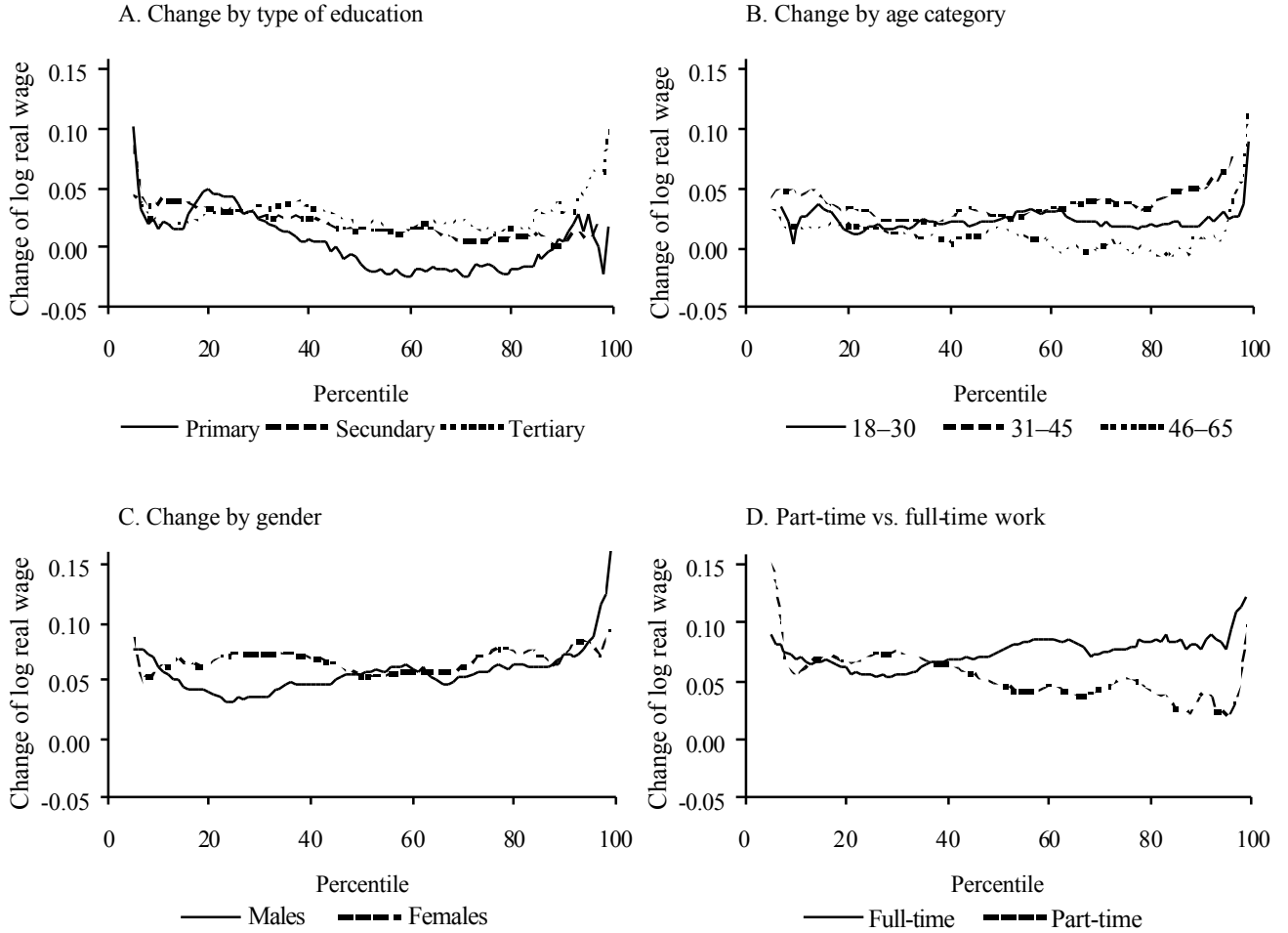
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<sup>2</sup>This figure is constructed as follows: all employees have been sorted according to their log real wages in both 2000 and 2005. We calculate the change in log real wage at each percentile between 2000 and 2005. Figure 1 gives the relation between percentile and change in log wage. If wages have increased relatively fast at either the lowest or the highest percentiles (in the centre of the distribution), inequality as defined by common measures like the Theil or Gini indexes would have increased (decreased).

Panel B compares wages of workers of different age. Age groups mainly differ in the level of growth. Wages of workers in their thirties and early forties have increased by 3.6 percent, wages of younger workers by 2.7 percent, and wages of older workers by 1.1 percent on average. This reduced inequality between groups. The most likely explanation for this phenomenon is a changing skill composition within the group of older workers. Well paid and higher educated workers are far more likely to continue working when they are old than less educated workers, but during the last decade policies targeted at increasing labor market participation of elderly workers have been implemented. As less educated workers are now also more likely to work in their fifties and sixties, the average level of education has decreased. This results in relatively low growth of wages for this group of workers. An alternative explanation is also related to changing institutions. Even though workers are generally thought to reach the top of their productivity between their forties and fifties, older workers have the highest wages for institutional and historical reasons. As the economy has become more competitive, inequality between older workers and workers of middle age could have decreased. Differences between trends in the distribution of wages within the different groups are relatively small. All ages show a similar above average growth of wages at the highest percentiles.

