The Glass Ceiling In The Croatian, Hungarian And German Labor Markets (2006-2012)

By

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Abstract

This thesis seeks to examine gender inequality in the labor markets in Croatia, Hungary and Germany in the period from 2006 to 2012. Specifically, the aim of the thesis is to discover whether glass ceiling effect (gender based discrimination that retains women from obtaining highly paid, top level positions inside the firms) is one of the characteristics of these labor markets. Analysis uses Labor Force Survey data for full time employees in order to establish the driving forces of the gender inequality. The main variable of interest is a binary variable that captures whether a person holds a supervisory position. During the analysis I point to the different conceptions of supervisory positions across countries and time. I use three methods in order to capture different parts of the glass ceiling effect. Linear probability model establishes differences between men and women in terms of the probability of holding a supervisory position. Results show the presence of the glass ceiling in all three labor markets. Blinder-Oaxaca decomposition of the linear model shows that human capital can explain part of the differences in the German labor market, while better human capital endowments of women in the Croatian and Hungarian labor markets don't help them to have advantage in obtaining a supervisory position. Blinder-Oaxaca decomposition for the logit model reveals that the size of the firm is also an important determinant of the differences in probabilities between men and women to hold high level positions.

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1. Introduction

Gender inequality in the labor market became an important question in labor economics and economics of discrimination during and after the burst of social movements concerning women's equality. Since then, economics as a discipline integrates different approaches in conceptualizing, discovering and measuring this phenomenon. One of the most frequently used method for discovering the differences between men and women in the labor market is the analysis of the gender wage gap. This method seeks to analyze distribution of wages for men and women and to establish whether there are important differences. Following this approach, one of the important questions is whether the difference between men and women differ along wage distribution. It turned out that frequently wage distribution exhibits such characteristics that the difference between men and women in terms of wages becomes bigger in the higher parts of the distribution. In other words, there is a bigger difference between men and women who earn a lot than between men and women who have average wages. This phenomenon is usually referred to as "the glass ceiling effect".

This term became popular in the 1980's and it is still being used to denote the inability of women to gain access to high level positions. Since then, the glass ceiling effect is used in different connotations to point to the various types of labor market discrimination. One of them is that which I described and it is closely related to the standard type of labor market discrimination; that is, discrimination of women in terms of salary. According to Cotter et all (2001), there are 4 different criterions for the existence of the glass ceiling. In a nutshell, the glass ceiling is the labor market discrimination against women that "isn't explained by other job-relevant characteristics of the employee … is greater at higher levels of outcome … represents inequality in the chances of advancements into higher levels and increases over the course of career", Cotter et all (2001). In this way, the gender difference in the labor markets isn't only looked through the differences in salaries but also through deeper structures of gender inequality. By exploring the glass ceiling, one explores power hierarchies in the firms that are always the product of cultural norms and reveal the construction of the gender identities of a certain society.

My aim in this thesis is to explore the glass ceiling with respect to this conceptualization in the labor markets of Croatia, Hungary and Germany in the period from 2006 to 2012. I will explore what is the difference in probability between men and women holding high level positions in their firms. In this way, my work fits into the analysis of gender inequality in the labor markets of these three countries. Until now most of the analysis used gender wage gap in order to discover labor market discrimination in wages (see Nestic (2010) for Croatia, Lovasz and Telegdy (2010) for Hungary, Pfeifer and Sohr (2008) for Germany). Few of them specifically dealt with the glass ceiling effect (see Busch and Holst 2009). My work aims to broaden up the scope of the analysis of labor market discrimination in a few aspects. First of all, it seeks to explore the glass ceiling in three countries, Croatia, Hungary and Germany, while earlier work was only done in Germany. Moreover it contributes to the literature in a way that it gives a comparative analysis of these labor markets that haven't been compared previously in this sense. In the end, it follows the methodological approach of exploring the probabilities of holding supervisory positions (see Zeng (2008), Baxter and Wright 2000; Elliott and Smith 2004) that hasn't been applied to the countries of my analysis.

In order to explore the glass ceiling effect I use three methods. Firstly, I use the single equation linear probability model. This model serves to establish whether women are disadvantaged compared to men in terms of holding supervisory positions. The model estimates the difference in probabilities between men and women while controlling for a variety of different factors. The results clearly show that women do have significantly smaller probabilities and that majority of the gender gap is not possible to explain with control variables. Since this model doesn't allow for different returns to controls for men and women, the next model I used overcomes this shortcoming.

The Blinder-Oaxaca decomposition for linear models show which part of the difference between men women can be explained by observable characteristics and which one stays unexplained. This unexplained part represents upper bound estimate of the labor market discrimination, thus reveals the glass ceiling effect. My results show that women in Croatia and Hungary do possess better labor market characteristics, on average, but they still have lower chances of holding supervisory positions than men. On the other hand, control variables do explain part of the differences between men and women in the German labor market, but the scope of the explained part is limited, taking into consideration the variety of control variables that are included in the model. It turns out that human capital (education and experience) and hours worked (except in Hungary) are the most important determinants of the difference between men and women out of all control variables. Since linear models only allow for constant marginal returns, I extended my analysis by including the Blinder-Oaxaca decomposition for nonlinear models.

I did the Blinder-Oaxaca decomposition for the logit model in order to discover whether some variables influence the outcome in nonlinear ways. It turns out that the size of the firm becomes statistically significant in all three countries, although with a very small influence in the Croatian and Hungarian labor market.

This thesis is organized in the following way. Firstly, I give descriptions of the variables and the data set I am using in the second chapter. Specifically, I discuss main variables of interest: its conceptualization across countries and potential influences of it on the results. Afterwards, in chapter three, I describe the models that I will use to estimate the glass ceiling effect. The three methods I used include the single equation linear probability model, the Blinder-Oaxaca decomposition for linear models and the Blinder-Oaxaca decomposition for nonlinear models. In chapter four, I present my results and compare them across countries. Lastly, in the discussion chapter, I connect my findings with the existing literature and propose possible extensions of my research.

2. Data description and descriptive statistics

I use the data obtained by Labor Force Surveys for Croatia, Hungary and Germany. Repeated cross-sectional data in this database is gathered from 2002 till 2012, but the main variable that I will use in my analysis, *supvisor*, is observed only from 2006 till 2012. This is a binary variable that takes value of one if a person is holding a supervisory position in a firm. This variable allows me to explore what is the probability of attaining high level position inside of firm.

Table 1. Question concerning supervisory position in the questionnaire in the original language and translated into English.

Country	Original question in the questionnaire	Translation into English
Croatia	Jeste li na svome glavnom poslu nekome šef?	In your main job, are you the boss/chief to anyone?
Hungary	Végez-e irányító tevékenységet (irányítja-e mások munkáját)?	Do you have supervisory responsibilities (do you supervise other persons job)?[1]
Germany until 2012	Welche tätigkeit führen sie in ihrer erwerbstätigkeit? management-, leitungs-, und führungstätigkeiten	Which position are you occupying in your employment? Management function, executive function and leading function.
Germany in 2012	Sind Sie in Ihrer weiteren Tätigkeit überwiegend als Führungs- oder Aufsichtskraft tätig?	In your further occupation/employment, are you mostly working as a manager or as a supervisor?

Before describing other variables and presenting descriptive statistics, I will discuss the differences in questionnaires between Croatia, Hungary and Germany. I want to present the question that is used to obtain the information on supervisory position. Table 1 contains the question in the original language and its translation to English. As we can see from Table

[1] This translation comes from the study by Bauer et all (2006), available at http://www.mzes.uni-mannheim.de/publications/papers/Supervisor_Function.pdf

1, the question differs across three countries and it changes in 2012 in Germany. For the other two countries (Croatia and Hungary) the question is the same during the entire period of time (2006-2012). The question in the German questionnaire in 2012 is more inclusive and broader than in 2011. When it comes to Croatia, the question takes the strictest form among these three countries. The key word "šef" literally translated means "boss/chief". This is the reason why the results from analysis of Croatian data will give the most confident answers about the glass ceiling effect. The supervisory position, defined in this way, reveals the position of power inside of a firm. On the other hand, the way the question is formulated in the Hungarian questionnaire, we can see that it incorporates a broader range of positions. Supervising other people in the workplace doesn't necessarily mean that a person is holding a position of power, described as "boss/chief". Moreover, it can happen that a worker supervises other workers in just one minor part of the main job, which again doesn't put him/her in a position of power (Bauer et all 2006). Taking all of this into consideration, there are two types of direct comparisons in this thesis. One is between Germany from 2006 till 2012 and Croatia, because they are characterized with stricter definition of supervisory position. The other one is between Germany in 2012 and Hungary since supervisory position takes broader form in their questionnaires than in the two previous cases. Other types of comparisons between countries will take into account the difference in conceptualization of supervisory position.

Since I'm exploring the existence of gender glass ceiling in the labor market, my main independent variable is gender of individuals (*female* equals to 1 if a person is women). The dataset I use contains a lot of important variables that can be used as control variables in the regressions. First of all I use education and experience as control variables. Experience is not given in the dataset, so I constructed the variable *exper*, which denotes potential experience. I calculated it by subtracting 5 (years before school) and the number of years spent in school from age of the individuals. I calculated years spent in school for each individual by looking at the highest level of schooling (*hatlevel*), given in ISCED levels[2]. I also included square of *exper* since this is the usual practice done in the models that deal with labor market differences between men and women, because it reflects diminishing marginal utility of experience (Mincer 1958, Blinder 1973, Oaxaca 1973) Education is taken from the list of derived variables (*hatlev1D*) and it has three levels: elementary school, high school and college (*elemsch*, *highsch* and *college*). I excluded from the sample those individuals that are younger than 15 and older than retirement age for each country.[3]

In order to get the estimates of the *female* coefficient, which measures discrimination, as close as possible given my data, I included other variables: number of hours usually spent at work (*hwusual*), dummies for the field of the highest level of education attained (teacher training and education science (*teacher*), humanities, (foreign) languages, and arts (*humanit*), social sciences, business and law (*socialsc*), science, mathematics and computing (*sciencomp*), life science (including biology and environmental science) and physical science (including physics, chemistry and earth science) (*lifescien*), computer science (*compscien*), agriculture and veterinary (*agri*), health and welfare (*health*) and services (*services*), special types of work (Sunday work (*sunw*), Saturday work (*satw*), evening work (*evenw*), night work (*nightw*) and shift work (*shiftw*)), dummies for the size of a firm (from 1 to 10 (*less10*), from 11 to 19 (*f11to19*), from 20 to 49 (*f20to49*) and more than 50 (*f50more*)), number of kids less than 2 years old (*hhnbch2*), number of kids from 2 years old till 5 years old (*hhnbch2*),number of kids from 5 years old till 8 years old (*hhnbch8*), number of kids from 8 years old till 11 years old (*hhnbch11*), number of kids from 11 years old till 14 years old

[2] ISCED is an international standard for levels of education that is used in this database to describe highest level of education for each individual (http://www.uis.unesco.org/Education/Pages/international-standard-classification-of-education.aspx).
[3] Retirement age is different for all three countries, so I adapted the sample based on that (http://en.wikipedia.org/wiki/Retirement_age)

(*hhnbch14*), number of kids from 14 years old till 17 years old (*hhnbch17*) and number of kids from 17 years old till 24 years old (*hhnbch2*), age of the youngest child in the household (*hhageyg*) and number of people in the household that are older than 65 (*hhnbold*).[4]

As I mentioned, education and experience are standard variables that are used in the regressions that measure labor market differences between men and women because they reflect human capital of each individual. I included dummies for the field of highest level of education in order to control for the choices individuals make about their investment in human capital. Number of people working in the firm is also an important control variable because, on average, women tend to have better possibilities of obtaining the leading positions in smaller firms (Bischoff 2010). The number of children and number of persons older than 65 in the household are important indicators of how strong the division between women and men is in terms of domestic labor. Together with the information about hours usually worked and special types of work, these variables can partly reveal how important are the cultural norms in formation of gender identities and the role of women and men in the labor market and its organization (Busch and Holst 2011, Bertrand 2011).

In this thesis I restrict my analysis to full time employment only, because there are big differences in the structure of part time employment across these three countries.[5] Part time work is more present in the German labor market than in the Croatian and Hungarian ones.

