Young Females -
Are They Doing Better in Economic Hot Spots?

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Abstract

This paper uses German social security micro data 1975-2004 to estimate the role of the metropolitan environements on the size and the development of the gender wage gap. Using a propensity score matching approach, we contrast the gender wage gap for young workers in economic hot spots on the one hand with that in rural areas on the other. We find a considerable gender wage gap for all skill groups and regions. For less and lower intermediate skilled workers the wage differential is higher in rural areas. It was narrowing from the mid-seventies to the end of the nineties. However, a reversion occurred in the last five. Surprisingly, the gender wage gap for the upper intermediate and high skilled group is – although not always statistical significant – more pronounced in the metropolitan environments than in rural areas. In contrast to all other skill groups, the wage differential between men and women for the highest skill group is almost constant over time in both areas.

Keywords:
Gender wage differential, urban-rural differences, matching.

JEL-classification: J16, J23

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1 Introduction

With a vast theoretical and empirical literature the gender wage gap is one of the hotly discussed topics in economics. Since the mid-nineties a growing number of studies have analyzed the gender wage gap, especially for industrialized countries. A substantial gender wage gap is found in almost all studies. Most of the empirical analyses are based on a human capital model predicting that remuneration is equal for equal productive workers. (Becker (1964), Mincer (1974)). As a consequence, the wage gap between men and women can be separated into two parts. Wage differentials can be explained on the one hand by a different human capital endowment like education, experience and observed differences between men and women. Having controlled for these characteristics the remaining part of the wage gap, the "unexplained" part, is attributed to discrimination or unobserved characteristics that cannot be controlled for. The first decomposition of wage differentials was presented by Blinder (1973) and Oaxaca (1973) which is, with extensions, widely used in the gender wage gap literature. For an overview of the huge literature concerning the gender wage gap and the different factors of influence see Blau and Kahn (1997) or Altonji and Blank (1999). A meta-analysis is provided by Weichselbaumer and Winter-Ebmer (2003).[1]

Although still of a considerable amount the gender wage gap tends to weaken in advanced OECD countries over the last few decades. Blau and Kahn (2000) detect a decreasing gender wage gap for West Germany, as well as for almost all OECD countries. Lauer (2000) arrives at the same conclusion. Taking into account changes in the wage distributions as well as cohort and life cycle effects Fitzenberger and Wunderlich (2002) find that the gender wage gap narrowed substantially at the bottom of the wage distribution but less at the upper part.

Several hypotheses are formulated in explaining the decline. First, structural and technological changes of the economy leads to diminishing employment shares of well-paid manufacturing industries typically dominated by male workers. In con-

[1] For (Western) Germany various aspects of the substantial gender wage gap have been analyzed. Just to mention some: see Kunze (2002) for differences in the entry wages and the evolution during the early career. Machin and Puhani (2003) studied the influence of the different subjects of university degree on the gender wage gap. Hinz and Hermann (2005) found that there is still a disadvantage for women in the same job within the same firm in comparison to their male collegues.

trast, the service-oriented sector is growing, which has in parts high employment shares of women. Second, the worldwide movement for the rights of women starting in the seventies has increased the society's awareness of discrimination related to gender. The idea of equal treatment is on the right path in society and is also fixed in various anti-discrimination laws. Third, conditional on both latter reasons the proportion of women going for a "typical male occupation" is increasing albeit there is still evidence for an occupational segregation. Fourth, traditional family structures fostering non-participation of females become less and less important. Improving systems of child care during the day is in public discussion in Germany. Furthermore, the increasing flexibility in working time, namely especially part-time jobs, allows women to balance job and family.

With respect to the labor market participation rates of females as well as anti-discrimination rules, the U.S. appears to be a leading country, whereas Germany is seen as a laggard.[2]

Many empirical studies have their main focus on the variation of the gender wage gap between different countries (see for instance Blau and Kahn (2000)). An aspect that has attracted almost no attention is the regional variation of the gender wage gap within the same country. It is especially the difference in the rural-urban environment which could play a prominent role in the explanation of the gender wage gap. There exist only few articles dealing with regional aspects for gender. [3]
According to a specific strand of the literature, the urban context can be seen as a trend-setter for the society as a whole. An important aspect of regional economics relates to diversity. As early as in 1969 Jane Jacobs (1969) attributes the success of cities to their industrial diversity. Quigley (1998) and Glaeser et al. (2001) identify the diversity of available services and consumption goods as one

[2]With respect to the female participation rate there are enormous differences between German regions. In eastern Germany, for instance, participation rates are substantially higher than in the western part of the country. This is due to history because high participation rates of females were strongly supported by the official policy in the former German Democratic Republic.

[3]The study of McCall (1998) focuses on the relation between regional restructuring and gender wage differentials. Phimister (2005) studies the differences of the rural and urban wage premia by gender.Olfert and Moebis (2006) examines the differences between rural and urban environments on the occupational segregation, whereas Robinson (2005) analyses the effect of the national minimum wage on the gender pay gap across regions in the UK.

of the attractive features of cities. Sassen (1994) studies the role of "global cities" in the innovation process and Bairoch (1998) sees cities and their diversity as engines of growth. In a number of contributions Florida (2002a, 2002b) stresses the importance of diversity in creative professions. "Diverse and tolerant cities" attract innovative and progressive people who are able to stimulate research and development as well as technological innovations. It is obvious to hypothesize that progressive environments also affect the attitudes towards the role of women in the world of employment.

Our paper aims at investigating the role of the urban environment for the size and the development of the gender wage gap. The basic idea is to contrast economic *hot spots* on the one hand with rural areas on the other.

Using large micro panel data we can control for several characteristics of workers such as qualification, experience and tenure as well as the size of the firm. Arguing that new social trends are first visible for entrants in the labor market and young workers we therefore limit our attention to a group of young workers.

The remainder of the paper is structured as follows. The next section outlines the empirical model and the estimation strategies for estimating the gender wage gap. Before presenting some first evidence in section 4, we give a description of the data in section 3. Our results are discussed in section 5. Section 6 concludes.

2 Methods

2.1 Propensity score matching

The raw gender wage differential is of limited information value as it neglects individual heterogeneity. In order to deal with observed heterogeneity, we can use regression analysis that controls for a number of personal characteristics and the Oaxaca-Blinder decomposition in order to get the amount of the gender wage gap not being explained by different endowments. A similar idea to that form of decomposition was proposed by Nopo (2004) using a matching approach.[4] Our

[4]Fröhlich (2007) also suggests a propensity score matching approach in the analysis of the gender wage gap. An application for the gender wage gap in Switzerland is given by Djurdjevic and Radyakin (2005). Hübler (2005) uses quantile regressions but calculated the counterfactuals

idea is to use male workers with otherwise the same characteristics as a control group for female workers.[5] According to a standard matching approach the best estimate of the outcome variable for (untreated) individuals of a specific group is the outcome of individuals with observationally equivalent characteristics in the reference group.