Panel C shows trends in wages of male and female workers. Wages of males have increased by 5.9 percent on average, wages of females by 6.8 percent. Wages of both genders thus increased faster than the aggregate wage growth of 5.4 percent. This is the result of increased female labor market participation. As wages of females are on average lower than wages of males (male wages were 24 percent higher in 2005), increased labor market participation of women reduces aggregate wage growth. The diversion of wages at the top is much more pronounced for male than for female workers. Also, male wage inequality has increased somewhat across almost the entire distribution, while remaining constant for females. Within group inequality of male workers has thus increased, and between gender inequality was reduced. Panel D compares wages of full-time workers with wages of part-time workers. Wages of full-time workers increased by 7.7 percent, substantially faster than wages of part-time workers, which increased by 5.4 percent. The fact that growth of full-time worker wages outpaced aggregate wage growth is the result of an increased share of part-time jobs. Payment of part-time jobs has become more equal, which is consistent with a decreasing importance of cohort effects. The increased share of part-time jobs is closely related to increased female labor market participation. Euwals et al. (2007) show that the participation rate of women (at a given age) increases as they are member of younger age cohorts, but find that this effect is now declining. Because of this, an increasing share of the part-time jobs is occupied by older workers (that have higher average wages). This results in a shift in percentiles.

**Figure 2. Trends in wage inequality by subgroup, 2000–2005**



We have thus far seen that composition effects explain at least a part of observed trends in the wage structure. The Mincerian wage regression is an often-used tool to analyze the structure of wages, as it separates variation in wages due to observed worker characteristics from a residual wage component. We have estimated a wage regression for each year separately,

$$w_{it} = X_{it}\beta_t + \varepsilon_{it} \quad (1)$$

which explains log wages  $w_i$  as a function of a constant and worker characteristics  $X_i$ , and a remainder  $\varepsilon_i$  that is attributed to unobserved differences between workers. We include education (years of educational attainment), age (as a proxy for experience), gender, whether a person works part-time or not, and whether a person is a foreign born or not. The results are presented in Table 2. The skill premium (e.g. the monetary value of having attended one additional year of education)



ranges from 6.2 percent to 6.7 percent, and is relatively stable. The returns to age or experience are concave, with an estimated top just above the age of 50. The career premium, measured as the expected *ceteris paribus* wage difference between an 18 year old worker and a worker at the career top ranges from 74 percent in 2001 to 80 percent in 2004. Male workers earn substantially more than females after correcting for other characteristics, full-time workers more than part-time workers, and native born workers more than foreign born. The latter is most likely at least partially the result of omitted variables, like social skills (for example language).

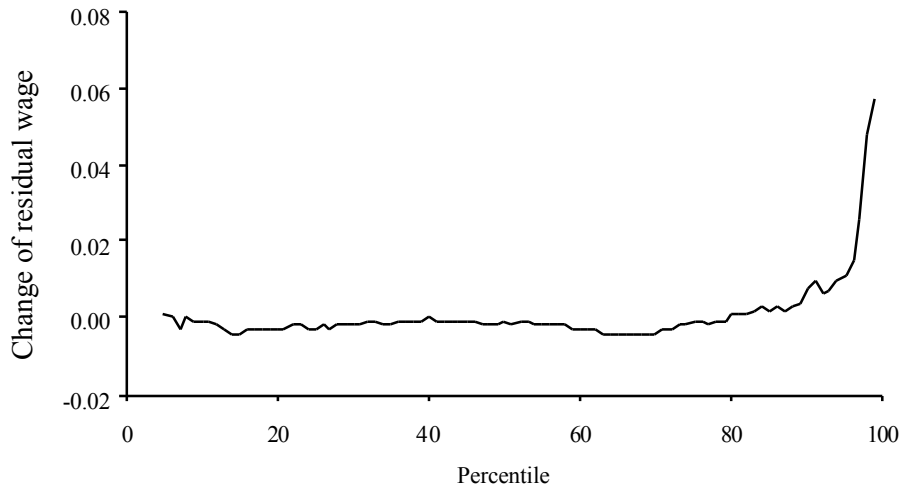
**Table 2. Estimation results wage regressions, 2000–2005**

	2000	2001	2002	2003	2004	2005
Education (years)	0.062 (102.2)	0.063 (99.9)	0.065 (108.7)	0.067 (147.3)	0.066 (145.4)	0.066 (148.9)
Age	0.074 (61.4)	0.071 (54.3)	0.071 (58.1)	0.069 (76.0)	0.078 (84.1)	0.071 (78.5)
Age-squared	-0.0007 (-48.0)	-0.0007 (-43.0)	-0.0007 (-46.0)	-0.0007 (-60.2)	-0.0007 (-67.9)	-0.0007 (-62.9)
Female	-0.130 (-28.6)	-0.129 (-26.7)	-0.111 (-23.9)	-0.124 (-35.4)	-0.123 (-35.1)	-0.114 (-33.1)
Part-time	-0.114 (-25.3)	-0.118 (-24.5)	-0.121 (-26.1)	-0.118 (-34.0)	-0.135 (-35.1)	-0.132 (-38.1)
Foreign born	-0.091 (-13.0)	-0.099 (-13.3)	-0.081 (-11.2)	-0.070 (-12.6)	-0.079 (-14.1)	-0.082 (-15.3)
R <sup>2</sup>	0.989	0.990	0.990	0.990	0.988	0.989

Note: t-statistics are between parentheses

The distribution of the unexplained wage component  $\varepsilon_i$  can be interpreted as inequality within groups on the labor market with narrowly defined worker characteristics. Sorting all workers in our sample by their residual wage gives the distribution of wages independent from observed human capital. Figure 3 shows trends in residual wage inequality, e.g. the change in residual wage inequality at each percentile between 2000 and 2005. The changes at the top of the residual wage distribution are striking. Residual wage growth at the 99<sup>th</sup> percentile was 5.7 percent above average. This is in clear contrast with all workers below the 90<sup>th</sup> percentile, where the distribution remained very flat. Even within the highest percentiles, it are only the top five percentiles who have gained more than one percent. When we compare Figure 3 with Figure 1, we see that almost all changes in aggregate wages (e.g. before correcting for human capital) are explained by the variables included in the Mincer equation. The resulting residual wage distribution is almost flat. The difference between the highest few percentiles and the rest of the distribution, however, are even more pronounced in Figure 1, providing strong evidence for increasing top wage inequality.