Now, I will present some of the descriptive statistics and graphs in order to examine the differences between probabilities of holding supervisory position between men and women. Table 2 shows what the percentages of women and men in supervisory positions are, in all three countries for all years and for Germany separately for the period 2006 to 2011 and

[4] Description of the variables is taken from the Labor Force questionnaires.
[5] For full statistics see OECD data on full time vs part time employment, available on http://stats.oecd.org/Index.aspx?DataSetCode=FTPTN_D

for 2012.

Table 2. Percentages of full time employed women in supervisory positions with total number of fully employed people holding supervisory positions.

Country	Croatia 2006-2012	Hungary 2006-2012	Germany 2006-2011	Germany 2012
Percentage of women holding supervisory position	**10**	**12.4**	**12.6**	**21.2**
Percentage of men holding supervisory position	**14.4**	**14.7**	**23.7**	**33.6**
Total number of people holding supervisory position	**9739**	**80353**	**15650**	**39472**

Source: I calculated percentages based on the pooled cross-section raw data from Labor Force Survey for Croatia (2006-2012), Hungary (2006-2012), Germany (2006-2011) and Germany (2012).

All percentages for women are lower than the ones for men in all countries. These initial results points into direction of seeking for stronger evidence for the existence of the glass ceiling. Also, the German labor market exhibits the largest differences in probabilities between men and women. Moreover the big change from 2011 to 2012 in the number of people in supervisory position, but also in the percentage of women and men holding one, in Germany, reflects the change in the survey question in 2012. Very large number of people in supervisory positions in Hungary, compared to the other two countries, also confirms the expectations based on the previous analysis of questionnaire.

Even though Table 2 gives certain evidence to support the existence of the glass ceiling effect in all three labor markets, further examinations of the data is needed for stronger evidence. Furthermore, the purpose of this thesis is not only to prove the existence of the glass ceiling effect, but also to provide the analysis of the structure of the glass ceiling.

Next, I present the average probabilities of becoming a supervisor with respect to different labor market characteristics. Table 3 contains information for men and women whose highest level of education is elementary school (column (1)), high school (column (2)), college (column (3)) and who have children younger than 5 years (column (4)).

When it comes to Croatia, we can see from Table 3 that the differences in probabilities of holding supervisory positions between men and women increase with higher levels of education. Surprisingly, the difference in probabilities for individuals who have small children is almost equal as average difference. This can be explained by low participation rates of women in the labor market. As suggested by Nestic, Croatia exhibited decline in the participation rates of women during and after the transition (Nestic 2010). I think that a self-selectivity bias in this case can explain small differences in probabilities. Furthermore, his findings show that even though women have higher education than men, they still receive smaller salaries. This finding goes in line with the results from Table 3, indicating that the probability of obtaining a supervisory position is 17% higher for men than for women, taken into consideration that they all have college degree.

Hungarian data show similarities in certain aspects with Croatian ones. Percentages are higher for Hungary in almost every category, but the pattern looks the same as in Croatia. A big difference between men and women with higher education is the characteristic of the labor market that is the same in Hungary and Croatia. When it comes to young children, Borbely reports that their presence widens the gap between wages for men and women in the Hungarian labor market (Borbely 2007). We see in Table 3 that children do have big effect on the gap between probabilities of holding a supervisory position in Hungary and in Croatia.

Lastly, Table 3 reveals that the gap between men and women in terms of measured percentages is the biggest in the case of Germany. Furthermore, the gap in the German data is almost the same before and after the change in questionnaire, but all of the presented probabilities become significantly higher in 2012. Also, the gap for highly educated people and for those people who have young children gets bigger in 2012, when the concept of supervisory position becomes broader. These differences between two periods in German data aren't in line with differences between Hungary and Croatia, taking into consideration similarities between the concepts of supervisory positions between Germany before 2012 and Croatia and Germany in 2012 and Hungary. This shows that cultural differences are more important than similarities in the definition of the supervisory roles in different countries.

Table 3. Average percentages of full time employed men vs women holding supervisory positions, with respect to different levels of education and number of children

Country		Elementary school (1)	High school (2)	College (3)	Children younger than 5 (4)
Croatia 2006-2012					
	Men	2.1	10.2	40.1	14.1
	Women	2.1	6.6	21.4	7.5
Hungary 2006-2012					
	Men	2.7	11.1	43.0	16.0
	Women	2.8	9.7	24.4	9.9
Germany 2006-2011					
	Men	3.1	16.8	50.3	29.2
	Women	2.4	10.0	27.1	12
Germany 2012					
	Men	6.8	26.9	59.7	39.2
	Women	5.2	17.7	37.7	20.8

Source: I calculated percentages based on the pooled cross-section raw data from Labor Force Survey for Croatia (2006-2012), Hungary (2006-2012), Germany (2006-2011) and Germany (2012).

Now I present probabilities of obtaining a supervisory position for people who work full time. I want to see how these probabilities change depending on the age of an individual. I created the graphs by aggregating the *supvisor* variable over its mean and creating 10 age groups, whose length is 4 years approximately. I added confidence intervals using next formulas. For the upper bond:

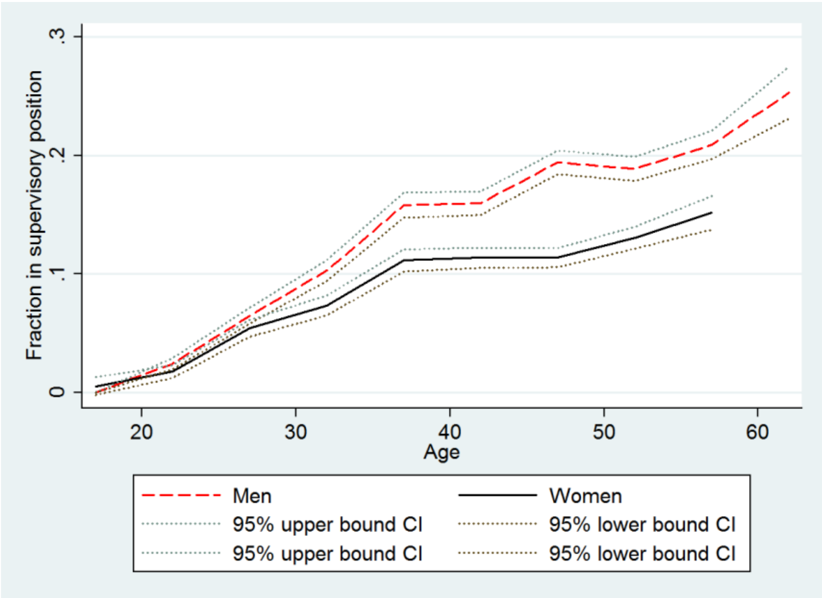
$$ci_{upper\ bond} = supvisor + 2 * SE$$

And for the lower bond:

$$ci_{lower\ bond} = supvisor - 2 * SE,$$

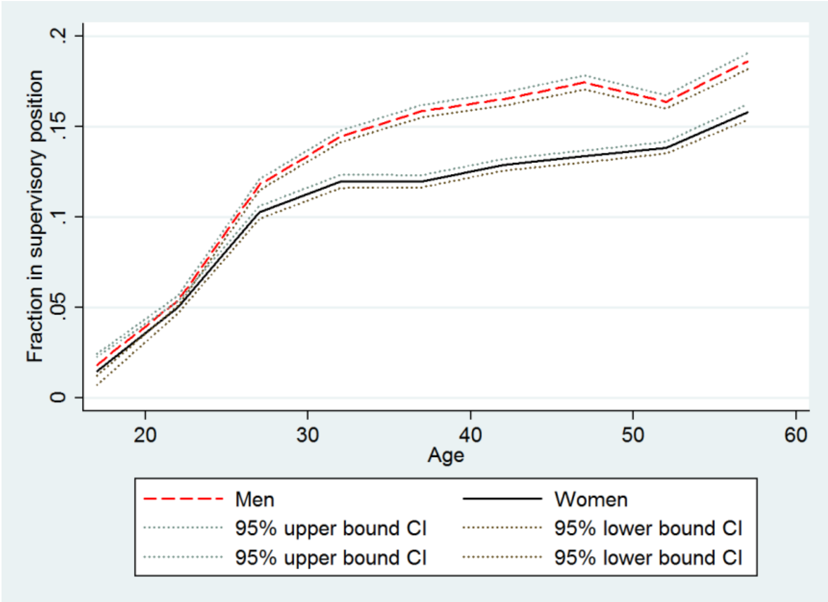
where $SE = \sqrt{supvisor(1 - supvisor)/N}$, and N is the number of observations.

Figure 1a. Mean probabilities of holding supervisory position for full time employees with respect to age; confidence intervals included: Case of Croatia



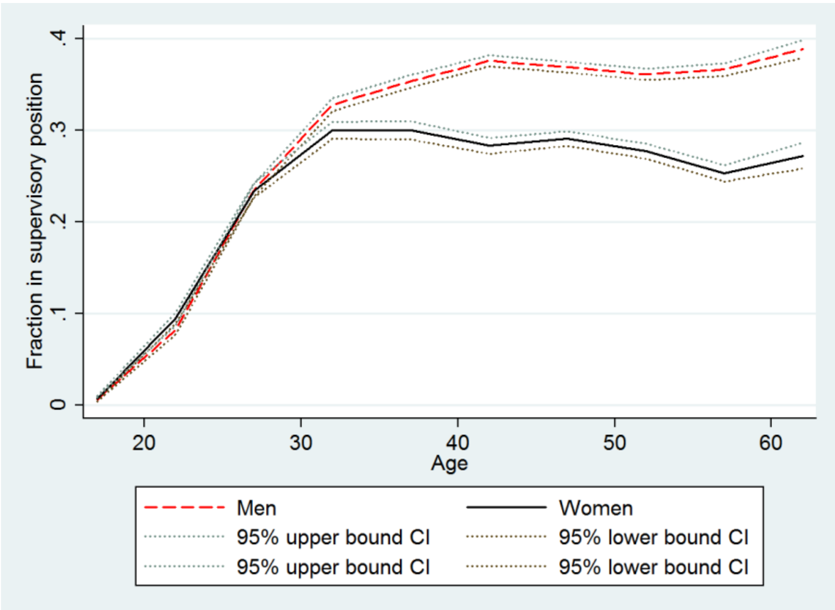
Source: I plotted the graph based on the pooled cross-section raw data from Labor Force Survey for Croatia for the period from 2006 to 2012.

Figure 1b. Mean probabilities of holding supervisory position for full time employees with respect to age; confidence intervals included: Case of Hungary



Source: I plotted the graph based on the pooled cross-section raw data from Labor Force Survey for Hungary for the period from 2006 to 2012.

Figure 1c. Mean probabilities of holding supervisory position for full time employees with respect to age; confidence intervals included: Case of Germany

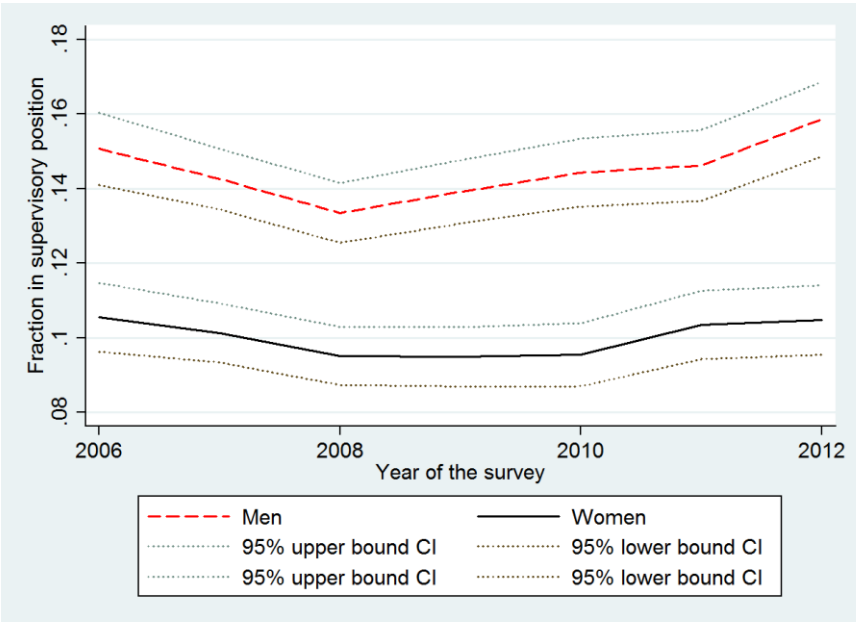


Source: I plotted the graph based on the pooled cross-section raw data from Labor Force Survey for Germany for the period from 2006 to 2012.