Let W^f and W^m denote two random variables of earnings for female ($i = 1, \cdots, I$) and male ($j = 1, \cdots, J$) workers, respectively. Furthermore, define $\mathbf{x}$ as a vector of characteristics. As the effect of gender on earnings we consider the difference between the expected outcome of a female with (observable) characteristics $\mathbf{x}$ and the hypothetical outcome this person could expect as a male worker with the same characteristics. The problem is to find a suitable estimate for the latter which is not directly observable. The potential outcome approach replaces the counter-factual with the observed outcome of an individual (or individuals) from the control group with ideally identical characteristics.

Assume for the moment that unobserved characteristics play no role in wage determination. Then the hypothetical expression $\mathrm{E}\left(W_i^f|X = X_i\right)$ can simply be replaced by the expected wage of a male worker with identical observed characteristics $\mathrm{E}\left(W_j^m|X = X_j = X_i\right)$. Put differently, one looks for a statistical twin in the control group of male workers and compares the earnings of a female worker to the earnings of this person in order get an estimate for the effect of gender.

With highly differentiated characteristics, finding exact matches is hardly possible even in large data sets. To circumvent the curse of dimensionality it has been proposed in the matching literature to base the comparison on similar rather than on necessarily identical individuals. A measure of similarity can be based on the propensity score $pr\left(D_i|X = X_i\right)$ of a probit or logit regression that describes the selection of individual i in the "treatment" group. The variable $D \in (0, 1)$ is a dummy variable indicating whether a person is female ($D_i = 1$) or male ($D_j = 0$). There are several possibilities of constructing the counter-factual. A simple one is the n-nearest neighbor method which uses the n observations in the control group being most similar to a chosen individual in the "treatment

using a local linear matching procedure.

[5] Since gender could, of course, not be considered as a treatment variable in the strict sense, a casual interpretation is excluded. However, the basic principles of the matching approach can be applied analogously.

group". A more sophisticated approach uses all observations of the control group but attaches weights to them which are lower the more distant the observation is from the observation in the treatment group. These weights are calculated using a kernel estimate of the distribution. Take the first nearest neighbor approach for simplicity. The upshot of the above considerations is that the effect of gender on earnings for individual i can be calculated as

$$\delta_i \quad = \quad W_i^f - W_{j^*}^m \tag{1}$$

where $j^*(i)$ is the nearest neighbor of female i in the control group of male workers

$$j^*(i) \quad = \quad \arg\min_j \left|\mathrm{pr}\left(D_i|X = X_i\right) - \mathrm{pr}\left(D_j|X = X_j\right)\right|. \tag{2}$$

The average treatment effect on the treated (ATT) is then simply

$$\mathrm{E}(\delta) \quad = \quad \frac{1}{I}\sum_{i=1}^{I}\delta_i, \tag{3}$$

where I is the total number of females. In the application here, a probit model was chosen for modelling the probabilities in equation 2.

For the construction of the counter-factual we analyzed the first nearest neighbor approach and kernel matching as two extreme cases. It turns out, however, that both alternative matching methods produce similar results. Therefore, we present the former only.[6]

In the probit regression we used all available characteristics of workers. In analogy to the fixed-effects method, the matching approach can also be based on wage growth rates rather than on levels. In the program evaluation literature (see, for example, Heckman et al., 1999; Smith and Todd, 2005) it is assumed that the impact of unobservable characteristics on the outcome is constant over time. Under this assumption, unobserved heterogeneity is differenced out by using difference-in-differences matching. In our empirical application we considered this as a further alternative.

A classification scheme developed by the *Bundesanstalt für Bauwesen und Raumordnung* (BBR) differentiates between nine types of regions at NUTS 3 level

[6]In the following analytical standard errors are presented if not stated otherwise. Alternatively, standard errors can be generated by bootstrapping (see, e.g. Heckman et al., 1998).

according to population density and accessibility. The classification scheme of the BBR distinguishes between areas with large agglomerations, areas with features of conurbation and areas of rural character. Within areas comprising large agglomerations, the classification scheme distinguishes between metropolitan core cities (BBR1), highly urbanized districts (BBR2) in the surroundings of those cities, urbanized districts (BBR3) and rural districts (BBR4). The second category contains core cities (BBR5) in regions with intermediate agglomerations, their urbanized surroundings (BBR6) and rural districts (BBR7). In the regions of rural character the differentiation is between urbanized districts (BBR8) and rural districts (BBR9).

As economic *hot spot* we selected the urban regions of West Germany's most prominent metropolitan areas: Hamburg, Cologne (Köln), Düsseldorf, Francfort (Frankfurt /M.), Stuttgart and Munich (München). All *hot spots* are of type BBR1. As rural regions we selected BBR types 7 to 9.

3 Data

3.1 Data source

Our study uses social security micro data from IAB-REG. IAB-REG is a 2% random sample from the employment register of Germany's Federal Labor Office.[7] The data set includes all workers, salaried employees and trainees obliged to pay social security contributions and covers more than 80% of all those employed. Civil servants, family workers and self-employed persons are excluded. The German social security system requires firms to record the stock of workers at least at the beginning and the end of each year. Additionally, all changes in employment relationships within the year (for instance, hirings, quits, dismissals) have to be reported with the exact information on the date when the change occurred. Therefore, the employment register traces detailed histories for each worker's time in covered employment as well as spells of unemployment for which the worker

[7] The establishment of IAB-REG dates back to 1973. Data are available from 1975 to 2004. The data is described briefly in Bender et al. (2000) and in more detail in Bender et al. (1996).

received unemployment benefits.[8] Because of legal sanctions for misreporting, the data's information on periods of coverage and the earnings is highly reliable.

IAB-REG also contains several variables describing workers' characteristics (like age, skill level, gender, job status, occupation, nationality) and some information on the employer (industry, location, size of the firm). As mentioned above, quantitative information on hours worked is not included. However, the data set comprises a qualitative variable distinguishing between full-time work and two forms of part-time work.

Due to the contribution ceiling in the German social security system, earnings are censored. Top coding, however, is not a severe problem in studies for relatively young workers.