**Figure 3. Trends in residual wage inequality, 2000–2005**



#### 4. Decomposition of changes in wage inequality

There are several methods to analyze changes in the structure of wages. Fishlow (1972) introduced a simple method to decompose overall change in inequality as measured by the Theil index in different between and within group components. Following the Blinder-Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973), several methods have been developed to decompose differences in log wages by using regression models. These methods typically decompose differences in average wages between groups of workers with certain characteristics (e.g. education, age, gender) in two sets of components: (i) changes in average observed worker characteristics, and (ii) changes in the estimated returns or prices of those characteristics. We use the technique developed by Juhn et al. (1993) to decompose trends in wage inequality into three components, (i) a part due to quantitative changes of observable worker characteristics – e.g. the number of workers on the labor market with certain characteristics, (ii) a part that can be attributed to price changes – representing the wages that are associated with each of these worker characteristics given their supply – and (iii) residual changes that are related to unobservable worker characteristics. The method thus takes residual wage inequality explicitly into account, a feature that other models lack. Another important advantage of the method is that it allows us to analyze the entire wage distribution, in stead of just the variance of wages. The method of Juhn et al. is based on estimating wage equations (this is just the Mincer equation, as presented in the previous Section),

$$w_{it} = X_{it}\beta_t + u_{it} \quad , \quad (2)$$

where  $w_{it}$  is a vector with the log hourly wage of individual  $i$  in year  $t$ ,  $X_{it}$  is a matrix with individual characteristics,  $\beta_t$  is a matrix vector with separate regression coefficients for each year and  $u_{it}$  an error term that captures all unobserved dimensions of the wage. In each year, we sort all workers according to their residual wage. The residual  $u_{it}$  can be separated in two components, the position of the individual in the residual wage distribution (a percentile rank),  $\theta_{it}$  and the distribution function of the residual wage  $F_t(\cdot)$ , which gives the relation between the percentile rank and the amount of residual wage inequality, which varies over time. We thus define  $u_{it}$  as

$$u_{it} = F_t^{-1}(\theta_{it} | X_{it}) , \quad (3)$$

where  $u_{it} = F_t^{-1}(\cdot | X_{it})$  is the inverse cumulative distribution of the residual wage of workers with the characteristics that were observed in  $X_{it}$ . There are three sources of wage inequality. (i) Composition effects, e.g. changes in the supply of workers with characteristics that are captured in  $X_{it}$ , (ii) changes in the prices of various observed characteristics, the estimated  $\beta_t$ 's and (iii) changes in the distribution of the residuals  $u_{it}$ . Changes in the residual wage distribution are changes in the relation between the percentile rank, and the residual wage. We define  $\bar{\beta}$  as the average price of observable characteristics, and  $\bar{F}_t^{-1}(\cdot | X_{it})$  as the average cumulative residual wage distribution (taking the average residual at each percentile over the years 2000–2005). Wage inequality can subsequently be decomposed in the sources described above as

$$w_{it} = X_{it}\bar{\beta} + X_{it}(\beta_t - \bar{\beta}) + \bar{F}_t^{-1}(\theta_{it} | X_{it}) + [F_t^{-1}(\theta_{it} | X_{it}) - \bar{F}_t^{-1}(\theta_{it} | X_{it})] . \quad (4)$$

The first term represents the effect of a changing labor market composition at fixed prices. The second term captures the effects of changing prices of the observables, keeping the quantities of each characteristic fixed, and the third and fourth term capture the effects of changes in the residual wage distribution. We can use (3) to reconstruct the wage under ceteris paribus conditions. At a given price level of worker characteristics and a given distribution of residual wages, the wage distribution is given by

$$w_{it}^q = X_{it}\bar{\beta} + \bar{F}_t^{-1}(\theta_{it} | X_{it}) . \quad (5)$$

If we keep only the residual wage distribution constant, such that both prices and observed characteristics of workers vary over time, the distribution of wages is given by

$$w_{it}^{p,q} = X_{it}\beta_t + \bar{F}_t^{-1}(\theta_{it} | X_{it}) . \quad (6)$$

If all three sources of wage change vary together, changes in wage inequality are captured by

$$w_{it}^{p,q,d} = X_{it}\beta_t + F_t^{-1}(\theta_{it} | X_{it}) = X_{it}\beta_t + u_{it} . \quad (7)$$

A convenient way to identify these different effects is to start by estimating equation (7), which is equivalent to equation (2). The regression coefficients of different years are used to obtain average prices  $\bar{\beta}$ . After sorting the residuals (in each year separately) we can determine the average residual over the years in each percentile. Next step is to calculate quantity effects, using equation (5), and price effects, by taking the difference of equations (6) and (5). The effects of changes in the residual wage distribution are given by the difference of (7) and (6).

Juhn et al. (1993) use their methodology to decompose changes in wage inequality in price and quantity effects for all worker characteristics together. We now propose a simple extension to their framework, which enables us to isolate effects of different worker characteristics. Let  $\mathbf{x}_{it}^m$  be a vector with the quantities of individual worker characteristic  $m$  with corresponding price  $\beta_t^m$ , and  $X_{it}$  a matrix with all other observed quantities (with prices  $\beta'_t$ ), such that  $\mathbf{x}_{it}^m \beta_t^m + X_{it}' \beta'_t = X_{it} \beta_t$ . We define  $\varphi_{it}$  to be the position of an individual in the conditional wage distribution  $F_t^{-1}(\varphi_{it} | X_{it}' \beta'_t)$ , representing the distribution of wages conditional on quantities and prices of all worker characteristics except characteristic  $m$ . As before,  $\beta_t^m$  and  $\beta'_t$  are estimated using equation (7) or its equivalent (2). By keeping  $F_t^{-1}(\varphi_{it} | X_{it}' \beta'_t)$  constant, we can isolate the effects of changes related to characteristic  $m$  from changes in both the residual distribution and changes in the wage distribution related to all other worker characteristics. The ceteris paribus effect of changes in the quantity of  $m$  is given by

$$w_{it}^q = \mathbf{x}_{it}^m \bar{\beta}_t^m + \bar{F}_t^{-1}(\varphi_{it} | X_{it}' \beta'_t) , \quad (8)$$

and the effect of changes in prices and quantities of characteristic  $m$  combined by

$$w_{it}^{p,q} = \mathbf{x}_{it}^m \beta_t^m + \bar{F}_t^{-1}(\varphi_{it} | X_{it}' \beta'_t) . \quad (9)$$