Graphs 1a and 1b for Croatia and Hungary respectively show a similar pattern. First of all probabilities show clear trend, which is expected concerning the fact that usually people with more experience get to higher level positions. More importantly, the gap is very small in the first part then it becomes larger and it shrinks down again. For Hungary the gap gets smaller at the end of the graph. On the other hand, Graph 1c clearly shows that the gap in probabilities increases constantly in the case of Germany, with a very steep increase from the beginning.

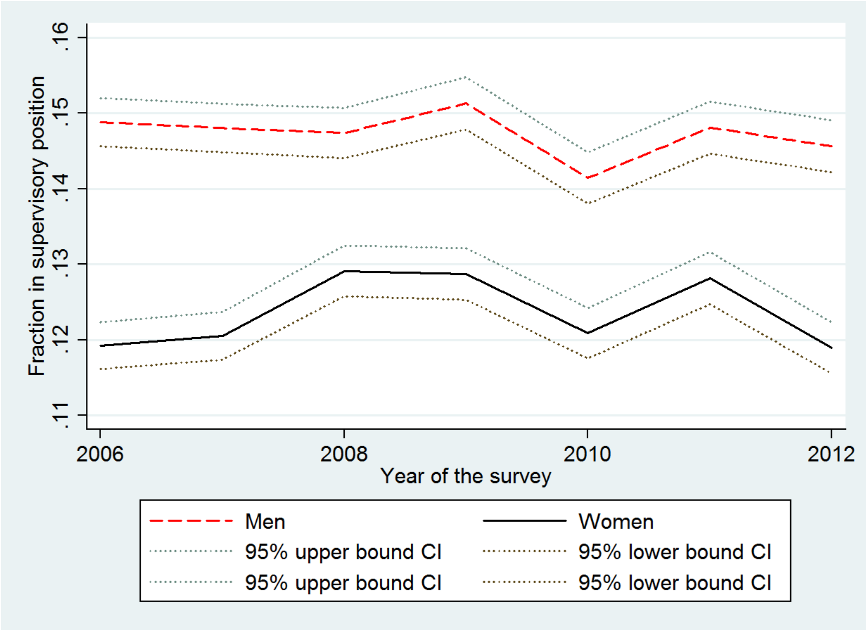
I plotted three more graphs that show how the probabilities of holding supervisory position change from 2006 till 2012, for men and for women. I plotted them in a simmilar way like the previous ones, just this time I aggregated data with respect to years of the surveys and not with respect to the age of individuals.

Figure 2a. Mean probabilities of holding supervisory position for full time employees across time; confidence intervals included: Case of Croatia



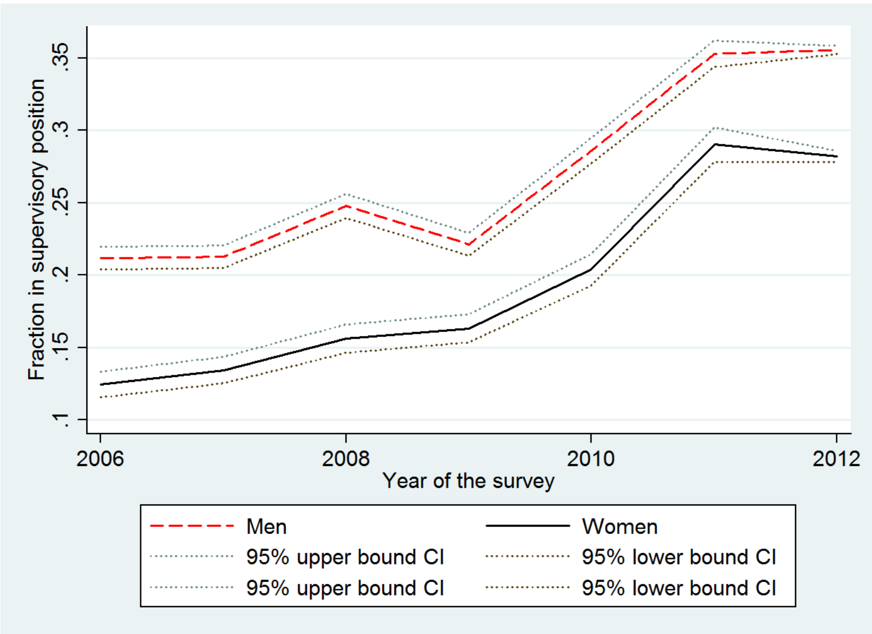
Source: I plotted the graph based on the pooled cross-section raw data from Labor Force Survey for Croatia for the period from 2006 to 2012.

Figure 2b. Mean probabilities of holding supervisory position for full time employees across time; confidence intervals included: Case of Hungary



Source: I plotted the graph based on the pooled cross-section raw data from Labor Force Survey for Hungary for the period from 2006 to 2012.

Figure 2c. Mean probabilities of holding supervisory position for full time employees across time; confidence intervals included: Case of Germany



Source: I plotted the graph based on the pooled cross-section raw data from Labor Force Survey for Germany for the period from 2006 to 2012.

We can observe from these graphs that in the case of Croatia volatility of probabilities is the smallest, while it is the biggest in the case of Hungary. In the case of Germany, we can see growing trend for both men and women. In all three countries two lines roughly follow each other, with an exception of Germany in 2008, when the probability of becoming a man supervisor rises. This result confirms one of the main findings by Cook and Glass (2013): women (minorities in general) are replaced by (white) men in CEO positions when firms go through the period of declining output.

3. Econometric models

In this chapter I will present theoretical foundations of the models that I will use in my econometric analysis. First of all I will present simple linear probability model. It will serve in the estimation part for the initial analysis of the existence of the glass ceiling effect. Then I will describe the Blinder Oaxaca decomposition of the linear model. In the end I will present the extension of the Blinder Oaxaca decomposition for nonlinear models. Specifically I will apply the Blinder Oaxaca decomposition to logit model. I will also point to the certain shortcomings of the models and their modifications.

3.1. Single equation linear probability model

In this section I want to describe the model I will use for estimating the probability of holding a supervisory position in the firms. As I mentioned earlier, dependent variable of interest – *supvisor*, is a binary variable that takes one if a person holds a supervisory position. The equation I will estimate looks in the following way

$$(1)\ supvisor_i = \alpha + \beta * X_i + \delta * female_i + u_i$$

X_i is an array of control variables that I already described in the previous chapter. I will estimate this equation with OLS. This equation resembles the Mincerian equation in certain aspects (Mincer 1958). It accounts for human capital (education, experience, field of study, etc.) in order to estimate certain labor market outcome (this time probability of holding supervisory position, unlike the original Mincerian equation that takes wages as dependent variable). Taking into account other control variables besides the ones that are considered to present human capital, the purpose of this equation is to establish the relationship between gender and possibility to hold highest level positions in the firm. The coefficient on *female* dummy captures the difference in probabilities between men and women. This coefficient is important because it can serve as a measure of the discrimination in the labor market. Under the standard assumptions of the OLS method, the coefficient is unbiased.

One of the greatest concerns with this method is selection of variables that should be included. On one hand it is good idea to include as many variables as possible, but one must be careful with the choice. For example even though there is a lot of research in the field of occupational segregation (see Weeden and Sørensen 2004, Hegewisch et all 2010, Lovasz and Telegdy 2010) that demonstrate gender discrimination inside certain occupations, including occupational dummies in the regression can lead to underestimation of the labor market discrimination. Blinder (1973) showed that the structure of the occupations is affected by so called "pre-labor market discrimination".

Moreover, single equation linear probability model I presented doesn't allow for differences in slopes between men and women. In different words, returns to human capital can be different for men and for women, but this linear model can't be used to establish this difference. This is the major shortcoming. In order to overcome this, various decompositions of the mean difference in the outcomes are developed (Blinder 1973). Blinder-Oaxaca decomposition is one that is used in most of the cases that deal with the gender discrimination in labor market. There are some others (see Oaxaca and Ransom 1994 and Ñopo 2008), but in this thesis I will concentrate on Blinder-Oaxaca only.

In the next two sections I will present two different versions of the Blinder-Oaxaca decomposition, explain their main characteristics and present the way in which they can be used to overcome shortcomings of the model I just described.

3.2. The Blinder-Oaxaca decomposition for linear model

In this section I will present the first version of the Blinder-Oaxaca decomposition. This decomposition uses linear model and divides the difference in the mean probabilities of holding high level position in a firm between men and women in two parts. One part represents the difference that is due to difference in endowments. This part is measurable. This part accounts for differences in slopes between men and women. If this part of decomposition is statistically significant, then linear probability model isn't the best estimate of the influence of control variables on the outcome probabilities. The second part is the part that is referred to as labor market discrimination. The model that I will estimate takes the following form

$$(2)\ \overline{supvisor}_m - \overline{supvisor}_w = \bar{X}_w\left(\bar{\beta}_m - \bar{\beta}_w\right) + (\bar{X}_m - \bar{X}_w)\bar{\beta}_m$$

Where $\overline{supvisor}_m$ and $\overline{supvisor}_w$ come from equation (1), such that (1) is evaluated at mean values of control variables (without *female* dummy), for men and women respectively. This version of the decomposition is called Blinder-Oaxaca decomposition (Blinder 1973, Oaxaca 1973). The second part on the right hand side of the equation represents the difference in endowments between men and women and is called the explained part. The first part is unexplained and thus refers to the labor market discrimination. It measures which portion of difference between men and women can't be attributed to the differences in endowments.

Since the main variable of interest in this thesis is binary variable, linear model isn't always the best solution. Nonlinear models in the case of binary variables allow for non-constant partial effect, which make them better prediction models than linear ones. They are also able to capture the influence of independent variables in a better way, which is crucial here since I want to estimate as accurate as possible which part of difference between men and women can be attributed to endowments effect and which one represents discrimination.

Taking this into consideration, in the next section I will present the method of decomposing nonlinear models and apply it specifically to the logit model.

3.3. The Blinder-Oaxaca decomposition for nonlinear model: The case of logit

In this section I follow the works of Fairlie (1999), Bauer and Sinning (2006) and Sinning et all (2008) in order to describe the Blinder-Oaxaca decomposition for the nonlinear models. I will take into account the fact that in my econometric analysis I'm using decomposition of the logit model. More specifically, I will adapt the decomposition for the logit model, as a special case of all nonlinear decompositions.

The main reason why nonlinear models require different decomposition than the linear ones is the fact that the mean value of nonlinear function isn't necessarily equal to the value of the function evaluated at mean values of independent variables. Taking this characteristics of nonlinear functions into account, Bauer and Sinning (2006) and Sinning et all (2006) start with transforming conditional expectation of dependent variable in two parts. In my case, this transformation will look in the following way

$$(4) \quad \overline{supvisor_m}^{\,l} - \overline{supvisor_w}^{\,l} =$$

$$= \left\{E_{\beta_w}(supvisor_m{}^l|X_m) - E_{\beta_w}(supvisor_w{}^l|X_w)\right\} + \left\{E_{\beta_m}(supvisor_m{}^l|X_m) - E_{\beta_w}(supvisor_m{}^l|X_m)\right\}$$

Where $supvisor_j{}^l = G(\beta_{0j} + \beta_j X_j)$, $G(z) = \frac{\exp(z)}{1+\exp(z)}$ and $E_{\beta_j}(supvisor_j{}^l | X_j)$ is conditional expectation of $supvisor_j{}^l$ evaluated with controls X_j and vector of coefficients β_J $(j = m, w)$.