For the following empirical analysis we use only observations for workers aged 25 to 34 in West Germany(?). We are aware of possible job instability for female workers. Therefore a series of actual rather than potential experience on the job was constructed where only periods of active employment were counted.[9] In a similar way a measure of tenure as the total time period worked with the same firm.

3.2 Corrections and multiple imputation of the skill indicator

The IAB-REG skill variable distinguishes between six categories: (i) low-skilled workers, (ii) workers without higher education and no vocational training completed, (iii) workers with higher education (*Abitur*), but no further training or education, (iv) workers with higher education (*Abitur* and vocational training completed, but no university-type of education), (v) graduates from a university of applied sciences (*Fachhochschule*), (vi) graduates from a university. Moreover, there is information on the status of training in a further variable ("position on the job"). This variable gives information on a possible master craftsman's diploma.

[8]Spells for which workers have no entitlement to unemployment benefits are not reported and therefore cannot be distinguished from periods of non-participation in the labor market.

[9]Note however, that for observations prior to 1988 the measure of actual experience might be biased due to left censoring of employment spells in the data.

A problem in the data set is that, despite a high precision for the earnings variable, information on personal characteristics might suffer from reporting errors. This could be especially severe for the skill variable. Moreover, this variable is missing for a relatively high number of spells.

Several attempts have been made for correcting the qualification information in IAB-REG. A widely used approach has been developed by Fitzenberger et al. (2008). The authors propose three different imputation procedures. The first suggestion is to extrapolate the highest level of education observed in the spells of an individual. Due to the risk of overreporting this acts as an upper bound of the true level of education. In the second procedure only degrees are extrapolated that are reported at least three times. The frequency of the reports is seen as a measure of reliability here. The last idea is to check the consistency of the firm's reporting behavior. Only information on education of reliable employers are extrapolated. The two latter suggestions form the lower bound of the true level of education.
Here we follow a different route. Since for most observations the data covers the complete training, employment and unemployment history, the skill measure can easily be checked according to the records. For each individual we calculated the cumulated length of the time period spent in vocational training. If the total length of vocational training exceeded three years and at least two different firms reported vocational training completed, then the individual would be considered as belonging to this category. Hence all records indicating lower qualification or qualification missing were corrected accordingly. Another question is whether a person has a school-leaving examination permitting university access (*Abitur*). We classified persons as belonging to this category if at least two different firms independently reported this. Again, the records were corrected accordingly.

Furthermore, the cumulated number of classifications for the different categories done by independent firms was calculated. If more than 75 percent of the firms classified a person in a certain way, this information was considered valid. Although the number of inconsistent observations could thereby be reduced substantially, the skill status of about 25 percent of the individuals still remained unclear. For these observations we used the following imputation technique: First we flagged the observations which could be considered as valid according to the procedure described above. With these observations, we estimated a Logit model where the actual as well as the cumulated number of classifications to different skill categories done by different firms, the age, the entrance year, and a nationality dummy was used. According to the pseudo-R-squared (typically above 0.8), the results were quite satisfactory. With the help of the estimated parameters we calculated the predicted probabilities for belonging to a specific skill category. Then simply the classification was chosen which gave the highest probability.[10]

3.3 Selection of skill groups

In order to keep the skill categories small, we decided to skip the IAB-REG category (iii) entirely because it is of minor importance. Graduates of a university of applied sciences and university graduates were combined in one category. Moreover, we separated workers in vocational training from IAB-REG category (i). This leaves us with four skill categories :

skill 1: workers without higher education and no vocational training completed,

skill 2: workers without higher education, but vocational training completed,

skill 3: workers with higher education (*Abitur*) and vocational training completed, but no university graduates,

skill 4: workers with university type of education.

For all groups we selected all persons aged 25 to 34 in the sample for a given year. The observation period is 1975 to 2004.

4 Descriptive Evidence

4.1 Distribution of the workforce by gender, skill group and type of region

Table 1 gives some basic evidence on the skill composition of the workforce in 1984, 1994 and 2004. In general we see the dominance of skill group 2 in both types of regions in all years. However, there are marked differences between types

[10] An alternative would be to use the estimated probabilities as weights in the regression. We also tried this but the results were very similar.

of regions and gender. In 1984, the share of females in the unskilled workforce was rather high. It exceeded the corresponding share of male workers by almost 5 percentage points in economic hot spots and by almost 10 percentage points in rural areas. Hence, the gender imbalance for unskilled young workers was stronger in rural areas compared to economic hot spots.

The share of skill group 2 is rather similar for both genders in 1984 as far as economic hot spots are concerned. Skilled male workers (skill group 2) are especially concentrated in rural areas, where their share reaches almost 90 percent. The share of females in this category is almost 10 percentage points lower. The share of skill category 3 does not vary a lot between both genders, but between types of regions. Persons with a German high school degree (*Abitur*) and vocational training completed are much more frequent in economic hot spot areas. The same is true for the high-skilled. With respect to this group, however, there is a clear concentration of high-skilled males. Compared to rural areas, the share of male workers holding a university degree is more than four times higher in the selected metropolitan areas, while it is only double its share for females.

In 2004 unskilled male workers are highly concentrated in hot spot areas, while the differences between both genders are low in rural areas. Skill group 2 is rather equally distributed with respect to gender in the selected metropolitan areas, while in this group male workers have higher shares in rural areas. There is an eye-striking difference in the shares of skill group 3. Almost 30 percent of female workers in hotspot areas belong to this group, but only 18 percent of their male counterparts. The shares of high-skilled with a university type degree is clearly in favor of male workers in hotspot areas, whereas there are only minor differences in rural areas.

Figure 1 shows the differences in the share of the four skill groups between hot spots and rural areas. It is evident that for both genders skill group 2 is significantly under-represented in economic hot spots, whereas the higher qualified (skill groups 3 and 4) are over-represented. However, also male unskilled workers (skill group 1) are over-represented in the metropolitan areas selected here. Over time, the discrepancies between the types of regions clearly accrue.

<+++ Figure 1 about here +++>

We then calculated the expected share of workers of the different skill categories disregarding gender classification. Figure 2 shows the differences between the actual and the expected share by gender and skill group. Male workers of skill categories 1 and four are clearly more concentrated in the selected metropolitan areas, whereas the reverse is true for categories 2 and 3. The figures for female workers mirror this pattern. Over time, there is a tendency for a certain assimilation, although the gender-specific differences in the skill composition of the workforce are still clearly visible in 2004. Low-skilled as well as high-skilled female workers are under-represented in the selected metropolitan areas. With respect to the latter a catch-up process can be observed.

To sum up, females are over-represented in the intermediate skill categories and under-represented in the very low and very high categories.