A difference between the above equations and equations (5) and (6) is that  $\mathbf{x}_{it}^m$  and  $\bar{F}_t^{-1}(\varphi_{it} | X_{it}' \beta'_t)$  are correlated, whereas  $X_{it}$  and  $\bar{F}_t^{-1}(\theta_{it} | X_{it})$  are independent. Within groups with similar characteristics, however, the distribution of  $\bar{F}_t^{-1}(\varphi_{it} | X_{it}' \beta'_t)$  remains to be

uncorrelated from  $\mathbf{x}_{it}^m$ . This implies that interdependencies between characteristic  $m$  and the distribution of wages related to all other worker characteristics (for example the fact that older workers are relatively skill abundant) is captured in  $\bar{F}_t^{-1}(\varphi_{it} | X_{it}^n \beta_t^r)$ , whereas changes in  $F_t^{-1}(\varphi_{it} | X_{it}^n \beta_t^r)$  that are the result of changes in  $\mathbf{x}_{it}^m$  are not captured. This implies that, for example, an increasing share of higher educated workers resulting from a higher participation rate of older workers – that have a higher average level of education – will not be captured. We can thus estimate a wage distribution corresponding to changed prices and quantities of characteristic  $m$  as if all other worker characteristics had remained unchanged.

Panel A in Table 3 gives the results of the decompositions for all worker characteristics combined. Changes in the 99–90<sup>th</sup> differential are partly due to composition effects (observed quantities) and observed prices, but mostly due to changes in the residual wage distribution. This is consistent with the findings of the previous section, that showed a strong increase of residual wage inequality at the highest percentiles. The slightly increasing 99–90<sup>th</sup> differential is the net effect of different opposite forces. Observed quantities have reduced inequality, whereas observed prices and a changing residual wage distribution tended to increase inequality. The lower half of the wage distribution shows a different pattern. Here, a changing labor market composition fully explains decreased inequality, though its effect is somewhat moderated by changing prices of human capital. Within group inequality remained unchanged. The panels B and C show the isolated effects of education and experience on the wage distribution (recall that all variables on human capital are still included in the regression analysis). The diverged pattern shows that education or experience alone do not provide a clear cut explanation for observed changes in the aggregate wage distribution. Different types of human capital have opposite or interacting effects on the wage distribution.

**Table 3. Decomposition of wage inequality**

Differential	Total change (1)	Observed quantities (2)	Observed prices (3)	Residual distribution (4)
A. All characteristics				
99–90 <sup>th</sup>	0.041	0.009	0.008	0.024
90–50 <sup>th</sup>	0.006	–0.014	0.012	0.007
50–10 <sup>th</sup>	–0.018	–0.026	0.007	0.001
B. Only education				
99–90 <sup>th</sup>	0.041	0.040	–0.021	0.022
90–50 <sup>th</sup>	0.006	–0.009	0.015	0.000
50–10 <sup>th</sup>	–0.018	0.009	0.002	–0.029
C. Only experience				
99–90 <sup>th</sup>	0.041	–0.018	0.001	0.057
90–50 <sup>th</sup>	0.006	–0.020	0.002	0.024
50–10 <sup>th</sup>	–0.018	–0.017	0.000	–0.001

The broad picture of Table 3 nevertheless seems to be consistent with the findings presented in Figure 2. It shows that wage inequality within groups of workers with homogeneous skill characteristics decreased for the lower percentiles (this is consistent with the negative slope in Panel A of Figure 2), whereas within group inequality remained stable for most of the above median workers (this implies a zero slope in Figure 2), and increased at the top few percentiles (positive slope in Figure 2). Wage inequality within groups with similar experience has stayed constant at the lower half of the distribution, and is increasing as we approach the highest percentiles.

## 5. Wage inequality and occupations

The previous sections have shown that changes in wage inequality follow a complex pattern, that is not fully explained by trends in observed and unobserved changes in human capital. As predicted by segmented labor market models, mobility between different occupations is limited. Recent contributions to the literature on U.S. wage inequality propose that the effects of skill biased technological progress and globalization are not limited to certain education or experience levels, but affect the labor market on the level of occupations (Autor et al., 2003, 2006 and 2008) or even tasks (Grossman and Rossi-Hansberg, 2008). For example, it is thought that housekeeping (which requires little skills or experience) is not affected by either biased technological progress or globalization, whereas jobs in accounting or bookkeeping are increasingly standardized and automated. Goos and Manning (2007) show that jobs that are vulnerable to biased technological progress tend to be located at the bottom of the wage distribution.

Table 4 shows the residual wage distribution – using the residuals that were obtained from estimating equation (1) in Section 3 – for nine occupation categories as defined in the EBB function classification of Statistics Netherlands. The average wage residual per job type is an indicator for inequality between occupations, as it represents the wage differential that is not explained by differences in the composition of the workforce in each occupation. Total inequality within each occupation (e.g. not corrected for worker characteristics) is presented in Table 5, where it is decomposed into different components. Column 1 of Table 4 shows average residual wages in 2005. Wages in personal and social care are over 30 percent lower than expected from observed worker characteristics. As there has already been corrected for the overrepresentation of females (earning 11.4 percent less than males *ceteris paribus*) and part-time workers (earning 13.2 percent less) in this sector, the remaining gap with other sectors is quite large. Managers, in contrast, earn the highest wages after correcting for observed worker characteristics, earning a 48 percent premium in 2005. Column 5 shows trends in inequality between occupations. The strongest increase in average residual wage (8.9 percent) was for management functions. The strongest decreases in residual wage were in the two sectors that already had the lowest residual wage level: personal and social care (–2.9 percent), and transport and communication (–6.1 percent). The correlation coefficient between

the level of residual wage and change in residual wage is very high: 0.91. The findings thus provide some evidence supporting the hypothesis of Autor et al. (2003) and others that inequality between occupations has increased.

