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Does market liberalisation reduce gender discrimination? Econometric evidence from Hungary, 1986–1998

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Abstract

An alleged achievement of socialism was gender equality in the labour market. Has its collapse shattered this accomplishment? The theoretical literature and attendant empirical evidence are inconclusive. Using data for 2.9 million wage earners in Hungary, we find that the male–female difference in log wages declined from 0.31 to 0.19 between 1986 and 1998 and that this is largely explained by a matching decline in "Oaxaca's discrimination," suggesting extraordinary improvement of women's relative situation. Further, we find that variation over time in the wage gaps is associated with public and large firms having progressively smaller gaps than their counterparts.

JEL classification: I2; J16; P3
Keywords: Hungary; Transition; Discrimination; Gender; Wage gap; Education

1. Introduction

An alleged achievement of socialism was gender equality in the labour market. Has the collapse of socialism undermined this accomplishment? The possibility of a deterioration of the relative position of women is based on the argument that, after the collapse of central planning, managers can choose to reward economically irrelevant characteristics

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such as gender. This collapse eliminated the strict rules for setting wages and could thus be responsible for a resurgence of gender discrimination in the labour market. A different, and opposite, possibility would be that the relative situation of women could improve after the collapse of socialism. One reason is that market forces can punish discriminatory wage-setting behaviour and thus reduce the gender wage gap (Becker, 1957). Another reason would be that transition presumably rewards sectors in which women had advantages (for instance, services).

This paper investigates male–female differences in the labour market before and during the transition from central planning to market economy. The relative situation of women in the labour market and the role of discrimination as an underlying determinant are important issues and the attendant literature is large.[1] This paper, we argue, extends the existing literature in several ways. First, we claim that ours is the first paper to use objective data[2] for sufficiently large and representative samples of wage earners before, during and after[3] the introduction of massive economic reform. The data covers 2.9 million Hungarian wage earners from 1986 to 1998. Second, the large sample sizes allow a correction for potential selection bias in our estimates that is, also, unique in the literature. Third, we provide estimates of standard errors for the male–female difference in log wages and for the estimates of discrimination so that it is possible to test whether the change over time is statistically significant. Such estimates are seldom provided in the literature and, consequently, these essential tests are not carried out. Last but not least, our examination of Hungary sheds light on a country which heretofore has received relatively less attention than many other transition countries. A focus on Hungary is particularly useful because it is in many ways representative of the Central European transition economies. The size of the Hungarian population is between that of Poland and Estonia, and almost identical to that of the Czech Republic. It also has a per capita GDP higher than those of Poland and Estonia, but lower than the Czech and Slovenian figures.[4]

How did market liberalisation take root and how did it affect wage-setting behaviour? In many respects, Hungary is also representative of labour market developments in Central Europe as it can be seen as far from the Estonian aggressive laissez-faire and equally far from the more guarded Slovenian approach.[5] Although Hungary was the only Visegrad country to

[1] Boeri and Terrell (2002), Brainerd (2000), Flanagan (1998) and Svejnar (1999) provide reviews of the literature on labour markets (including gender issues) in transition economies. Altonji and Blank (1999) list the study of changes in gender wage differentials as a crucial direction for future research.

[2] By "objective data" we simply mean "not retrospective data," that is, data that do not suffer potential recall bias.

[3] Despite its volume, this literature has few studies that present estimates for the communist and transition periods. Data availability is clearly the binding constraint. Data collected before 1989 (that is, under communism) exist in large quantities, yet most has to be re-coded. Ours is unique in that primary data were carefully re-coded to (current) standard international classifications.

[4] Among the former socialist economies, Hungary was a forerunner to join the European Union. A requirement for joining is the adoption of a legal and institutional framework (the acquis communitaire). One aspect of the acquis is "Social Policy and Employment" which demands equal treatment for women and men in the labour market. This is an area where Hungary is viewed as "...already well advanced regarding both transposition, implementation and enforcement" (Commission of the European Communities, 2001, p. 61).

[5] For comprehensive analyses of labour market reform in Hungary, see Fazekas and Koltay (2002) and Hovarth et al. (1999). For an examination of wage determinants during reform, see Campos and Jolliffe (2002).

start the transition with a working legal framework in place to cope with unemployment (Boeri and Pulay, 1998), it does not differ from others in that the disappearance of the strict central planning wage setting system was swift (Kollo, 2002). The government's attempts at setting-up collective bargaining frameworks were met with limited success: "The new Hungarian system of wage setting is based on the principle of bargaining freedom, but actual wage evolution is far more dependent on employers' decisions and the immediate impact of market forces than on collective agreements with low coverage and poor contents" (Koltay, 2002, p. 61).

This paper investigates male–female differences in the labour market before and during the transition from central planning to market economy in Hungary from 1986 to 1998. The main results from our analysis are the following. First, the relative situation of women improved dramatically: the female to male wage ratio (in levels) increased from 73% in 1986 to 80% in 1998. Our estimates show that the male–female difference in log wages declined drastically from 0.31 to 0.19 during this period. Second, the role of "discrimination" also declined markedly: using standard Oaxaca decomposition, we find that between 1986 and 1998 the component of the log wage differential that cannot be explained by the model declined by 0.11. Notice that from 1986 to 1998, the male–female difference in log wages declined by an amount of 0.12 and almost this entire decline can be explained by the drop in the unexplained or "discrimination" component of the Oaxaca decomposition. Third, by examining gender wage differentials by firm size and firm ownership we are able to throw light on a number of previously unexplored issues. For instance, we find that over time public firms and large firms show progressively smaller gender wage gaps than their counterparts.