<+++ Figure 2 about here +++>

4.2 Wages by gender, skill group and type of region

The gross daily median wages differ considerably by skill, gender and region type (see table 2). From these values we first calculated the raw skill-specific gender wage gaps for the different region types. Table 3 contains the results. For all skill groups and region types earnings of male workers exceed those of their female counterpart. The raw gender wage gap lies between 15 and 36 percent. The raw gender wage differential (measured at the median of the wage distribution) shows no tendency from 1984 to 1994, but increases from 1994 to 2004. Moreover, especially high gender wage gaps are found for rural regions. Except for the higher qualification groups in 1984, the raw gender wage gaps are always higher in rural areas than in the selected metropolitan areas. An especially high value is found for skill group 2 (workers with vocational training completed, but without higher qualifications), where the gender wage gap in rural region exceeds that in the highly urbanized environment by more than 16 percentage points.

<+++ Table 2 about here +++>
<+++ Table 3 about here +++>

Table 4 shows the raw urban wage premium calculated at median wages. The raw urban wage premium ranges from low or (in 2004) even negative values for low-skill male workers to high values of roughly 50 percent for skilled female workers. The difference between the urban wage premium of males and females is – with two exections in 1984 – always negative, indicating that average pay for full-time female worker in economic hot spots markedly exceeds that of their counterparts with the same skills in rural areas by more than for male workers. Hence the urban environment seems to be favorable for female workers at first glance. This is especially so for skill group 2.

<+++ Table 4 about here +++>

Table 5 contains skill premia calculated as the relative difference to the total median specific to gender and region type. Low-skilled workers are especially low paid relative to median earnings in economic hotspots. This is so for both genders and all years. Whereas the skill premium for high-skilled males is quite similar between the two region types – at least for 1994 and 2004 – , there are marked differences in the skill premium for their female counterparts. Interestingly the skill premium of female workers of the hightest category in rural areas exceeds that found for the selected metropolitan areas. Comparison of skill premia of male and female workers does not give a clear picture.

<+++ Table 5 about here +++>

5 Estimation Results

5.1 The evolution of the gender wage gap

For each of the years 1975 to 2004 we then applied the matching approach to calculate the gender wage gap for the four skill groups in (i) economic hot spots and (ii) in rural areas as defined above.

We first present the results of the matching approach in levels. For the selected year 2004 we compared the un-matched and matched selection of males and females in both types of regions.

The matching variables comprise:

- the actual on-the-job experience and its square

- the actual tenure and its square
- the size of the firm
- an industry classification (41 industries).

In addition, we included a (0,1)-dummy variable for persons with a master craftsman's diploma in the specification for skill group 2 and the same for the type of the university degree for skill group 4.

We then calculated the "average treatment of the treated" (ATT) with male workers of the same skill category as the control group. For all years and in all types of regions we find a statistically significant negative ATT. Hence the existence of a gender wage gap is clearly confirmed by our data. That is, young full-time employed females in Germany (still) earn significantly less than their male counterparts with the same (observed) characteristics.

A closer look at the results reveals that the results vary markedly for the different skill groups and region types. Partly the patterns are changing over time.

We start the more detailled description of our results with the largest group of workers, i.e. those with intermediate qualifications (skill group 2). Figure 4 shows that, controlled for experience, tenure, firm size and industry classification, the gender wage differential in economic hot spot areas is significantly lower than in rural areas in all years. In the mid-seventies the gender wage differential was 20 percent in the selected metropolitan cities compared to about 35 percent in rural areas. Over time, there was a clear erosion of the differential. In 1997 female workers of skill group 2 with otherwise the same characteristics as their male counterparts earned about 10 percent less in hot spots than males of the same category. The gender wage differential for rural areas has shrinked even stronger. From 1975 to 1997 it declined by about 15 percentage points (from roughly 35 percent in 1975 to about 20 percent in 2004). Up to this point figure 4 confirms the hypothesis of an overall declining trend in the gender wage differential. In addition, the hypothesis of a smaller differential in leading economic (and social) places is corroborated. However, there seems to be a structural break appearing in the late nineties of the last century. In both types of regions the trend towards a smaller gender wage differential appears to be reversed. Moreover, the developments in the two region types is quite parallel. In the average, the gender wage differential increases after 1997 by roughly five percentage points. As a result, the gender differential in 2004 stands at a value of about 15 percent in the selected metropolitan cities and 29 percent in rural areas.

The differences between advanced and laggard regions are less clear for the group of low-skilled workers (see figure 3). Although the gender wage differential is lower in economic hot spot areas in all years, the 95 confidence bands typically overlap, hence the differences are statistically not significant. The decline in the gender wage gap between 1975 and 1997 is only visible for economic hot spot areas and in any case less marked than for skill group 2. Up to 1997, the values for the selected metropolitan cities vary between -20 and -15 log percent and around -25 log percent for the rural areas. At the end of our sample period (after 1997) our estimate of the gender differential varies widely from year to year. Again the development in the two types of regions is correlated. In 2004 the highest values for the gender wage gap over the whole sample period appear (30 log percent points for hot spot areas and even more than 40 log percent for rural areas).

For the intermediate skill group (group 3) a high variation concerning the gender wage gaps in both regions occurs like it is shown in figure 5. These fluctuations, especially for the rural area from 1975 until 1985, are due to the low number of observations in this skill group. From 1985 onwards these fluctuations are narrowing but still persistent. In the year 2004, however, the gender wage gap of the rural area is almost equal to that of the metropolitan area, namely about -23 to -20 log percent. In general no evidence for a narrowing time trend for both wage gaps is existing for this wage group. What seems puzzling is that for this skill group the gender wage differential is rural areas is less pronounced than in economic hot spots (although the difference is not always statistically significant).

Figure 6 gives the results for the high-skilled. In general, the gender wage differential for this skill group seems to be markedly lower. The development over time is quite flat for both types of regions. As for the intermediate skill group a smaller wage differential between men and women is detected in the rural area. But again there is no overall statistical significance for the difference. According to these estimates the gender wage differential for the high skilled is between 8 and 15 log percent. In contrast to the fluctuations that appeared for the first two skill groups, there is nothing comparable in Figure 6.

6 Conclusions

The main purpose of this paper is to study the influence and the evolution over time of a metropolitan environments on the gender wage gap in comparison to rural areas. We differentiate between four different skill groups. Using large micro panel data from 1975 to 2004 we are able to control for individual characteristics like qualification, experience and tenure as well as for firm specific properties. For estimation we use a propensity score matching approach searching for counterfactual (male) observations with otherwise similar characteristics. Calculating the earning differences between the "pairs" we obtain the gender wage gap for both regions and skill groups.