In order to get the final expressions for the decomposition, the conditional expectations are approximated with the expressions for the conditional expectations in discrete case (with sums). Integrating Fairlie's (1999) findings for the nonlinear functions with the equations from my model, I get the following expression for the Blinder-Oaxaca decomposition of the logit model

$$(6) \qquad \overline{supvisor_m}^{\,l} - \overline{supvisor_w}^{\,l} =$$

$$= \left\{ \sum_{i=1}^{N_m} \left(\frac{G(\beta_{0m} + \beta_m X_m)}{N_m} \right) - \sum_{i=1}^{N_w} \left(\frac{G(\beta_{0w} + \beta_w X_w)}{N_w} \right) \right\}$$
$$+ \left\{ \sum_{i=1}^{N_m} \left(\frac{G(\beta_{0m} + \beta_m X_m)}{N_m} \right) - \sum_{i=1}^{N_m} \left(\frac{G(\beta_{0w} + \beta_w X_m)}{N_m} \right) \right\}$$

Where N_w and N_m are the number of people in the sample who declare their gender as woman and man, respectively.

The first part on the right hand side represents the part of the differences that is due to differences in endowments, while the second part stands for the unexplained effects, so called labor market discrimination.

In the end of this chapter I will address some of the main criticism of the Blinder-Oaxaca decomposition, referring to Springel (2011). First of all, even though Bllinder-Oaxaca decomposition can only be applied to the decomposition over the mean, different choices of dependent variables can overcome this problem. In the case when the dependent variable is wage, Blinder-Oaxaca decomposition can't be used for discovering the existence of the glass ceiling effect. On the other hand if the dependent variable refers to the possibility of holding high level position in a firm, then Blinder-Oaxaca decomposition can be used to establish which factors are the most prevailing ones in the formation of the glass ceiling, because this dependent variable reflects the glass ceiling.

Furthermore, as I showed in this section Blinder-Oaxaca decomposition isn't restricted to the linear models only. Following the work of Fairlie (1999), Bauer and Sinning (2006) and Sinning et all (2008), it is possible to apply Blinder-Oaxaca decomposition to the larger family of functions than just linear ones. This is especially relevant for this thesis, because the main dependent variable is a binary variable. This extension of the Blinder-Oaxaca decompositions helps to improve the accuracy of the results.

One major shortcoming of all of the methods presented is the fact that none of them deal with the problem of selection into the labor market. This is an important issue concerning women's employment and some of the results from my analysis will point to it. On the other hand, the reason why exploring the problems of selection is not possible to do is lack of credible instruments.

4. Results

In this chapter I will present the results from my empirical analysis. I will follow the structure of the previous section: first I will present a linear model, then the Blinder-Oaxaca decomposition for linear and in the end for nonlinear model. I will also connect my results with the existing literature in the field and provide interpretation of the results.

4.1. Single equation linear probability model

Firstly I present the coefficients of interest (*female*) from the linear models, for each year and each country. These coefficients come from estimating (1). The full regression results are given in the Appendix. Tables A1a, A1b and A1c from the Appendix contain results for all seven years for Croatia, Hungary and Germany respectively. Here in Table 4 I only present the *female* coefficients because they are the most important for the research question of this thesis. This coefficient measures the difference in probabilities of holding a supervisory position in a firm. More accurately, it represents the difference in intercepts between two regression lines: One that comes from equation (1) without *female* variable, and is evaluated for men only and the other one evaluated for women.

Table 4. Coefficients on *female* variable in linear models for each year (with and without control variables)

Year	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Croatia	-0.075***	-0.063***	-0.074***	-0.092***	-0.079***	-0.07***	-0.089***
	-0.067***	-0.070***	-0.064***	-0.068***	-0.063***	-0.054***	-0.080***
Hungary	-0.071***	-0.077***	-0.066***	-0.067***	-0.066***	-0.064***	-0.066***
	-0.054***	-0.053***	-0.044***	-0.042***	-0.041***	-0.041***	-0.045***
Germany	-0.065***	-0.067***	-0.108***	-0.071***	-0.086***	-0.053***	-0.074***
	-0.147***	-0.141***	-0.196***	-0.161***	-0.181***	-0.196***	-0.187***

*** p<0.01, ** p<0.05, * p<0.1

The negative sign of the coefficient indicates that women are disadvantaged in terms of obtaining the high level positions. The first thing that we can observe from Table 4 is the fact that all of the coefficients are negative and statistically significant on all levels. This means, that when controlled for specified variables, women are still disadvantaged on the labor markets in all three countries during the entire period from 2006 to 2012. The inability to explain the difference with the control variables points into direction of the glass ceiling. We can also see from the table that the coefficients for Hungary are the least volatile and in 2012 it is evident that the smallest difference between men and women is in Hungary. On the other hand, the biggest one is in Croatia, which as we've seen in the descriptive part has the strictest definition of supervisory position. This finding suggests that the glass ceiling gets even thicker in the top of the high level positions.

We can see that even when variety of controls is included in the estimation, the differences in probabilities don't differ much from the raw differences (see also Figures 2a, 2b, 2c). This result suggests that majority of the difference is due to labor market discrimination and can't be explained with differences in endowments. In the next two sections I will explore this result more thoroughly.

Moreover a decline in the value of *female* coefficient in the German data in 2008 is in line with the change in probability of men holding supervisory positions, which we've already seen in the Figure 2c. This can be the effect of the financial crisis, since I already mentioned that this phenomenon can be found in the existing literature (see Cook and Glass 2013).

4.2. The Blinder-Oaxaca decomposition for linear model

In this section I will present results for the Blinder-Oaxaca decomposition for the linear model. The main aim is to capture which variables can explain the glass ceiling and to examine which part of the gap is considered to be labor market discrimination. One of the main reasons for including Blinder-Oaxaca into this analysis is to allow for the possibility of different marginal returns to control variables. I did decomposition according to the specificities of the supervisory positions that I described earlier. I did Blinder-Oaxaca decomposition for the entire period from 2006 to 2012 for Croatia and Hungary, since there is no change in the conception of supervisory position in these countries. On the other hand I divided the sample for Germany in two subsamples, one from 2006 to 2011 and the other one for 2012 and did decomposition for both subsamples separately. Furthermore, the period of seven years is a short period of time, so it's hardly expected that there will be some major change in the way certain variables influence the mean difference between men and women. Decomposition for the bigger sample, on the other hand, will give more reliable results in terms of the structure of the supervisory positions and their gender dynamics.

Table 5 contains the results from the Blinder-Oaxaca decomposition for the linear models. It is the estimation of the equation (2). It's worth noting that the presentation of these results differs from the presentation in the previous section in that way that they show the advantage of men in the labor market. This is based on the way the equation (2) is framed: differences are positive this time. Table 6 follows the same pattern of presenting the results.

Table 5 shows which part of the difference in mean probabilities of holding supervisory position between men and women is explained by control variables and which one isn't. Endowments part is the explained part. Negative coefficients given in the explained parts of this table mean that women have advantage in terms of endowments, but they are still, on average worse off in terms of possibility to hold supervisory position.

Table 5. The Blinder-Oaxaca decomposition for linear model

Country	Croatia 2006-2012	Hungary 2006-2012	Germany 2006-2011	Germany 2012
Difference	0.067 (20.49)**	0.044 (34.64)**	0.118 (20.03)**	0.123 (23.73)**
Endowments	-0.010 (5.15)**	-0.017 (21.70)**	0.045 (9.71)**	0.052 (12.75)**
Coefficient	0.082 (23.96)**	0.084 (62.29)**	0.059 (9.88)**	0.074 (14.33)**
Interaction	-0.006 (2.55)*	-0.023 (23.52)**	0.014 (2.95)**	-0.003 (0.83)
Number of observations	42,728	304,752	24,362	40,255

* $p<0.05$; ** $p<0.01$

As we can see from Table 5, the Croatian and Hungarian labor markets have similarities in terms of the endowments effect. Women in both labor markets have lower probability of holding supervisory position, despite the fact that they have better endowments. On the other hand, in the case of Germany, 38% of the difference is explained by endowments effect in the period from 2006 to 2012. This percentage decreases in 2012, but still the fair amount of differences is explained by it. Even though the explained part is the biggest in the case of Germany, taking into account the fact that I included wide variety of control variables, gender discrimination is very persistent in all three labor markets.

In order to capture which variables in the endowments effect are the most important, I did detailed Blinder-Oaxaca decomposition by connecting certain variables into groups. In Table 6 I present these results. I decided to show 5 groups that are the most important in the literature about gender differences in the labor markets. The rest of the results are in the Appendix. The first is *human capital.* It contains education dummies, experience and square of *exper*. Investments in human capital usually differ between men and women because of gender roles that are specific to each society. Gender differentiation that occurs according to the cultural norms of a society assigns different types of behavior to “different” genders. For example it is expected that women have, on average, less experience than what they would have had if they weren’t the only ones who mostly take care of the children and household. Having this in mind, number of children can also be one of the determinants of the difference between men and women in terms of probability to hold high level positions in the firms, so I present the group *children* which contains dummies for the number of children. Moreover, field of study is a category that is examined in terms of gender difference in the labor market because it is the starting point of gender segregation into certain occupations (Holst and Busch 2009), so I wanted to see whether it will have an important explanatory power in the data I am using. In the end, firm size and hours worked are important indicators of the structure of the firms and how working conditions are related to the gender gap in the supervisory positions. In this way all of the previously mentioned variables have the potential to serve as explanations of the gender difference in labor market.

Table 6. Detailed Blinder-Oaxaca decomposition for linear model with grouped effects

Country		Human capital	Hours worked	Field of study	Firm size	Children
Croatia 2006-2012	Endowments	-0.014**	0.004**	0	0.001	0
	Coefficient	0.139**	-0.092*	0	0.020	0.018**
Hungary 2006-2012	Endowments	-0.021**	0	-0.001**	0**	0.003*
	Coefficient	0.085**	0.001	0	0.014**	0.016**
Germany 2006-2011	Endowments	0.021**	0.015**	0	0	-0.038
	Coefficient	0.072**	0.042	0	0.012	0.039
Germany 2012	Endowments	0.019**	0.018**	0	-0.001	0.053
	Coefficient	0.088**	0.018	0	0.028**	0.178

* *p*<0.05; ** *p*<0.01

As expected, *human capital* variables are statistically significant in all countries. Even though, as discussed earlier, there are similarities between Croatian conceptualization of supervisory position and German one before 2012, and German during 2012 and Hungarian, sign of the human capital coefficients reveal results that doesn't support these similarities. Women in Croatia and Hungary have, on average, better human capital endowments than men, but they still have worse possibility of becoming supervisors in the firms. On the other hand, positive coefficients for *human capital* in Germany in both periods show that differences in human capital explain part of the difference in the probability of holding high level positions. This result suggests that the differences between countries in terms of culture are still more important than similarities in the conceptualization of the power position in the firms. This time, it turns out that Croatia and Hungary are more culturally closer than any of them is to Germany. It also points out to the importance of cultural norms in the formation and dynamics of the labor market.

More importantly, it is evident from Table 6 that even though human capital manages to explain part of the difference, still the unexplained part is significantly larger than explained one.

Surprisingly, number of children, field of study and size of the firm don't seem to have an influence on the gender structure of the high level positions in the firms.

4.3. The Blinder-Oaxaca decomposition for nonlinear model: The case of logit

In this section I will present nonlinear version of the Blinder-Oaxaca decomposition. I used the same control variables, only this time I allowed for the nonlinear relationship between *supvisor* and independent variables.

Table 7 contains the results from estimating equation (6). Like Table 5, it gives overall picture about the importance of control variables in explaining the gender gap in supervisory probabilities.

Table 7. The Blinder-Oaxaca decomposition for logit model

Country	Croatia 2006-2012	Hungary 2006-2012	Germany 2006-2011	Germany 2012
Difference	0.067 (20.50)**	0.044 (34.64)**	0.118 (20.05)**	0.123 (23.75)**
Explained	-0.082 (5.32)**	-0.185 (37.16)**	0.433 (17.36)**	0.303 (18.42)**
Unexplained	0.149 (9.91)**	0.229 (46.68)**	-0.315 (13.23)**	-0.180 (11.48)**
Number of observations	42,728	304,752	24,362	40,255

* $p<0.05$; ** $p<0.01$

Most of the information from Table 7 is the same as in the Table 5. Again the explained part for Croatia and Hungary is negative and for Germany it's positive in both periods. One major difference is the sign of the unexplained part for Germany. Unlike in the Table 5 where this part was positive, here we have negative. This part refers to the effects of discrimination. This unexpected result represents small puzzle in the German data.