Columns 2 to 4 provide information about residual wage inequality within occupations. There exist substantial differences in inequality between job categories. The lowest residual wage inequality is found in education and related jobs, whilst inequality is relatively high in management functions, and transport and communication. Especially the differences between the 99<sup>th</sup> and 90<sup>th</sup> percentile are striking. In transport and communication, employees at the 99<sup>th</sup> percentile earn 75 percent more than those at the 90<sup>th</sup> percentile, whereas this is as little as 33 percent for workers in functions related to education. For most occupations, there exists a strong relationship between the 99–90<sup>th</sup>, 90–50<sup>th</sup> and 50–10<sup>th</sup> differentials (the correlation coefficients range from 0.51 to 0.66). The finding that there are significant differences in trends in residual inequality – which does not capture any changes due to aggregate prices and quantities of worker characteristics – between job types, indicates that a general approach under the (implicit) assumption that jobs are homogeneous is insufficient to fully understand changes in the wage structure.

Trends in residual wage inequality within occupations are presented in columns 6 to 8. Even though aggregate residual inequality has changed little, except for a 4.9 percent increase of the 99–90<sup>th</sup> percentile differential, there are substantial changes within some occupations. In functions related to behavior and society, the 99–90<sup>th</sup> differential has increased by as much as 8.5 percent. Top wage inequality decreased for managerial functions (the 99–90<sup>th</sup> differential decreased by –5.3 percent), but at the same time the 90–50<sup>th</sup> differential increased by 8.1 percent for managers. Changes in inequality below the 90<sup>th</sup> percentile were much smaller. For most industries the 90–50<sup>th</sup> differential increased slightly, whereas the 50–10<sup>th</sup> differential decreased.

**Table 4. Residual wage distribution for different occupations**

Occupations	Level (2005)				Change (2000–2005)			
	average (1)	99–90 <sup>th</sup> (2)	90–50 <sup>th</sup> (3)	50–10 <sup>th</sup> (4)	average (5)	99–90 <sup>th</sup> (6)	90–50 <sup>th</sup> (7)	50–10 <sup>th</sup> (8)
All occupations	0.000	0.532	0.348	0.334	0.000	0.049	0.009	0.000
Education, incl. staff	0.153	0.330	0.233	0.219	0.009	0.019	–0.004	–0.014
Technicians	0.002	0.408	0.353	0.310	0.007	–0.014	0.018	–0.002
Transport, communication	–0.184	0.751	0.402	0.350	–0.061	0.016	0.051	–0.010
Medical, paramedical	0.021	0.561	0.331	0.313	0.012	0.043	0.031	0.020
Econ., commer., admin.	0.000	0.513	0.350	0.341	–0.003	0.043	0.008	–0.003
Jud., gov., law enf	0.177	0.338	0.347	0.315	0.012	0.002	0.035	0.010
Behavior and society	0.146	0.410	0.302	0.311	0.008	0.085	0.011	0.003
Personal and social care	–0.309	0.494	0.352	0.328	–0.029	0.058	–0.008	–0.021
Management	0.481	0.521	0.514	0.322	0.089	–0.053	0.081	0.000

Even though Table 4 indicated increasing inequality between occupations, the number of occupations is kept small such that we can present statistics for separate job types. Our data allows us to check whether such a relation also exists when using a more detailed occupation classification. Following Goos and Manning (2007) and Autor et al. (2008), we use the initial wage level within occupation categories as a simple proxy for job quality. Figure 4 plots change in average log real wages between 2000 and 2005 for 96 ISCO occupation categories at the 3-digit level, as a function of the average wage in 2000. The slope of the fitted regression line is positive (with coefficient 0.057 and a t-statistic of 2.4), even though the relationship is not as strong as in Table 4. The regression coefficient can be interpreted as an elasticity, which implies that a job category with a 1 percent higher average wage is expected to have experienced 0.057 percent more wage growth between 2000 and 2005. The findings thus once again provide some evidence for increasing wage inequality between occupations.

**Figure 4. The relation between job quality and wage growth**

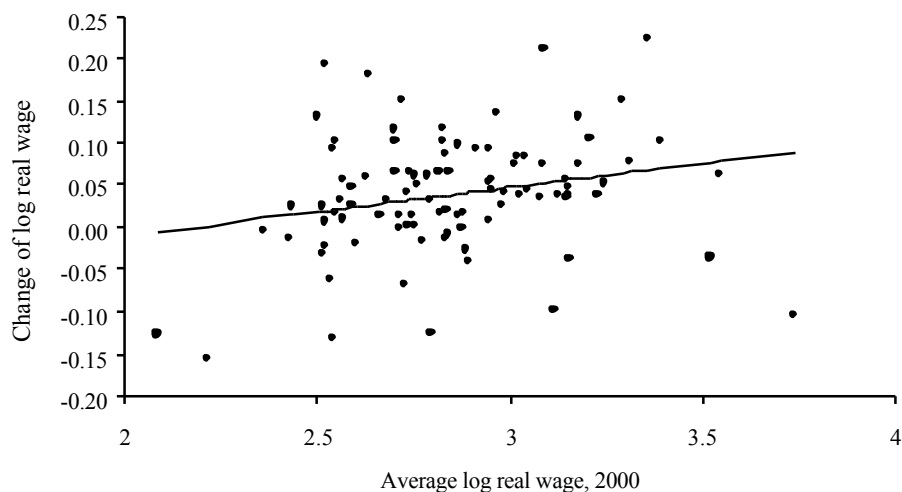


Table 5 presents the results of decompositions of trends in prices and quantities of worker characteristics, and changes in the residual distribution of different occupations. We again apply the methodology that was introduced in the previous section, to shed some light on trends in wage inequality within occupations. Keeping occupations constant is likely to keep some disturbances due to unobserved heterogeneity out of the analysis.