To summarize, we find that the gender wage gap for low and intermediate skilled (workers without higher education, but vocational training completed) workers in rural areas is higher than in metropolitan areas. The gap in both regions is narrowing over time. Nevertheless, in both types of regions and for both skill levels the trend towards a smaller wage gap differential appears to be reversed in the late nineties. Surprisingly, the wage gap differentials for the intermediate skill group 3 (workers with higher education and vocational training completed) and the high-skilled workers are smaller in laggard than in the advanced regions although the difference is not always statistically significant. Especially for the high skilled, the gender wage differentials in both region are staying constant over time.

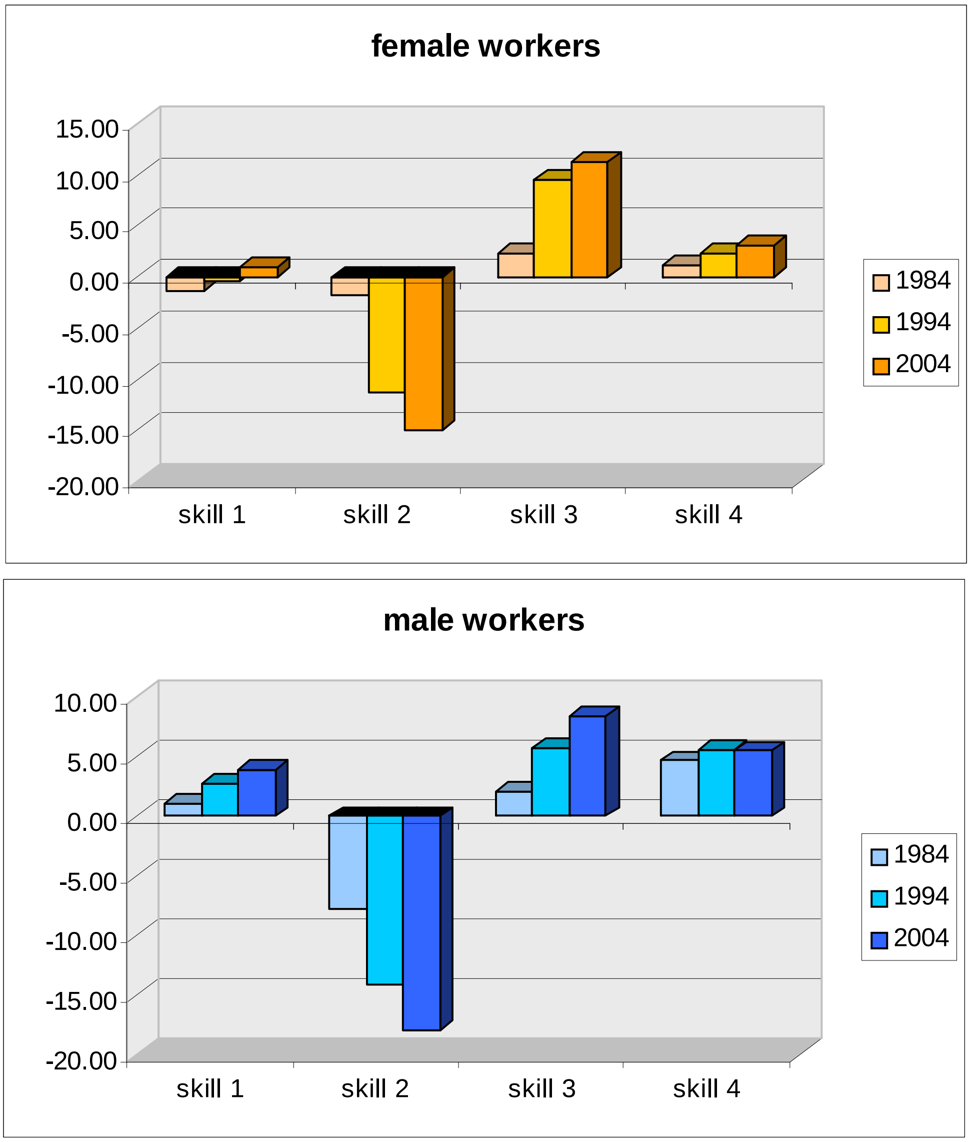

Figure 1: Differences in the share of workers between economic hot spots and rural areas by gender and skill groups in 1984, 1994 and 2004