The next table resembles Table 6, just this time Table 8 contains results for the detailed decomposition of the logit model. Groups of variables are the same as in the previous section.

Table 8. Detailed Blinder-Oaxaca decomposition for logit model with grouped effects

Country		Human capital	Hours worked	Field of study	Firm size	Children
Croatia 2006-2012	Explained	-0.144**	0.024**	-0.002	0.010**	-0.002
	Unexplained	0.258**	-0.114*	0.002	0.011**	0.019**
Hungary 2006-2012	Explained	-0.213**	0	-0.003**	0.002**	0.009*
	Unexplained	0.257**	0.001	0.003**	0.012**	0.005
Germany 2006-2011	Explained	0.269**	0.085**	0	0.014**	-0.300
	Unexplained	-0.169**	-0.026	0	0.001	0.287
Germany 2012	Explained	0.151**	0.092**	0	0.013**	0.087
	Unexplained	-0.044**	-0.056	0	0.019	0.080

* p<0.05; ** p<0.01

Results from Table 8 confirm most of the results that we've already seen. Explained part of the *human capital* group still has negative sign in the case of Croatia and Hungary and positive in the case of Germany, only this time taking into consideration the magnitude of these coefficients, it is even more convincing evidence for the conclusions from the previous section.

On the other hand there are three important differences between these results and the results from the linear decomposition. First of all, the hours worked becomes statistically significant variable in the Croatian data as well. This variable becomes more important in explaining the gender difference in the German data, as well. This result confirms previous conclusions about the importance of cultural norms for the self-selectivity of women in the labor market. This result also goes in line with the difference between two conceptions of supervisory position in Croatia and Hungary. Since the Croatian conceptualization is more close to the status of higher positions of power, bigger responsibilities and more flexible and longer working hours characterize these positions. Taking this into consideration it is reasonable that the hours worked play more important role in explaining the gender differences in the supervisory positions in the Croatian labor market than in the Hungarian one.

Second of all, group of variables containing dummies on the firm size become statistically significant in the nonlinear decomposition. This shows that the influence of the size of the firm matters in explaining the differences in probability of holding a supervisory position. One of the possible explanations, taking also into consideration the coefficients on the size of the firm dummies in tables A1a, A1b and A1c, is the fact that larger firms usually have more egalitarian promotion patterns. This finding is in contrast with the finding about the German labor market in the analysis done by Bischoff (2010) and, who claims that smaller firms provide women with better chances for holding high level positions. In the end it also notable that the coefficients for the unexplained part of the hours worked in the German data has negative sign, as well.

Lastly, one of the most interesting observations from this section is the fact that unexplained part of the human capital and hours worked change sign in the German data.

5. Discussion

In this chapter I recall some of the main findings from the previous chapters and compare them with the results from the literature.

My main finding in this thesis is the fact that I discovered that there is a statistically significant difference between men and women in the probability of holding a supervisory position in all the labor markets. This difference does behave differently across time and across countries. Even though there are similarities between the questions about supervisory position between Croatia and Germany (2006-2011) and Hungary and Germany (2012), my analysis shows that the behavior of the differences is more similar between Hungary and Croatia.

Another important result concerns the structure of the differences in probabilities of holding the supervisory positions. I showed that in the case of Hungary and Croatia control variables I used aren't able to explain the majority of difference. On contrary they show that women do possess better endowments, but they still have lower probability of holding high level position. In the case of Germany, some of the difference is explained with the differences in endowments.

Blinder-Oaxaca decompositions showed that the difference in probability of holding supervisory position depend mostly on the human capital group of variables. Another important variable is hours worked. Nonlinear decomposition showed that firm size influences the outcome probabilities as well, but not in a linear way. It also gave rise to the puzzle in the German data: sign of the unexplained part of human capital and hours worked changes from linear to nonlinear decomposition.

When it comes to Croatia, there is only one research that is known to me that partly deals with the glass ceiling in Croatia. Nestic (2010) used Blinder-Oaxaca decomposition of the wages and quantile regression in order to examine the glass ceiling effect. According to his findings, glass ceiling effect isn't present in the Croatia in the period from 1998 to 2008, although he points to the possibility of its formation in the end of 2008, when the gap in the 90th percentile widens. Contrary to his findings, results from the linear regression that I just presented show that there is persistently smaller probability of holding supervisory position for women (table 4). Moreover Blinder-Oaxaca decompositions point to the fact that very little of the difference between men and women can be explained with the control variables. As, I mentioned, it is evident from the table that women have better human capital endowments than men. This finding is in line with the findings by Nestic (2010). He reports that women do possess better educational characteristics. One of the possible explanations for this finding is the low participation rate of women in the Croatian labor market, as indicated by Nestic (ibid). He reports that the participation rate even declines in the later phases of transition. It is a surprising result that none of the other variables have influence on the gender gap. For example number of children is expected to differently influence men and women's possibility to hold supervisory positions. Taking into account the nature of the Croatian laws concerning the care of children, it would be reasonable to anticipate that women will have less chances to hold these positions if they have young children (ibid). Findings from this thesis concerning Croatia point to the necessity for the further analysis of the labor market and specifically of the gender aspects of positions of power in the firms.

In the case of Hungary, Endre et all (2011) show that the glass ceiling is present in the Hungarian labor market, as measured in terms of gender wage gap in period from 2009 to 2011. They report that the wage gap increases with respect to the age of the workers. After the analysis I did in this thesis, I can relate my results to their findings and extend the scope of the inquiry. As reported in Table 1, women have significantly lower probability of holding supervisory positions, compared to men, even though these probabilities show increasing trend. From the same table we can see that in absolute values, the number of people holding supervisory positions in Hungary is around 8 times bigger than in case of Croatia. This finding can be explained in terms of difference between two conceptions of supervisory position. Moreover, Table 4 shows that coefficients on *female* are negative and they exhibit a small decline in the observed period of time. These results, supplemented with the descriptive statistics, reaffirm the findings from the literature about the existence of the glass ceiling in the Hungarian labor market. Moreover, like in Croatia, women that are in the labor market show higher educational attainments than men. Again this result can be the consequence of the decline in the women's participation rate in the labor market.[6] Contrary to the results from the Croatian data, number of children, field of study and firm size has a statistically significant influence on the gap difference, but the magnitude of it is negligibly small. One of the reasons for this result might be again self-selectivity, because women in Hungary who have young children tend not be in the labor market and the percentage of those women is big compared to Germany for example (Cseres-Gergely and Scharle 2010).

There are few recent studies that deal with the glass ceiling effect in the German labor market. Findings from this thesis confirm their results about the disadvantage of women to hold managerial position (Holst 2006; Holst and Schrooten 2006). They use gender wage gap and its decomposition to establish the differences between men and women in the labor market. Holst and Busch (2009) use Blinder-Oaxaca decomposition of the wage gap in order to examine whether the German labor market is characterized with the glass ceiling effect. They find convincing evidences for the presence of this effect in the data from 2006. Results from table 4 in this chapter confirm their discoveries and present an extension of their study.

[6]Participation rates in the labor market are published in The Hungarian Labor Market Yearbooks, available at http://econ.core.hu/english/publications/lmyb.html

In the period from 2006 to 2012, average percent of disadvantage of women to hold supervisory position is around 7.5. It turns out that human capital endowments are more important when it comes to the selection process into the highest level management position, in another words in these places gender of an individual plays less important role. This finding is in contradiction with the findings from Busch and Holst (2011), who claim that the German labor market exhibits vertical segregation in such way that the higher the hierarchy of management is, the bigger the discrimination against women is.

6. Conclusion

In this thesis I explored the existence of the glass ceiling effect in the labor markets of Croatia, Hungary and Germany in the period from 2006 to 2012. I showed that all three labor markets exhibit certain degree of discrimination in the high level position in the firms. My analysis was based on the examination of the probability of holding supervisory position. I presented the questions that are asked for obtaining the information about the supervisory position in each country and I showed similarities and differences between countries in this respect. German questionnaire from 2006 to 2011 and Croatian one have stricter versions of the supervisory position than German in 2012 and Hungarian. This difference does influence the number of people that report holding supervisory positions and in this respect there are similarities between countries with closer definitions of the position. On the other hand, the dynamics of the supervisory position tend to be more similar between Hungary and Croatia, while the German data suggest divergence from Hungary and Croatia in terms of the structure of the gender gap. I showed that majority of the difference between men and women can't be explained with differences in endowments in any of the three countries. Blinder-Oaxaca decomposition shows that women have better endowments in Hungary and Croatia, but still they tend to have lower probabilities for obtaining the high level positions. In the case of Germany, some part of the difference can be explained with the differences in the endowments, but the magnitude of it is fairly small.

In the first part of this thesis I presented four different versions of the questionnaires and pointed to the main differences between countries. Questions in the German survey from 2006 to 2011 and in Croatian one reflect the high level management positions and in this way results from these two countries reveal more accurately the position of women in the power hierarchies of the firms. On the other hand information form German data from 2012 and from Hungarian data, show the broader context of the labor market structures in which a person occupies a supervisory position if he/she has subordinates in any part of the main job. I showed that the number of people drastically changes when the change of question occurs in the German questionnaire. One of the main findings from the first part is the fact that the difference between men and women is particularly high among highly educated people. Moreover the age of individuals seems to play an important role too. Hungary and Croatia exhibit similar patterns with respect to this characteristic. Unlike in Germany, where the gap widens when individuals grow older, in Hungary and Croatia the gap shrinks in the end for the individuals who are older than 55. Another similarity between Croatia and Hungary is with respect to the influence of children on the gender structure of supervisory roles in the firms.

In the third chapter of the thesis I presented results from the three models that I used in order to discover the structure of the difference between men and women in terms of the probability of holding supervisory positions. I used single equation linear probability model in order to estimate the difference between men and women, when controlled for different variables such as education, experience, hours worked, filed of study, number of children, etc. Based on these results, I concluded that the glass effect is present in all three labor markets, because women are disadvantaged in all seven years in a way that they have significantly smaller probabilities of holding supervisory position. Furthermore I did Blinder-Oaxaca decomposition for linear model in order to allow for the different marginal returns for men and women. This analysis showed how much of the difference can be explained with different control variables. The dynamics of the difference is clearly more similar between Hungary and Croatia than between Germany and any of the two other countries. Most importantly, human capital variables fail to explain the difference in probabilities in Hungary and Croatia, unlike in Germany. Moreover, it is evident from the Blinder-Oaxaca results that women have better endowments in terms of human capital in Hungary and Croatia, but they still tend to have, on average, a smaller probability of holding supervisory position. Nonlinear Blinder-Oaxaca decomposition was also used to discover if some control variables weren't statistically significant in the linear case and to allow for broader types of connections between control variables and outcome probability. It turns out that size of the firm becomes statistically significant part of the explained part of the difference between men and women.

Nonlinear decomposition revealed one peculiar thing in the German data that needs more attention. The sign of the unexplained part for endowments effect (for human capital and hours worked specifically) is negative, unlike in linear decomposition, and this puzzle can be one of the starting points of some future research. This study can also be extended in few possible ways. First of all, one extension can include examination of the promotion probabilities in these countries; that is new research can take as its main variables rates of change to and from supervisory position. Zeng (2008) looks at how "rates of upward mobility and downward mobility" (ibid) to and from high level positions, change with respect to gender. This approach reveals the glass ceiling effect and tests whether the labor market displays characteristics that are (culturally) inherited from the previous periods of time or there was a change in the disadvantage of women obtaining high level positions. Another extension would include different methodology with respect to the way the question about supervisory position is framed. This approach would take into account the differences between labor markets in different countries, but also the differences in the cultural conception of what it means to hold the position of power inside of the firm, so the results can be more easily comparable across countries.