Table 5 shows, again, very large differences between occupations. Since composition and price effects are important determinants of wage inequality – as was shown in Sections 3 and 4 – changes in total inequality are much larger than the changes in residual wage inequality that were presented earlier in this Section. When looking at trends in total inequality (column 1), changes in some occupations are especially striking, taking into account that our data covers only five years.



The wage gap between the 99<sup>th</sup> and the 90<sup>th</sup> percentile increased by 17.5 percent in medical and paramedical functions, while also increasing within all other occupations with the exception of one job category: in judicial occupations, government and law enforcement it decreased by 10.9 percent. The 90–50<sup>th</sup> and 50–10<sup>th</sup> percentile differentials were somewhat more stable for most occupations, as changes of the 90–50<sup>th</sup> differential ranged from –6.3 percent in economic, commercial and administrative functions to 6.7 percent in personal and social care, while changes of the 50–10<sup>th</sup> were even smaller.

Changes in observed quantities had a downward pressing effect on wage inequality within most occupations and across almost the entire wage distribution. Occupations related to education, medical and paramedical functions, personal and social care, and management are in contrast to this. Here, composition effects have resulted in a higher 99–90<sup>th</sup> percentile wage differential. It is interesting to see that inequality at the highest percentiles due to observed quantities has increased especially in occupations that are often publicly funded. There has been strong political pressure in the Netherlands in recent years to decrease top wages paid from public money. The share of highly paid workers (because of their observed characteristics) has, however, increased.

Price effects have generally resulted in higher inequality, which is consistent with the results of decompositions of aggregate wage that were presented in Table 3. The effect of observed prices is, however, larger in magnitude for separate occupations than for all occupations combined. We did some additional research to this, and found that in many occupations, this is mostly due to substantial increases in observed skill prices. In management, both the large decrease of inequality due to observed prices at the highest percentiles and the increase in the rest of the distribution are largely explained by changing skill prices. If observed quantities and the residual wage distribution would have remained unchanged, changes in observed prices would have resulted in a 19.2 percent increase of the difference between managers at the 90<sup>th</sup> and their colleagues at the 10<sup>th</sup> percentile.

The residual wage distribution has resulted in higher inequality within most occupations. There is an especially strong increase of the 99–90<sup>th</sup> percentile differential in transport and communication, where *ceteris paribus* wage inequality within groups with similar observed characteristics has increased by 15.9 percent. In management, the residual distribution has resulted in a strong decrease of 99–90<sup>th</sup> percentile inequality. The general trend of increasing residual (within group) inequality that was observed in the previous section is in fact not as strong when looking at different occupations, but a net result of changes in different directions.

This section provides strong support for the view that it is useful to extend the traditional view on skill biased technological progress and globalization (considering employees with a similar skill level as a homogeneous group) such that different occupations and tasks are treated differently.

**Table 5. Trends in prices and quantities of worker characteristics in different occupations**

Differential	Total change (1)	Observed quantities (2)	Observed prices (3)	Residual distribution (4)
A. Education, including staff				
99–90 <sup>th</sup>	0.081	0.077	0.039	–0.036
90–50 <sup>th</sup>	–0.055	–0.032	–0.018	–0.004
50–10 <sup>th</sup>	0.030	0.006	0.025	–0.001
B. Technicians				
99–90 <sup>th</sup>	0.035	–0.096	0.082	0.049
90–50 <sup>th</sup>	0.014	–0.010	0.014	0.009
50–10 <sup>th</sup>	–0.016	–0.044	0.034	–0.006
C. Transport and communication				
99–90 <sup>th</sup>	0.122	–0.114	0.077	0.159
90–50 <sup>th</sup>	0.036	0.014	–0.001	0.023
50–10 <sup>th</sup>	0.001	–0.126	0.135	–0.008
D. Medical and paramedical				
99–90 <sup>th</sup>	0.175	0.087	0.051	0.037
90–50 <sup>th</sup>	0.006	–0.055	0.046	0.015
50–10 <sup>th</sup>	–0.036	–0.069	0.020	0.013
E. Economic, commercial and administrative				
99–90 <sup>th</sup>	0.014	–0.054	0.060	0.008
90–50 <sup>th</sup>	0.004	–0.011	0.009	0.007
50–10 <sup>th</sup>	–0.035	–0.077	0.035	0.007
F. Judicial, government and law enforcement				
99–90 <sup>th</sup>	–0.109	–0.114	0.040	–0.035
90–50 <sup>th</sup>	0.067	–0.081	0.129	0.019
50–10 <sup>th</sup>	–0.046	–0.016	–0.035	0.004
G. Behavior and society				
99–90 <sup>th</sup>	0.056	–0.051	0.058	0.048
90–50 <sup>th</sup>	0.016	–0.025	0.029	0.012
50–10 <sup>th</sup>	–0.002	0.018	–0.010	–0.010
H. Personal and social services				
99–90 <sup>th</sup>	0.097	0.057	–0.006	0.046
90–50 <sup>th</sup>	–0.063	0.007	–0.051	–0.018
50–10 <sup>th</sup>	–0.003	–0.039	0.045	–0.009
I. Management				
99–90 <sup>th</sup>	–0.082	0.135	–0.097	–0.120
90–50 <sup>th</sup>	0.065	–0.028	0.055	0.038
50–10 <sup>th</sup>	0.030	–0.100	0.137	–0.007

## 6. The regional dimension of wage inequality<sup>3</sup>

Wages do not only vary across workers with different human capital endowments and across occupations, there are also substantial regional wage differences. This is to some extent explained by spatial heterogeneity in the distribution of workers and economic activities (and thus different job types), but after correcting for these, there remain regional wage disparities due to differences in the level of productivity that are quite large in some countries. The Randstad agglomerations have the highest share of skilled jobs (in 2005, 47 percent of the employees had tertiary education, vs. only 32 percent in the North). The share of high skilled jobs has been increasing somewhat faster in the Randstad between 2000 and 2005 than in the aggregate economy. If skill biased technological progress or globalization have indeed changed the structure of the labor market making it less equal, this should have resulted in increased inequality between regions as well as different trends in inequality within regions.