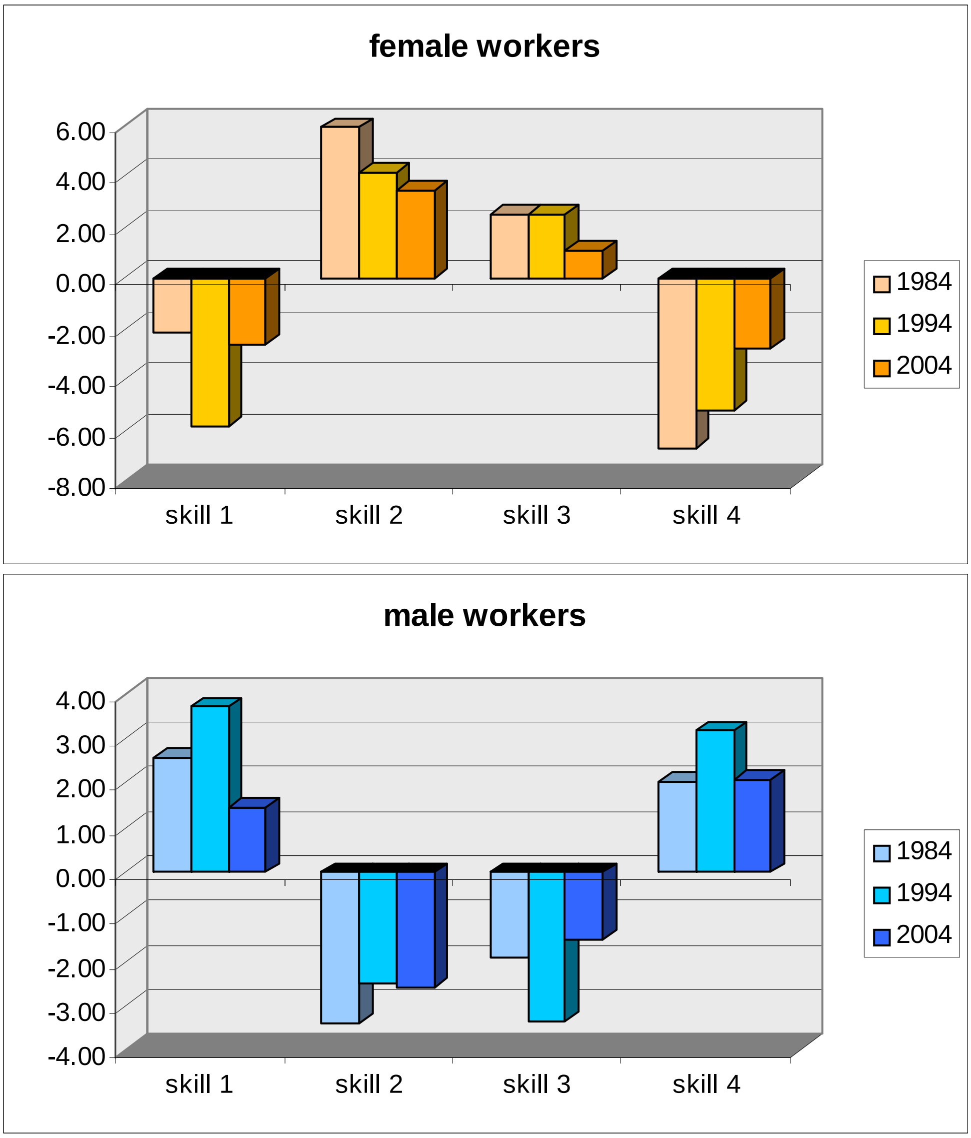

Figure 2: Differences between the actual and the expected share of workers in economic hot spots by gender and skill group in 1984, 1994 and 2004

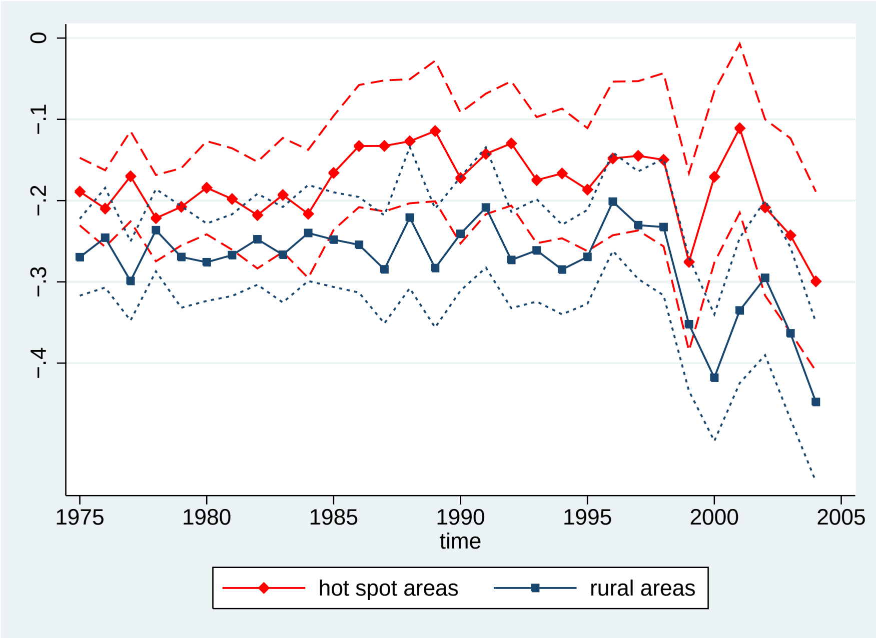

Figure 3: The gender wage gap for low-skilled workers (skill group 1) in West Germany by type of region 1975 to 2004

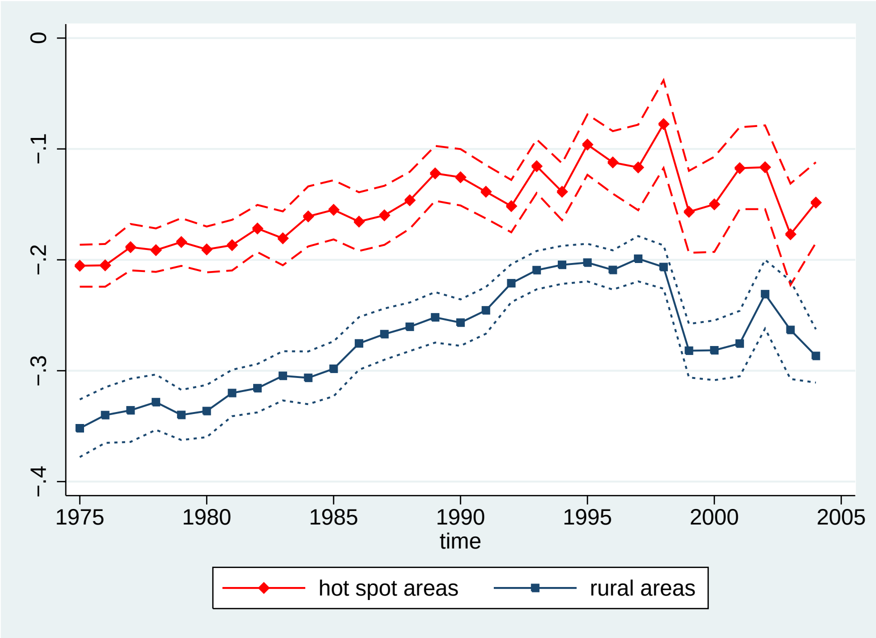

Figure 4: The gender wage gap for intermediate skilled workers (skill group 2) in West Germany by type of region 1975 to 2004

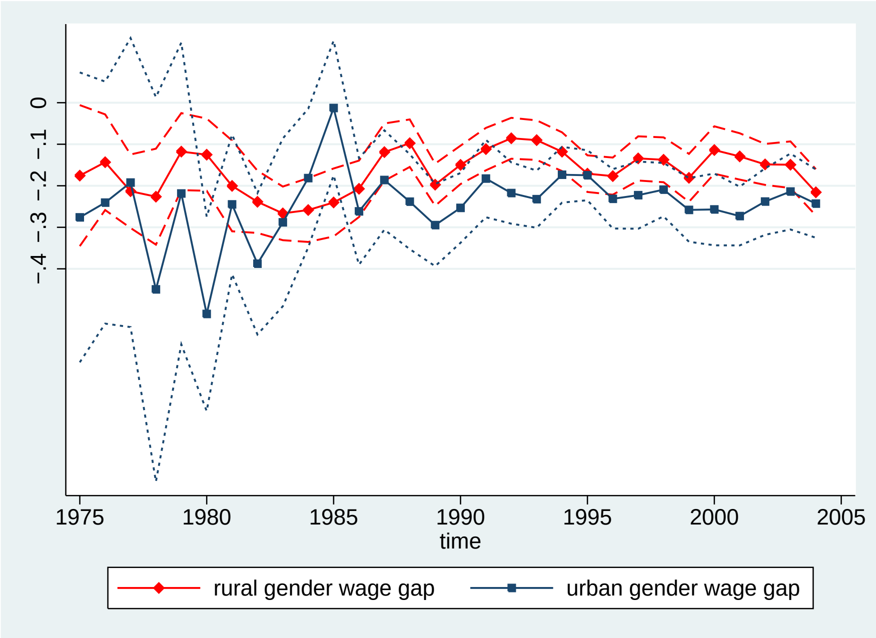

Figure 5: The gender wage gap for intermediate skilled workers (skill group 3) in West Germany by type of region 1975 to 2004