Appendix

Table A1a. Linear probability model: Case of Croatia.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	2006	2007	2008	2009	2010
female	-0.0746***	-0.0632***	-0.0740***	-0.0924***	-0.0792***
	(0.00944)	(0.00807)	(0.00794)	(0.00805)	(0.00880)
highsch	0.0855***	0.0768***	0.0838***	0.0894***	0.0797***
	(0.0146)	(0.0119)	(0.0121)	(0.0129)	(0.0142)
college	0.354***	0.358***	0.334***	0.336***	0.334***
	(0.0177)	(0.0147)	(0.0149)	(0.0153)	(0.0167)
exper	0.0127***	0.0131***	0.0133***	0.0143***	0.0138***
	(0.00211)	(0.00171)	(0.00168)	(0.00173)	(0.00192)
exper2	-0.000198***	-0.000194***	-0.000205***	-0.000237***	-0.000219***
	(4.61e-05)	(3.74e-05)	(3.68e-05)	(3.80e-05)	(4.11e-05)
hwusual	0.00311***	0.00325***	0.00414***	0.000786	0.000164
	(0.00106)	(0.000923)	(0.000947)	(0.000972)	(0.00110)
sunw	0.0443***	0.00689	0.0221**	0.0348***	0.0438***
	(0.0129)	(0.0112)	(0.0111)	(0.0115)	(0.0125)
satw	0.0186	0.0284***	0.0183*	0.0135	0.0393***
	(0.0115)	(0.00982)	(0.00973)	(0.0100)	(0.0111)
nightw	-0.0280*	-0.00192	-0.0407***	-0.0427***	-0.0181
	(0.0152)	(0.0129)	(0.0129)	(0.0136)	(0.0145)
evenw	-0.0243*	-0.0120	0.0181	5.23e-05	-0.0241*
	(0.0139)	(0.0121)	(0.0117)	(0.0120)	(0.0132)
shiftw	0.0158	0.00252	-0.0139	-0.0138	-0.00199
	(0.0133)	(0.0114)	(0.0114)	(0.0116)	(0.0129)
fulltime	-0.0168	0.00887	0.0110	0.0547	0.0594

	(0.0433)	(0.0391)	(0.0358)	(0.0383)	(0.0444)
teacher	-0.226	-0.0783	-0.0185	0.000100	-0.0351
	(0.189)	(0.129)	(0.126)	(0.0893)	(0.101)
humanit	0.250	-0.119	-0.0306	-0.211	0.0353
	(0.232)	(0.183)	(0.140)	(0.221)	(0.317)
socialsc	0.152***	0.191***	0.212***	0.0985**	-0.00258
	(0.0553)	(0.0429)	(0.0479)	(0.0486)	(0.0508)
sciencomp	-0.0239	-0.000370	-0.328	-0.137	-0.252
	(0.232)	(0.224)	(0.307)	(0.155)	(0.225)
lifescien	-0.248				
	(0.328)				
compscien	-0.0218			-0.0147	-0.0608
	(0.232)			(0.308)	(0.225)
eng	0.00269	0.309***	0.209***	-0.0394	0.0330
	(0.0678)	(0.0652)	(0.0619)	(0.0750)	(0.0852)
agri	0.432*	0.218	-0.0773	-0.402***	
	(0.232)	(0.159)	(0.109)	(0.154)	
health	-0.337*	0.0394	-0.148	-0.100	-0.101
	(0.189)	(0.120)	(0.103)	(0.138)	(0.106)
serv	0.110	-0.116	0.0161	-0.0302	-0.0989
	(0.0777)	(0.112)	(0.0632)	(0.0709)	(0.0715)
job1	-0.000456	-0.0366*	-0.0263	-0.00584	0.0217
	(0.0224)	(0.0193)	(0.0181)	(0.0195)	(0.0218)
f11to19	-0.00749	-0.0263**	0.0123	0.0117	0.0179
	(0.0154)	(0.0130)	(0.0128)	(0.0133)	(0.0146)
f20to49	0.00126	-0.0363***	-0.0244**	0.00665	0.0263*
	(0.0145)	(0.0126)	(0.0123)	(0.0123)	(0.0138)
f50more	0.0190*	-0.00694	0.00621	0.0174*	0.0397***
	(0.0114)	(0.00944)	(0.00929)	(0.00945)	(0.0104)

jobind	0.0262***	0.0174**	-0.00467		
	(0.0101)	(0.00856)	(0.00856)		
hhnbch2	0.0116	-0.0122	-0.0116	0.00643	-0.00319
	(0.0159)	(0.0140)	(0.0143)	(0.0160)	(0.0168)
hhnbch5	0.0102	0.0105	0.00839	-0.0193	-0.0427***
	(0.0138)	(0.0118)	(0.0120)	(0.0130)	(0.0134)
hhnbch8	-0.0166	-0.0165*	-0.00327	0.00491	-0.000900
	(0.0113)	(0.00989)	(0.0101)	(0.0108)	(0.0122)
hhnbch11	0.0289***	-0.00166	0.0117	0.00849	0.00153
	(0.0100)	(0.00847)	(0.00885)	(0.00971)	(0.0105)
hhnbch14	-0.00279	0.00471	0.00220	0.0136	-0.00773
	(0.0100)	(0.00814)	(0.00827)	(0.00855)	(0.00946)
hhnbch17	0.00844	0.00614	0.00390	0.00898	-0.00269
	(0.00983)	(0.00803)	(0.00809)	(0.00854)	(0.00927)
hhnbch24	0.0151	0.0132	0.0109	0.0149*	0.00683
	(0.0105)	(0.00861)	(0.00860)	(0.00898)	(0.00959)
hhageyg	6.19e-05	-0.000932	-0.000148	-0.000324	-0.00136
	(0.00139)	(0.00121)	(0.00121)	(0.00129)	(0.00137)
hhnbold	-0.0274***	-0.00925	-0.0211***	-0.0145*	-0.0103
	(0.0102)	(0.00845)	(0.00794)	(0.00822)	(0.00759)
flang			0.533***	-0.261	0.164
			(0.178)	(0.218)	(0.228)
Constant	-0.280***	-0.255***	-0.320***	-0.251***	-0.251***
	(0.0604)	(0.0532)	(0.0520)	(0.0543)	(0.0598)
Observations	5,744	7,415	7,165	6,669	5,797
R-squared	0.129	0.144	0.136	0.141	0.136

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A1a cont. Linear probability model: Case of Croatia.

VARIABLES	(1) 2011	(2) 2012
female	-0.0696***	-0.0891***
	(0.00936)	(0.00944)
highsch	0.0738***	0.0927***
	(0.0154)	(0.0158)
college	0.307***	0.349***
	(0.0180)	(0.0183)
exper	0.0179***	0.0176***
	(0.00209)	(0.00209)
exper2	-0.000317***	-0.000300***
	(4.42e-05)	(4.43e-05)
hwusual	0.00388***	0.00659***
	(0.00134)	(0.00154)
sunw	0.0451***	0.0106
	(0.0129)	(0.0129)
satw	0.0400***	0.0629***
	(0.0118)	(0.0120)
nightw	-0.0100	0.00829
	(0.0150)	(0.0151)
evenw	0.00108	-0.00177
	(0.0132)	(0.0125)
shiftw	-0.0345***	-0.0283**
	(0.0130)	(0.0125)
fulltime	-0.0116	-0.0717
	(0.0471)	(0.0519)
teacher	-0.0396	0.105
	(0.161)	(0.122)
humanit	-0.0124	0.0306
	(0.161)	(0.186)
socialsc	0.0687	0.127**
	(0.0492)	(0.0624)
sciencomp	0.105	-0.00844
	(0.231)	(0.188)
eng	0.0455	-0.0533
	(0.0742)	(0.0786)
agri	0.188	-0.410
	(0.144)	(0.321)
health	0.170	0.165
	(0.122)	(0.107)
serv	-0.0321	0.172
	(0.0726)	(0.122)
job2	-0.0439*	
	(0.0242)	
f11to19	0.0124	0.0192
	(0.0150)	(0.0158)

f20to49	0.0269*	-0.00350
	(0.0149)	(0.0147)
f50more	0.0352***	0.0227**
	(0.0107)	(0.0107)
hhnbch2	0.00648	-0.000989
	(0.0177)	(0.0186)
hhnbch5	-0.0264*	0.0149
	(0.0147)	(0.0154)
hhnbch8	-0.0116	-0.00146
	(0.0128)	(0.0135)
hhnbch11	0.00314	0.0199*
	(0.0115)	(0.0118)
hhnbch14	0.00688	0.00659
	(0.0101)	(0.0102)
hhnbch17	-0.0224**	0.00739
	(0.00981)	(0.00981)
hhnbch24	0.00703	0.00282
	(0.00941)	(0.00926)
hhageyg	-0.000355	0.00126
	(0.00142)	(0.00147)
hhnbold	0.00319	-0.00776
	(0.00782)	(0.00831)
job1		-0.0130
		(0.0249)
Constant	-0.354***	-0.443***
	(0.0622)	(0.0696)
Observations	5,289	5,195
R-squared	0.122	0.142

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A1b. Linear probability model: Case of Hungary.

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010
female	-0.0712***	-0.0765***	-0.0664***	-0.0673***	-0.0662***
	(0.00309)	(0.00319)	(0.00333)	(0.00334)	(0.00335)
highsch	0.0712***	0.0655***	0.0663***	0.0747***	0.0682***
	(0.00411)	(0.00431)	(0.00452)	(0.00466)	(0.00472)
college	0.336***	0.331***	0.326***	0.321***	0.306***
	(0.00532)	(0.00555)	(0.00575)	(0.00577)	(0.00580)
exper	0.0103***	0.0128***	0.0112***	0.0106***	0.0118***
	(0.000720)	(0.000752)	(0.000771)	(0.000787)	(0.000794)
exper2	-0.000157***	-0.000214***	-0.000187***	-0.000175***	-0.000196***
	(1.57e-05)	(1.64e-05)	(1.68e-05)	(1.70e-05)	(1.70e-05)
hwusual	0.000105	6.20e-05	-0.000513***	0.000146	0.000460**
	(0.000149)	(0.000159)	(0.000173)	(0.000181)	(0.000179)

sunw	0.0178***	0.0134**	0.0303***	0.0174***	0.00724
	(0.00535)	(0.00560)	(0.00606)	(0.00587)	(0.00591)
satw	0.00304	0.0186***	0.00769	0.0128**	0.0187***
	(0.00457)	(0.00466)	(0.00517)	(0.00503)	(0.00504)
nightw	-0.00618	-0.00383	-0.00969	-0.0178***	-0.00363
	(0.00598)	(0.00634)	(0.00668)	(0.00624)	(0.00614)
evenw	0.0157***	-0.0139**	-0.0193***	0.0115*	0.00902
	(0.00559)	(0.00594)	(0.00638)	(0.00598)	(0.00598)
shiftw	-0.0240***	-0.0184***	-0.0158***	-0.0217***	-0.0235***
	(0.00426)	(0.00457)	(0.00487)	(0.00494)	(0.00492)
fulltime	0.0490***	0.0537***	0.0533***	0.0396***	0.0301***
	(0.00797)	(0.00806)	(0.00817)	(0.00786)	(0.00792)
teacher	-0.0184	0.00864	-0.0297	0.0920***	-0.0623
	(0.0245)	(0.0262)	(0.0304)	(0.0344)	(0.0419)
humanit	0.0234	0.00708	-0.0735	-0.0310	-0.0154
	(0.0528)	(0.0631)	(0.0648)	(0.0629)	(0.0683)
flang	-0.185*	0.348***	-0.0327	0.0514	-0.0838
	(0.108)	(0.0876)	(0.135)	(0.0808)	(0.0908)
socialsc	0.0974***	0.0822***	0.0424**	0.0503**	0.115***
	(0.0155)	(0.0183)	(0.0196)	(0.0210)	(0.0236)
lifescien	-0.0363	-0.0718	-0.0148	-0.136	0.0402
	(0.0979)	(0.104)	(0.135)	(0.111)	(0.0986)
physcien	-0.223	-0.136	-0.232*	-0.106	-0.297
	(0.187)	(0.104)	(0.125)	(0.332)	(0.189)
mathstat		-0.356**	-0.317	-0.316*	-0.0406
		(0.164)	(0.330)	(0.166)	(0.133)
compscien	0.133***	0.137**	-0.00575	-0.256***	-0.109
	(0.0460)	(0.0562)	(0.0674)	(0.0831)	(0.0793)
compuse	-0.00316	-0.0241	0.207***	0.160**	0.00523
	(0.0677)	(0.0989)	(0.0648)	(0.0763)	(0.0770)
eng	0.130***	0.0882**	0.147***	0.244***	0.133***
	(0.0308)	(0.0352)	(0.0373)	(0.0441)	(0.0426)
agri	0.0624	0.119	0.205**	0.191**	-0.156
	(0.0726)	(0.0819)	(0.0882)	(0.0922)	(0.109)
health	0.0994***	0.0412	-2.95e-05	-0.0325	0.0293
	(0.0282)	(0.0289)	(0.0315)	(0.0330)	(0.0343)
serv	0.0818*	0.200***	0.137***	0.152***	0.240***
	(0.0431)	(0.0435)	(0.0434)	(0.0485)	(0.0569)
job1	-0.0878***	-0.101***	-0.101***	-0.0447***	-0.0534***
	(0.0105)	(0.0111)	(0.0117)	(0.0110)	(0.0108)
f11to19	0.00788*	0.00275	-0.00637	0.00618	-0.00447
	(0.00443)	(0.00452)	(0.00482)	(0.00498)	(0.00489)
f20to49	-0.0118***	-0.0121***	-0.0139***	-0.0113**	-0.0179***
	(0.00422)	(0.00430)	(0.00450)	(0.00463)	(0.00466)
f50more	0.00860**	0.0161***	0.0180***	0.0195***	0.0182***
	(0.00369)	(0.00378)	(0.00395)	(0.00400)	(0.00399)
jobind	0.000317	-0.00332	0.0112***		
	(0.00326)	(0.00334)	(0.00350)		
hhnbch2	0.0104*	0.0111*	-0.000466	-0.000429	0.00924
	(0.00619)	(0.00654)	(0.00666)	(0.00689)	(0.00677)