We have divided the 96 ISCO occupations that were used to construct Figure 4 into three groups – based on average wage in 2005 – labeled good jobs (containing the 25 percent workers in jobs with the highest average wages), average jobs (50 percent of the work force), and bad jobs (25 percent of the work force). As can be observed from Table 7, good and bad jobs are spread very unevenly, whereas average jobs have a close to 50 percent share in all regions. The share of good paid jobs is almost twice as high in the Randstad agglomerations (with a 32.6 percent share) than it is in the northern peripheral area (17.8 percent). Furthermore, growth of the share of good jobs (which increased in all regions), has been higher in the Randstad agglomerations (2.4 percent growth) than in other regions (0.8 percent growth across all regions). Outside the Randstad, there is no general relation between levels and trends in the share of different job types visible. In the North, for example, the share of good jobs increased by 2.4 percent, even though it remained the region with the least favorable labor market composition in terms of good, average and bad jobs. There are thus no signs of increasing inequality or polarization within regions (the strongest employment growth was experienced in the middle), while Table 6 does provide some evidence indicating increasing inequality between economic cores (the large cities in the Randstad) and peripheral areas.

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<sup>3</sup> The six regions for which we present results are specified as follows: (i) Randstad agglomerations: the municipalities of Utrecht, Amsterdam, Haarlem, Leiden, The Hague, Rotterdam, Dordrecht and Amersfoort, (ii) other agglomerations: Groningen, Leeuwarden, Zwolle, Enschede, Apeldoorn, Arnhem, Nijmegen, Breda, Tilburg, 's Hertogenbosch, Eindhoven, Geleen/Sittard, Heerlen and Maastricht, (iii) North: the provinces of Friesland, Groningen and Drenthe with the exception of the main agglomerations defined in (i) and (ii), (iv) East: Overijssel, Gelderland and Flevoland, (v) South: Noord-Brabant, Limburg and Zeeland, and (vi) Noord-Holland, Zuid-Holland and Utrecht.

**Table 6. Percentage shares of good, average and bad jobs**

Region	Level (2005)			Change (2000–2005)		
	Good jobs (1)	Average jobs (2)	Bad jobs (3)	Good jobs (1)	Average jobs (2)	Bad jobs (3)
All regions	25.0	50.0	25.0	0.8	1.7	–2.5
Agglomerations Randstad	32.6	49.9	17.4	2.4	1.3	–3.7
Other agglomerations	26.2	50.4	23.4	–0.2	1.9	–1.7
North	17.8	52.3	29.9	2.4	1.0	–3.5
East	20.2	52.0	27.8	0.1	2.2	–2.4
South	20.2	50.8	29.1	0.7	1.5	–2.1
West	23.3	51.7	24.9	–0.4	2.5	–2.1

Table 7 shows levels and trends in the distribution of residual wages between and within regions. Jobs in the Randstad agglomerations pay a 5.6 percent premium (column 1), while jobs in peripheral municipalities in the west part of the Netherlands also pay a small premium. In all other regions the average spatial residual is negative, ranging from –2.3 percent in the main agglomerations to –3.9 percent in the East of the Netherlands. Both average wages (8.3 percent growth) and residual wages (1.8 percent) have increased far above the national average in the Randstad agglomerations. This is consistent with the hypothesis that regions that are specialized in skilled jobs should experience relatively high wage growth. The lowest growth (again both of average and residual wage), however, was observed in the large agglomerations outside the Randstad. In peripheral regions, wage growth was relatively high in the North, while relatively low in the West. When we exclude the Randstad, wage differences between regions have thus become smaller.

When looking at the percentile ratio's for different regions presented in the columns 2 to 4 in Table 7, it appears that there are almost no regional differences in the residual distribution below the median. A potential explanation for this is that institutions – that do not differ between regions – are more important at the bottom of the wage distribution than at the top. Above the median, and especially at the top of the distribution, there are some substantial differences. As expected – given the presence of many high quality jobs – the 90–50<sup>th</sup> percentile differential is slightly higher in the Randstad agglomerations (workers at the 90<sup>th</sup> percentile earn 37.0 percent more than workers at the 50<sup>th</sup>) than in the rest of the Netherlands (where the difference is 34.8 percent on average). It is also relatively high in the peripheral areas in the West. Differences between all other regions are negligible, with residual log wage differentials ranging from 32.0 to 32.9 percent. The highest 99–90<sup>th</sup> percentile differential is found outside the large cities in the West (0.560), while it is the lowest in the North (0.428). In the Randstad (0.538), the difference between wages at the 99<sup>th</sup> and the 90<sup>th</sup> percentile is slightly larger than on average.

As was the case with different occupations in the previous Section, there is again a strong relation between initial (above median) inequality and trends in inequality. In case of regions, there

is a correlation coefficient of 0.42 for the 99–90<sup>th</sup> differential and 0.88 for the 90–50<sup>th</sup> percentile differential. In the Randstad, growth of the 99–90<sup>th</sup> residual wage differential was larger than in any other region. The 90–50<sup>th</sup> differential increased slightly in the Randstad agglomerations and other parts in the west of the Netherlands, while remaining unchanged or decreasing in all other regions.