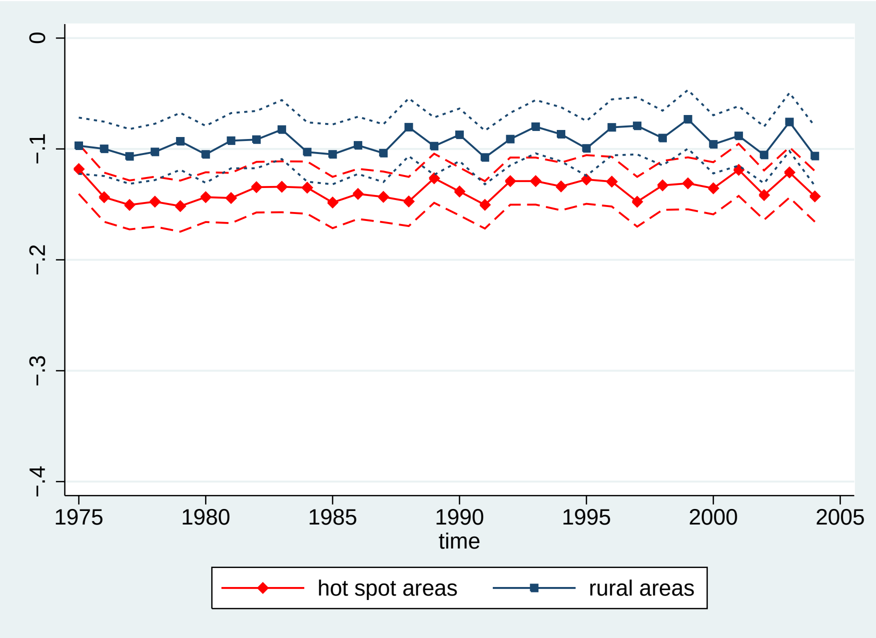

Figure 6: The gender wage gap for high-skilled workers (skill group 4) in West Germany by type of region 1975 to 2004

References

Altonji, J. G. and Blank, R. M.: 1999, Race and gender in the labor market, *in* O. Ashenfelter and D. Card (eds), *Handbook of Labor Economics*, Vol. 3C, North Holland, Amsterdam, pp. 3143–3259.

Becker, G.: 1964, *Human Capital - A Theoretical and Empirical Analysis with Special Reference to Education*, 3rd. edn, Chicago University Press, Chicago.

Bender, S., Haas, A. and Klose, C.: 2000, IAB employment subsample 1975-1995: Opportunities for analysis provided by the anonymised subsample, *Discussion Paper 117*, IZA.

Bender, S., Hilzendegen, J., Rohwer, G. and Rudolph, H.: 1996, Die IAB-Beschäftigtenstichprobe 1975-1990, *Beiträge zur Arbeitsmarkt- und Berufsforschung 197*, IAB, Nürnberg.

Blau, F. D. and Kahn, Lawrence, M.: 1997, Swimming Upstream : Trends in the Gender Wage Differential in the 1980s, *Journal of Labor Economics* **15**(1).

Blau, F. D. and Kahn, Lawrence, M.: 2000, Gender Differences in Pay, *Journal of Economic Perspectives* **14**(4), 75–99.

Blinder, A. S.: 1973, Wage Discrimination: Reduced Forms and Structual Estimates, *Journal of Economic Perspectives* **8**(4), 436–455.

Djurdjevic, D. and Radyakin, S.: 2005, Decomposition of the Gender Wage Gap Using Matching: an Application for Switzerland, *Darmstadt Discussion Papers in Economics 155*.

Fitzenberger, B., Osikominu, A. and Völter, R.: 2008, Imputation Rules to Improve the Education Variable in the IAB Employment Subsample, *forthcoming in: Schmollers Jahrbuch (Journal of Applied Social Sciences)*.

Fitzenberger, B. and Wunderlich, G.: 2002, Gender Wage Differences in West Germany: A Cohort Analysis, *German Economic Review* **3**(4), 379–414.

Fröhlich, M.: 2007, Propensity Score Matching without Conditional Independence Assumption - With an Application to the Gender Wage Gap in the United Kingdom, *Econometrics Journal* **10**, 359–407.

Hübler, O.: 2005, Is There a Varying Unexplained Gender Wage Gap in Germany?, *Applied Economics Quarterly* **51**, 29–48.

Hinz, T. and Hermann, G.: 2005, Lohnunterschiede zwischen Frauen und Männern in Branchen, Berufen und Betrieben, *Discussion Paper 4/2005*, IAB.

Kunze, A.: 2002, Gender Differences in Entry Wages and Early Career Wages, *Discussion Paper 626*, IZA.

Lauer, C.: 2000, Gender Wage Gap in West Germany: How Far Do Gender Differences in Human Capital Matter?, *Discussion Paper 00-07*, ZEW.

Machin, S. and Puhani, P. A.: 2003, Subject of Degree and the Gender Wage Differential: Evidence from the UK and Germany, *Economics Letters* **79**, 393–400.

McCall, L.: 1998, Spatial Routes to Gender Wage (In)Equality: Regional Restructuring and Wage Differentials by Gender and Education, *Economic Geography* **74**(4), 379–404.

Mincer, J.: 1974, *Schooling, Experience and Earnings*, Columbia University, New York.

Nopo, H.: 2004, Matching as a Tool to Decompose Wage Gaps, *Discussion Paper 981*, IZA.

Oaxaca, R.: 1973, Male-Female Wage Differentials in Urban Labor Markets, *International Economic Review* **14**(3), 693–709.

Olfert, R. M. and Moebis, D. M.: 2006, The Spatial Economy of Gender-Based Occupationall Segregation, *The Review of Regional Studies* **36**(1), 44–62.