hhnbch5	-0.00185	-0.00101	0.00921*	0.00195	0.00169
	(0.00483)	(0.00516)	(0.00533)	(0.00539)	(0.00538)
hhnbch8	0.00201	0.00653	-0.00641	-0.0110**	-0.00368
	(0.00407)	(0.00433)	(0.00446)	(0.00453)	(0.00458)
hhnbch11	0.000422	-0.0116***	-0.00827**	-0.00175	0.00383
	(0.00359)	(0.00381)	(0.00404)	(0.00408)	(0.00407)
hhnbch14	0.00116	-0.00225	-0.0105***	-0.0128***	-0.00735**
	(0.00323)	(0.00336)	(0.00346)	(0.00363)	(0.00363)
hhnbch17	-0.00816***	-0.0191***	-0.0126***	-0.00958***	-0.0109***
	(0.00310)	(0.00322)	(0.00331)	(0.00339)	(0.00343)
hhnbch24	0.00317	-0.0113***	-0.00949***	0.00319	0.00432
	(0.00328)	(0.00336)	(0.00340)	(0.00337)	(0.00339)
hhageyg	-0.000176	0.00132***	0.000738	0.000126	0.000851
	(0.000487)	(0.000508)	(0.000520)	(0.000528)	(0.000525)
hhnbold	-0.0177***	-0.000389	0.00680	0.00245	0.00109
	(0.00411)	(0.00440)	(0.00448)	(0.00451)	(0.00469)
Constant	-0.0434**	-0.0527***	-0.0120	-0.0795***	-0.102***
	(0.0173)	(0.0182)	(0.0189)	(0.0186)	(0.0185)
Observations	51,985	49,732	46,255	44,773	42,999
R-squared	0.118	0.116	0.110	0.103	0.101

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A1b cont. Linear probability model: Case of Hungary.

VARIABLES	(1) 2011	(2) 2012
female	-0.0641***	-0.0659***
	(0.00339)	(0.00341)
highsch	0.0679***	0.0717***
	(0.00481)	(0.00471)
college	0.315***	0.310***
	(0.00587)	(0.00571)
exper	0.0106***	0.0112***
	(0.000792)	(0.000810)
exper2	-0.000174***	-0.000178***
	(1.70e-05)	(1.73e-05)
hwusual	7.28e-06	0.000329*
	(0.000176)	(0.000187)
sunw	0.0167***	0.0203***
	(0.00587)	(0.00580)
satw	0.00811	0.0230***
	(0.00504)	(0.00503)
nightw	-0.00541	-0.0258***
	(0.00611)	(0.00607)
evenw	0.00564	0.0152**
	(0.00596)	(0.00590)

shiftw	-0.0148***	-0.0240***
	(0.00500)	(0.00509)
fulltime	0.0496***	0.0457***
	(0.00722)	(0.00725)
teacher	-0.0780**	0.0484
	(0.0347)	(0.0344)
humanit	-0.0560	-0.0523
	(0.0504)	(0.0478)
flang	-0.257**	-0.109
	(0.125)	(0.146)
socialsc	0.0716***	0.0700***
	(0.0217)	(0.0232)
lifescien	0.223**	0.114
	(0.0995)	(0.146)
physcien	-0.302	
	(0.190)	
mathstat	-0.341	-0.0341
	(0.330)	(0.189)
compscien	-0.0714	-0.0942
	(0.0738)	(0.0642)
compuse	-0.210**	0.0270
	(0.0953)	(0.116)
eng	0.0719*	0.0500
	(0.0396)	(0.0401)
agri	-0.0749	0.0479
	(0.117)	(0.0630)
health	0.0253	0.00537
	(0.0357)	(0.0383)
serv	0.0311	0.112**
	(0.0477)	(0.0513)
job1	-0.0730***	
	(0.0109)	
f11to19	0.00125	-0.000583
	(0.00491)	(0.00506)
f20to49	-0.00872*	-0.00728
	(0.00474)	(0.00472)
f50more	0.0144***	0.0235***
	(0.00401)	(0.00401)
hhnbch2	0.000791	-0.00323
	(0.00664)	(0.00652)
hhnbch5	-0.00863	-0.0117**
	(0.00537)	(0.00514)
hhnbch8	-0.0136***	-0.00677
	(0.00460)	(0.00436)
hhnbch11	-0.00384	-0.0142***
	(0.00406)	(0.00396)
hhnbch14	-0.0114***	-0.00533
	(0.00377)	(0.00377)
hhnbch17	-0.00854**	-0.00735**
	(0.00343)	(0.00349)

hhnbch24	0.00681**	0.00138
	(0.00332)	(0.00338)
hhageyg	-0.000666	-0.00122**
	(0.000522)	(0.000518)
hhnbold	-0.00308	-0.00661
	(0.00479)	(0.00460)
job2		0.0384***
		(0.0113)
Constant	-0.0455**	-0.141***
	(0.0182)	(0.0146)
Observations	42,974	41,942
R-squared	0.107	0.106

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A1c . Linear probability model: Case of Germany.

VARIABLES	(1) 2006	(2) 2007	(3) 2008	(4) 2009	(5) 2010
female	-0.0651***	-0.0669***	-0.108***	-0.0707***	-0.0862***
	(0.0109)	(0.0110)	(0.0125)	(0.0114)	(0.0135)
highsch	0.0352***	0.0546***	0.0486***	0.0316**	0.0856***
	(0.0127)	(0.0128)	(0.0151)	(0.0140)	(0.0164)
college	0.237***	0.285***	0.278***	0.273***	0.299***
	(0.0149)	(0.0152)	(0.0173)	(0.0160)	(0.0188)
exper	0.00640***	0.00676***	0.00585***	0.00911***	0.0112***
	(0.00181)	(0.00185)	(0.00206)	(0.00198)	(0.00232)
exper2	-6.79e-05	-0.000101**	-4.89e-05	-0.000128***	-0.000184***
	(4.19e-05)	(4.38e-05)	(4.78e-05)	(4.64e-05)	(5.36e-05)
hwusual	0.00431***	0.00405***	0.00584***	0.00452***	0.00512***
	(0.000694)	(0.000703)	(0.000768)	(0.000713)	(0.000856)
sunw	0.0119	0.00533	0.0509***	0.0122	0.0159
	(0.0125)	(0.0128)	(0.0137)	(0.0139)	(0.0155)
satw	0.0209**	0.0227**	0.00576	0.0121	0.0127
	(0.0105)	(0.0106)	(0.0118)	(0.0115)	(0.0134)
nightw	-0.0556***	-0.0276*	-0.0455***	-0.0233	-0.0144
	(0.0142)	(0.0147)	(0.0157)	(0.0160)	(0.0179)
evenw	0.0965***	0.0983***	0.0729***	0.0894***	0.0872***
	(0.0108)	(0.0108)	(0.0118)	(0.0112)	(0.0129)
shiftw	-0.133***	-0.135***	-0.116***	-0.110***	-0.0958***
	(0.0140)	(0.0140)	(0.0152)	(0.0151)	(0.0171)
fulltime	-0.00280	0.00878	-0.0289	0.00427	-0.00376
	(0.0189)	(0.0191)	(0.0210)	(0.0197)	(0.0230)
job2	0.0527***				
	(0.0204)				
f11to19	-0.0232	0.00638	-0.0117	-0.0336**	-0.0166
	(0.0145)	(0.0155)	(0.0166)	(0.0160)	(0.0185)

f20to49	0.000508	-0.0113	-0.0301*	0.00205	-0.0228
	(0.0141)	(0.0143)	(0.0154)	(0.0151)	(0.0180)
f50more	0.0121	0.00894	-0.00885	-0.00969	0.00846
	(0.0107)	(0.0112)	(0.0122)	(0.0117)	(0.0140)
jobind	0.00800	-0.0257***	-0.00597		
	(0.00945)	(0.00960)	(0.0105)		
hhnbch2	-0.0161	0.0143	-0.0217	0.00631	-0.00694
	(0.0169)	(0.0172)	(0.0184)	(0.0181)	(0.0212)
hhnbch5	0.00256	-0.00561	0.0197	-0.00848	0.00508
	(0.0131)	(0.0130)	(0.0137)	(0.0133)	(0.0166)
hhnbch8	0.00312	0.00267	0.0148	0.00940	0.00361
	(0.0109)	(0.0114)	(0.0120)	(0.0118)	(0.0138)
hhnbch11	0.00477	0.0138	0.00500	-0.00540	-0.0371***
	(0.00996)	(0.0102)	(0.0111)	(0.0101)	(0.0125)
hhnbch14	-0.000197	0.00218	0.00691	5.10e-05	0.00935
	(0.00899)	(0.00957)	(0.0105)	(0.00990)	(0.0118)
hhnbch17	-0.00296	0.00878	0.00516	0.0107	0.00962
	(0.00932)	(0.00983)	(0.0112)	(0.0100)	(0.0122)
hhnbch24	0.00924	0.00236	0.0150	0.0246**	0.00834
	(0.0123)	(0.0122)	(0.0136)	(0.0124)	(0.0156)
hhageyg	-0.00122	-0.000277	-0.00138	-0.000794	-0.00159
	(0.00152)	(0.00154)	(0.00170)	(0.00163)	(0.00192)
hhnbold	-0.0232	-0.0446*	-0.0385	0.0169	-0.0151
	(0.0264)	(0.0269)	(0.0308)	(0.0302)	(0.0362)
job1		0.0242	-0.0336	0.0190	-0.0276
		(0.0218)	(0.0228)	(0.0229)	(0.0250)
Constant	-0.158***	-0.190***	-0.109**	-0.194***	-0.155***
	(0.0324)	(0.0392)	(0.0424)	(0.0411)	(0.0481)
Observations	6,428	6,338	5,931	6,188	5,585
R-squared	0.186	0.206	0.220	0.212	0.184

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A1c cont. Linear probability model: Case of Germany.