**Table 7. Residual wage distribution for different regions**

Region	Level (2005)				Change (2000–2005)			
	average (1)	99–90 <sup>th</sup> (2)	90–50 <sup>th</sup> (3)	50–10 <sup>th</sup> (4)	average (5)	99–90 <sup>th</sup> (6)	90–50 <sup>th</sup> (7)	50–10 <sup>th</sup> (8)
All regions	0.000	0.532	0.348	0.334	0.000	0.049	0.009	0.000
Agglomerations Randstad	0.056	0.538	0.370	0.332	0.018	0.055	0.013	–0.011
Other agglomerations	–0.023	0.490	0.329	0.325	–0.023	0.031	0.002	0.012
North	–0.031	0.428	0.320	0.343	0.009	0.031	–0.005	0.003
East	–0.039	0.438	0.327	0.335	–0.008	–0.001	–0.011	–0.009
South	–0.028	0.500	0.328	0.328	–0.001	0.033	–0.001	0.014
West	0.013	0.560	0.356	0.334	–0.008	0.019	0.013	–0.004

Again, we have applied the methodology of Juhn et al. (1993), to decompose trends in regional wage inequality in prices and quantities of worker characteristics and changes in the residual distribution. When looking at trends in total inequality (column 1), there are large changes visible at the top of the wage distribution. There is no clear pattern in changes of total inequality. In the South, the 99–90<sup>th</sup> percentile wage differential has increased by 17.7 percent, whereas it has increased by only 4.1 percent in the North. The Randstad agglomerations are somewhere in the middle. In most regions, inequality between the 10<sup>th</sup> and the 90<sup>th</sup> percentile increased as well, even though changes were generally relatively small.

With few exceptions, trends in observed quantities of worker characteristics reduced inequality within regions (column 2), thus balancing the effects of observed prices which caused upward trends in inequality (column 3). In some regions the effect of observed quantities was very strong. If observed prices and the residual distribution would have remained unchanged, the 50–10<sup>th</sup> differential would have decreased by as much as 18.0 percent in the Randstad and 11.9 percent in peripheral areas in the West. In contrast, all other things being equal, observed prices of worker characteristics would have resulted in higher inequality in all regions and across the entire wage distribution. This effect is especially large at the bottom of the wage distribution, where it results in inequality growth ranging from 11.3 percent in the East to 18.2 percent in the large agglomerations outside the Randstad. At the highest few percentiles, it increased inequality as well. The increasing 99 – 90<sup>th</sup> percentile gap in the Randstad agglomerations is mostly explained by increasing prices of worker characteristics. In some regions, a changing residual distribution has resulted in slightly increasing inequality. At the rest of the distribution, however, it explained a relatively small part of total trends in inequality.

**Table 8. Regional differences in quantities and prices of worker characteristics**

Differential	Total change (1)	Observed quantities (2)	Observed prices (3)	Residual distribution (4)
A. Agglomerations Randstad				
99–90 <sup>th</sup>	0.091	0.000	0.077	0.014
90–50 <sup>th</sup>	0.001	–0.040	0.030	0.012
50–10 <sup>th</sup>	–0.016	–0.180	0.166	–0.002
B. Other agglomerations				
99–90 <sup>th</sup>	0.113	–0.027	0.081	0.059
90–50 <sup>th</sup>	0.007	–0.035	0.033	0.009
50–10 <sup>th</sup>	0.088	–0.098	0.182	0.004
C. North				
99–90 <sup>th</sup>	0.157	–0.072	0.188	0.041
90–50 <sup>th</sup>	0.067	0.059	0.000	0.008
50–10 <sup>th</sup>	0.054	–0.072	0.114	0.013
D. East				
99–90 <sup>th</sup>	0.041	–0.092	0.175	–0.043
90–50 <sup>th</sup>	0.089	0.036	0.039	0.015
50–10 <sup>th</sup>	0.007	–0.094	0.113	–0.011
E. South				
99–90 <sup>th</sup>	0.177	–0.016	0.125	0.068
90–50 <sup>th</sup>	0.022	–0.014	0.030	0.006
50–10 <sup>th</sup>	0.007	–0.114	0.117	0.004
F. West				
99–90 <sup>th</sup>	0.064	–0.059	0.106	0.018
90–50 <sup>th</sup>	0.021	0.005	0.017	–0.001
50–10 <sup>th</sup>	0.019	–0.119	0.141	–0.003

## 7. Conclusions

This paper has examined levels and trends in the Dutch wage structure between 2000 and 2005, using microdata from Statistics Netherlands. It has been shown that (real pre-tax) wage inequality has increased across different dimensions, especially at the top of the wage distribution. Without accounting for changes in the composition of the work force, the 99–10<sup>th</sup> percentile differential increased by 4.1 percent, the 90–50<sup>th</sup> differential by 0.6 percent, while the 50–10<sup>th</sup> ratio decreased by 1.8 percent. When we correct for trends in observed worker characteristics by estimating Mincerian wage equations, changes in residual inequality are respectively 4.9 percent, 0.9 percent and 0.0 percent growth. In addition, we found that wages and employment increased faster in jobs with a higher initial wage. Inequality, especially above the median, also increased faster within the group of employees working in occupations with a higher initial wage. Residual wage growth has also been faster in regions with a higher initial wage, especially in the large agglomerations in the Randstad. This study finds, consistent with previous work, that changes of wage inequality are moderate in the Netherlands, compared to the United States and other advanced economies. It is

shown, however, that this is in fact the net effect of much larger underlying changes, as there are substantial differences in trends in the structure of wages between occupations and regions.

Changes in the composition of the labor market – or observed quantities of worker characteristics in the terminology of Juhn et al. (1993) – have generally resulted in lower inequality. This is, however, the net effect of a changing composition with respect to age, resulting in decreasing inequality, and a changing skill composition resulting in higher inequality. Increasing skill prices are the main explanation for the higher 90–50<sup>th</sup> percentile ratio, whereas changes in the residual wage distribution provide an explanation for changes in the 99 – 90<sup>th</sup> percentile ratio. The findings of the paper are consistent with the empirical implications of both skill biased technological progress as well as globalization (due to similar empirical implications of the two). We do not find evidence for polarization in the Netherlands, in contrast with the findings of Goos and Manning (2007) on the U.K. and Autor et al. (2008) on the U.S. labor market. Further research will be needed to isolate the empirical effects of different potential explanations for observed changes in the structure of the Dutch labor market.

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