Phimister, E.: 2005, Urban Effects on Participation and Wages: Are there Gender Differences?, *Journal of Urban Economics* **58**(3), 513–536.

Robinson, H.: 2005, Regional Evidence on the Effect of the National Minimim Wage on the Gender Pay Gap, *Regional Studies* **39**(7), 855–872.

Weichselbaumer, D. and Winter-Ebmer, R.: 2003, A Meta-Analysis of the International Gender Wage Gap, *Discussion Paper 906*, IZA.

Table 1: Composition of the workforce by gender and region type (1984, 1994 and 2004)

	female		male		male-female
skill group	N	%	N	%	Diff.
			1984		
			economic hotspots		
1	818	13.34	751	8.55	-4.80
2	4629	75.51	6540	74.45	-1.07
3	419	6.84	511	5.82	-1.02
4	264	4.31	983	11.19	6.88
total	6130	100.00	8785	100.00	
			rural areas		
1	977	16.25	743	6.71	-9.54
2	4762	79.21	9800	88.49	9.28
3	144	2.40	219	1.98	-0.42
4	129	2.15	313	2.83	0.68
total	6012	100.00	11075	100.00	
			1994		
			economic hotspots		
1	506	5.76	1011	9.09	3.33
2	5823	66.25	7665	68.91	2.66
3	1814	20.64	1231	11.07	-9.57
4	646	7.35	1216	10.93	3.58
total	8789	100.00	11123	100.00	
			rural areas		
1	936	6.60	1254	5.15	-1.45
2	11996	84.53	21760	89.36	4.82
3	752	5.30	666	2.73	-2.56
4	507	3.57	672	2.76	-0.81
total	14191	100.00	24352	100.00	
			2004		
			economic hotspots		
1	576	6.81	1112	12.48	5.67
2	4757	56.24	5172	58.03	1.80
3	2422	28.63	1626	18.25	-10.39
4	704	8.32	1002	11.24	2.92
total	8459	100.00	8912	100.00	
			rural areas		
1	571	5.18	936	6.17	0.98
2	9126	82.81	13117	86.40	3.59
3	986	8.95	747	4.92	-4.03
4	337	3.06	381	2.51	-0.55
total	11020	100.00	15181	100.00	

Notes: Own calculations using IAB-REG.

Table 2: Daily gross median wages by gender, skill group and region type (1984, 1994 and 2004)

		hot spots		rural areas	
		female	male	female	male
1984	skill 1	37.22 €	45.84 €	32.84 €	43.90 €
	skill 2	46.27 €	54.72 €	35.90 €	48.30 €
	skill 3	49.93 €	65.69 €	42.84 €	54.25 €
	skill 4	64.67 €	78.01 €	61.34 €	73.61 €
	total	45.54 €	56.08 €	35.64 €	48.36 €
1994	skill 1	45.10 €	56.38 €	41.77 €	55.60 €
	skill 2	63.83 €	75.25 €	46.18 €	60.76 €
	skill 3	77.17 €	93.78 €	59.82 €	73.48 €
	skill 4	92.47 €	114.06 €	70.65 €	89.06 €
	total	66.19 €	78.22 €	47.25 €	61.14 €
2004	skill 1	35.60 €	48.67 €	34.84 €	54.90 €
	skill 2	68.61 €	83.00 €	45.90 €	69.25 €
	skill 3	82.34 €	107.97 €	61.99 €	85.65 €
	skill 4	103.78 €	142.94 €	82.62 €	114.05 €
	total	71.46 €	87.30 €	46.87 €	69.58 €

Notes: Own calculations using IAB-REG.

Table 3: Raw skill-specific gender wage gap by region type (1984, 1994 and 2004)

	skill specific gender wage gap		
	metropolitan urban areas	rural areas	difference urban/ rural
		1984	
skill 1	-18.79	-25.19	6.39
skill 2	-15.44	-25.69	10.25
skill 3	-24.00	-21.02	-2.97
skill 4	-17.11	-16.67	-0.44
median	-18.79	-26.29	7.51
		1994	
skill 1	-20.00	-24.89	4.89
skill 2	-15.18	-23.99	8.82
skill 3	-17.71	-18.60	0.89
skill 4	-18.93	-20.67	1.74
median	-15.38	-22.72	7.34
		2004	
skill 1	-26.87	-36.54	9.68
skill 2	-17.34	-33.72	16.37
skill 3	-23.74	-27.63	3.88
skill 4	-27.40	-27.56	0.16
median	-18.15	-32.63	14.48

Notes: Own calculations using IAB-REG.

Table 4: Urban wage premium by gender and skill group (1984, 1994 and 2004)

	urban wage premium		
	female	male	Diff.
		1984	
skill 1	13.34	4.42	-8.92
skill 2	28.90	13.28	-15.62
skill 3	16.53	21.09	4.56
skill 4	5.43	5.98	0.55
total	27.77	15.96	-11.81
		1994	
skill 1	7.99	1.39	-6.60
skill 2	38.21	23.85	-14.37
skill 3	29.01	27.62	-1.39
skill 4	30.87	28.07	-2.80
total	40.07	27.92	-12.15
		2004	
skill 1	2.19	-11.33	-13.52
skill 2	49.47	19.86	-29.61
skill 3	32.82	26.06	-6.77
skill 4	25.61	25.34	-0.27
total	52.44	25.47	-26.97

Notes: Own calculations using IAB-REG.

Table 5: Skill premia by gender, skill group and type of the region (1984, 1994 and 2004)

	hot spots		rural areas		male/ female diff.	
	female	male	female	male	hot spots	rural
			1984			
skill 1	-18.27	-18.27	-7.86	-9.23	0.01	-1.37
skill 2	1.60	-2.43	0.71	-0.11	-4.02	-0.82
skill 3	9.62	17.13	20.19	12.17	7.51	-8.02
skill 4	41.98	39.10	72.08	52.21	-2.88	-19.87
			1994			
skill 1	-31.86	-27.92	-11.62	-9.06	3.94	2.56
skill 2	-3.57	-3.79	-2.27	-0.63	-0.23	1.64
skill 3	16.59	19.90	26.58	20.18	3.31	-6.40
skill 4	39.70	45.82	49.52	45.66	6.12	-3.86
			2004			
skill 1	-50.18	-44.24	-25.68	-21.10	5.94	4.58
skill 2	-3.98	-4.92	-2.08	-0.47	-0.93	1.61
skill 3	15.23	23.68	32.25	23.11	8.45	-9.14
skill 4	45.24	63.74	76.26	63.91	18.50	-12.34

Notes: Skill premium defined relative to the total median. Source: Own calculations using IAB-REG.