VARIABLES	(1) 2011	(2) 2012
female	-0.0531***	-0.0738***
	(0.0137)	(0.00434)
highsch	0.121***	0.111***
	(0.0175)	(0.00542)
college	0.428***	0.344***
	(0.0194)	(0.00611)
exper	0.0117***	0.0127***
	(0.00242)	(0.000763)
exper2	-0.000196***	-0.000200***
	(5.57e-05)	(1.74e-05)

hwusual	0.00685***	0.00667***
	(0.000872)	(0.000273)
sunw	0.0434***	0.0281***
	(0.0164)	(0.00525)
satw	-0.0131	0.0126***
	(0.0142)	(0.00444)
nightw	-0.0278	-0.00977
	(0.0193)	(0.00603)
evenw	0.0883***	0.0808***
	(0.0137)	(0.00436)
shiftw	-0.0880***	-0.0881***
	(0.0184)	(0.00569)
fulltime	-0.00964	-0.00606
	(0.0236)	(0.00731)
job1	0.0126	-0.0283***
	(0.0238)	(0.00750)
f11to19	0.0188	0.00676
	(0.0192)	(0.00618)
f20to49	0.00772	0.00995*
	(0.0182)	(0.00582)
f50more	0.0662***	0.0222***
	(0.0144)	(0.00454)
hhnbch2	0.0102	0.000992
	(0.0218)	(0.00681)
hhnbch5	0.0269	-0.00188
	(0.0165)	(0.00522)
hhnbch8	0.0180	0.00139
	(0.0140)	(0.00451)
hhnbch11	0.00397	-0.00718*
	(0.0132)	(0.00410)
hhnbch14	0.00632	-0.00197
	(0.0118)	(0.00373)
hhnbch17	0.0173	-0.00866**
	(0.0130)	(0.00403)
hhnbch24	0.0358**	0.00122
	(0.0148)	(0.00496)
hhageyg	-0.00179	-0.00126**
	(0.00196)	(0.000617)
hhnbold	-0.0387	-0.00208
	(0.0362)	(0.0112)
Constant	-0.325***	-0.228***
	(0.0479)	(0.0155)
Observations	5,510	59,343
R-squared	0.269	0.197

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2a. Blinder-Oaxaca for linear model: Case of Croatia

Differential	Prediction_1	0.165 (66.56)**
	Prediction_2	0.099 (47.13)**
	Difference	0.067 (20.49)**
Endowments	humcap	-0.014 (11.33)**
	hwusual	0.004 (6.16)**
	field	-0.000 (1.13)
	typesofwork	-0.001 (0.53)
	job1	0.000 (1.60)
	firmsize	0.001 (2.54)*
	children	-0.000 (0.80)
	hhageyg	0.000 (0.01)
	hhnbold	0.000 (1.09)
	Total	-0.010 (5.15)**
Coefficients	humcap	0.139 (7.57)**
	hwusual	-0.092 (2.47)*
	field	-0.000 (0.87)
	typesofwork	-0.006 (1.31)
	job1	0.015 (0.98)
	firmsize	0.020 (4.03)**
	children	0.018 (2.43)*
	hhageyg	-0.004 (0.33)
	hhnbold	-0.001 (0.64)
	_cons	-0.007 (0.15)
	Total	0.082 (23.96)**
Interaction	humcap	-0.011 (8.32)**

	hwusual	-0.002
		(2.46)*
	field	0.000
		(0.46)
	typesofwork	0.007
		(3.85)**
	job1	-0.000
		(0.98)
	firmsize	0.001
		(1.42)
	children	-0.000
		(0.38)
	hhageyg	0.000
		(0.33)
	hhnbold	0.000
		(0.57)
	Total	-0.006
		(2.55)*
N		42,728

* p<0.05; ** p<0.01

Table A3a. Blinder-Oaxaca for nonlinear model: Case of Croatia

Differential	Prediction_1	0.165
		(66.60)**
	Prediction_2	0.099
		(47.16)**
	Difference	0.067
		(20.50)**
Explained	humcap	-0.144
		(11.78)**
	hwusual	0.024
		(6.99)**
	field	-0.002
		(1.07)
	typesofwork	0.029
		(3.23)**
	job1	0.002
		(1.23)
	firmsize	0.010
		(4.66)**
	children	-0.002
		(0.55)
	hhageyg	0.001
		(0.49)
	hhnbold	0.001
		(1.18)
	Total	-0.082
		(5.32)**

Unexplained	humcap	0.258 (14.27)**
	hwusual	-0.114 (2.69)**
	field	0.002 (0.86)
	typesofwork	-0.028 (3.24)**
	job1	0.014 (0.86)
	firmsize	0.011 (2.30)*
	children	0.019 (2.70)**
	hhageyg	-0.005 (0.42)
	hhnbold	-0.001 (1.08)
	_cons	-0.007 (0.14)
	Total	0.149 (9.91)**
N		42,728

* $p<0.05$; ** $p<0.01$

Table A2b. Blinder-Oaxaca for linear model: Case of Hungary

Differential	Prediction_1	0.166 (179.41)**
	Prediction_2	0.122 (140.89)**
	Difference	0.044 (34.64)**
Endowments	humcap	-0.021 (53.62)**
	hwusual	0.000 (0.37)
	field	-0.001 (3.77)**
	typesofwork	0.003 (10.58)**
	job1	0.001 (9.96)**
	firmsize	0.000 (2.91)**
	children	0.003 (2.49)*
	hhageyg	-0.003 (3.60)**
	hhnbold	-0.000 (2.20)*

	Total	-0.017
		(21.70)**
Coefficients	humcap	0.085
		(11.82)**
	hwusual	0.001
		(0.17)
	field	-0.000
		(0.35)
	typesofwork	-0.003
		(3.08)**
	job1	0.024
		(2.77)**
	firmsize	0.014
		(7.66)**
	children	0.016
		(6.03)**
	hhageyg	-0.024
		(4.48)**
	hhnbold	-0.002
		(4.43)**
	_cons	-0.029
		(1.95)
	Total	0.084
		(62.29)**
Interaction	humcap	-0.022
		(43.33)**
	hwusual	-0.000
		(0.17)
	field	0.000
		(0.83)
	typesofwork	-0.002
		(4.20)**
	job1	-0.000
		(2.74)**
	firmsize	0.000
		(2.54)*
	children	-0.004
		(3.51)**
	hhageyg	0.004
		(4.48)**
	hhnbold	0.000
		(4.16)**
	Total	-0.023
		(23.52)**
N		304,752

* $p<0.05$; ** $p<0.01$

Table A3b. Blinder-Oaxaca for nonlinear model: Case of Hungary

Differential	Prediction_1	0.166 (179.43)**
	Prediction_2	0.122 (140.91)**
	Difference	0.044 (34.64)**
Explained	humcap	-0.213 (56.99)**
	hwusual	-0.000 (0.22)
	field	-0.003 (4.60)**
	typesofwork	0.021 (11.34)**
	job1	0.003 (10.23)**
	firmsize	0.002 (5.57)**
	children	0.009 (1.96)*
	hhageyg	-0.004 (1.02)
	hhnbold	0.000 (1.63)
	Total	-0.185 (37.16)**
Unexplained	humcap	0.257 (36.84)**
	hwusual	0.001 (0.18)
	field	0.003 (4.55)**
	typesofwork	-0.022 (12.01)**
	job1	0.021 (1.85)
	firmsize	0.012 (6.75)**
	children	0.005 (1.04)
	hhageyg	-0.018 (2.82)**
	hhnbold	-0.002 (4.66)**
	_cons	-0.029 (1.77)
	Total	0.229 (46.68)**
N		304,752

* p<0.05; ** p<0.01

Table A2c. Blinder-Oaxaca for linear model: Case of Germany (2006-2011)

Differential	Prediction_1	0.294
		(86.65)**
	Prediction_2	0.176
		(36.50)**
	Difference	0.118
		(20.03)**
Endowments	humcap	0.021
		(9.07)**
	hwusual	0.015
		(7.29)**
	field	0.000
	typesofwork	0.006
		(3.19)**
	job1	0.001
		(1.60)
	firmsize	-0.000
		(0.39)
	children	-0.038
		(0.69)
	hhageyg	0.003
		(0.57)
	hhnbold	0.036
		(0.64)
	Total	0.045
		(9.71)**
Coefficients	humcap	0.072
		(3.72)**
	hwusual	0.042
		(0.79)
	field	0.000
	typesofwork	-0.007
		(1.35)
	job1	0.035
		(1.12)
	firmsize	0.012
		(0.99)
	children	0.039
		(0.20)
	hhageyg	-0.016
		(0.53)
	hhnbold	-0.032
		(0.16)
	_cons	-0.087
		(1.25)
	Total	0.059
		(9.88)**

Interaction	humcap	0.008
		(3.18)**
	hwusual	0.002
		(0.79)
	field	0.000
	typesofwork	0.001
		(0.24)
	job1	-0.000
		(1.08)
	firmsize	0.004
		(2.85)**
	children	-0.014
		(0.21)
	hhageyg	0.004
		(0.53)
	hhnbold	0.011
		(0.16)
	Total	0.014
		(2.95)**
N		24,362

* *p*<0.05; ** *p*<0.01

Table A2d. Blinder-Oaxaca for linear model: Case of Germany (2012)

Differential	Prediction_1	0.396
		(139.12)**
	Prediction_2	0.274
		(63.54)**
	Difference	0.123
		(23.73)**
Endowments	humcap	0.019
		(8.79)**
	hwusual	0.018
		(9.07)**
	field	0.000
	typesofwork	0.012
		(6.78)**
	job1	0.001
		(2.23)*
	firmsize	-0.001
		(1.21)
	children	0.053
		(1.05)
	hhageyg	0.009
		(1.83)
	hhnbold	-0.058
		(1.11)
	Total	0.052
		(12.75)**

Coefficients	humcap	0.088
		(4.83)**
	hwusual	0.018
		(0.42)
	field	0.000
	typesofwork	-0.013
		(2.84)**
	job1	0.022
		(0.94)
	firmsize	0.028
		(2.70)**
	children	0.178
		(1.02)
	hhageyg	0.031
		(1.16)
	hhnbold	-0.181
		(1.06)
	_cons	-0.097
		(1.71)
	Total	0.074
		(14.33)**
Interaction	humcap	0.000
		(0.01)
	hwusual	0.001
		(0.42)
	field	0.000
	typesofwork	-0.007
		(3.51)**
	job1	-0.000
		(0.92)
	firmsize	0.005
		(4.41)**
	children	-0.063
		(1.03)
	hhageyg	-0.006
		(1.16)
	hhnbold	0.067
		(1.05)
	Total	-0.003
		(0.83)
N		40,255

* $p<0.05$; ** $p<0.01$

Table A3c. Blinder-Oaxaca for nonlinear model: Case of Germany (2006-2011)

Differential	Prediction_1	0.294
		(86.70)**
	Prediction_2	0.176

		(36.56)**
	Difference	0.118
		(20.05)**
Explained	humcap	0.269
		(13.29)**
	hwusual	0.085
		(13.41)**
	field	0.000
	typesofwork	0.038
		(5.08)**
	job1	0.001
		(1.13)
	firmsize	0.014
		(2.89)**
	children	-0.300
		(1.30)
	hhageyg	0.061
		(2.86)**
	hhnbold	0.264
		(1.12)
	Total	0.433
		(17.36)**
Unexplained	humcap	-0.169
		(7.40)**
	hwusual	-0.026
		(0.39)
	field	0.000
	typesofwork	-0.038
		(4.51)**
	job1	0.034
		(0.95)
	firmsize	0.001
		(0.08)
	children	0.287
		(1.06)
	hhageyg	-0.071
		(2.05)*
	hhnbold	-0.247
		(0.90)
	_cons	-0.087
		(1.10)
	Total	-0.315
		(13.23)**
N		24,362

* $p<0.05$; ** $p<0.01$

Table A3d. Blinder-Oaxaca for nonlinear model: Case of Germany (2012)

Differential	Prediction_1	0.396
		(139.16)**
	Prediction_2	0.274

		(63.60)**
	Difference	0.123
		(23.75)**
Explained	humcap	0.151
		(11.69)**
	hwusual	0.092
		(16.62)**
	field	0.000
	typesofwork	0.034
		(7.00)**
	job1	0.002
		(2.80)**
	firmsize	0.013
		(4.33)**
	children	0.087
		(0.55)
	hhageyg	0.037
		(2.69)**
	hhnbold	-0.115
		(0.69)
	Total	0.303
		(18.42)**
Unexplained	humcap	-0.044
		(2.56)*
	hwusual	-0.056
		(1.16)
	field	0.000
	typesofwork	-0.042
		(6.67)**
	job1	0.021
		(0.82)
	firmsize	0.019
		(1.78)
	children	0.080
		(0.39)
	hhageyg	-0.004
		(0.14)
	hhnbold	-0.058
		(0.28)
	_cons	-0.097
		(1.64)
	Total	-0.180
		(11.48)**
N		40,255

* $p<0.05$; ** $p<0.01$

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