The paper is organised as follows. The next section reviews the literature, Section 3 discusses data, the estimation strategy and our method for sample selection correction, Section 4 has our main results and Section 5 concludes.

2. The empirical evidence

The econometric evidence on the relative situation of women in the labour market and the role of discrimination as an underlying determinant is voluminous. Yet the vast majority of this literature examines wage gaps at a fixed point in time,[6] or the few studies examining the change over two points in time do so typically for years close together and/or solely during the transition period. Further, the results from the literature are mixed as to whether transition has resulted in an improvement or deterioration of women's wages relative to average male wages.

Orazem and Vodopivec (1995) show that during the early years of transition in Slovenia, the large decline in real wages coincided with the relative improvement of women's wages. The male–female difference in log wages was 0.13 in 1987 and this

[6] For examples of research on gender wage gaps at one point in time for Central and Eastern and European countries, see Paternostro and Sahn (1999), Pailhé (2000), Jurajda (2003), Jolliffe (2002) and Ogloblin (1999).

declined to 0.10 in 1991.[7] They further show that the relative improvement for women was largely due to greater demand for better-educated labourers and also because women worked disproportionately in sectors that benefited from transition. Within sectors, though, women lost relative to men.

In contrast, a study from China indicates that women's wages have deteriorated relative to men's wages during the transition. Liu et al. (2000) examine the change in the male–female wage differential in China during economic reform. Using data from Shanghai and Jinan, they find that economic reform leads to increases in the male–female difference in the log wage but a decrease in the relative importance of discrimination in explaining the log wage difference. The primary explanation for their results is that privatisation increases the returns to education and experience, and males in Shanghai and Jinan are better endowed with these characteristics. It is noteworthy that also in this respect, China differs from many CEE countries in that in the latter men and women have had fairly equal levels of schooling and experience.

In a comprehensive study, Brainerd (2000) examines the change in male–female wage differences during transition in nine Central and Eastern European and three Former Soviet Union countries. Brainerd's main result suggest a pattern of declining male–female wage differences in post-transition Eastern Europe but of increasing gaps in the male–female wage difference in the Former Soviet Union countries. In particular, she shows that the male–female difference in log wages increased 0.27 in the Ukraine and 0.15 in Russia, both indicative of a severe deterioration of relative wages for women.[8] Using qualitative data, Linz (1996) finds support for the hypothesis that transition to a market economy led to the relative decline of the welfare of women in the Russian labour market.

Reilly's (1999) results on Russia contrast to the above as he finds no change in the Russian male–female wage gap during the transition. His estimate of the male–female difference in hourly log wages in 1992 is 0.25 and in 1996 this estimate is 0.24. As with all of the studies discussed here, there are no estimates of standard errors so it is not possible to determine if this change is statistically significant. Whether the decline is statistically significant or not, it is qualitatively fairly small.

All seven CEE countries Brainerd examined showed improvement of women's wages relative to male wages. The difference between the pre-transition and transition log wage differentials range from -0.03 in Slovenia to -0.14 in Estonia, with estimates from Hungary, the Czech and Slovak Republics, Poland, and Eastern Germany falling in between.[9] In contrast to Brainerd, Jones and Ilayperuma (1994) show that for Bulgaria, female wages declined relative to male wages between 1989 and 1992.

[7] Orazem and Vodopivec do not provide estimates of standard errors so it is not possible to determine if this decline is statistically significant.

[8] The reported changes in gender gap (log wages) are -0.096 for Hungary, -0.124 for Poland, -0.063 for the Czech Republic, -0.092 for Slovakia, and -0.030 for Slovenia. Standard errors are also not reported in this study, so it is not possible to determine if the relatively small samples affect the interpretation of the estimated changes. For instance, the post-transition results from Hungary are based on responses from 922 men and 805 women.

[9] More precisely the reported measures are $\{\overline{\ln(w_{\mathrm{m}})} - \overline{\ln(w_{\mathrm{f}})}\}^{\mathrm{Post}} - \{\overline{\ln(w_{\mathrm{m}})} - \overline{\ln(w_{\mathrm{f}})}\}^{\mathrm{Pre}}$, where $\ln(w)$ is log wages, the bar denotes average, the m and f subscripts are for male and female, the superscripts mark whether the measures are from pre- or post-transition.

Newell and Reilly (2001) examine gender wage gaps in 11 transition economies (six Central European and five former Soviet Union countries). Their two main findings are that there seem to be little difference in terms of wage gaps between these two groups of countries and, second, there seem to be very little evidence that those gaps have increased during the transition.

In conclusion, there are two sound yet opposite hypothesis on the effect of economic reforms on the relative situation of women in the labour market. One would imagine that the empirical literature would be helpful in evaluating their comparative merits. Yet, as shown above, this is not the case: the evidence is still very much mixed. Some studies report increases in the wage gaps during the transition, others report decline. We believe that data-related difficulties are partly to blame for this inconclusiveness.[10] In what follows, we present results based on data from a consistent questionnaire kept over long periods of time for a representative and sufficiently large sample of wage earners.

3. Data and empirical specification

The data used in our analysis come from the Wage and Earnings Survey (WES) of the National Employment Office in Hungary, and contains information on wages, education, type of employment, and other demographic data. We use data from the five years of 1986, 1989, 1992, 1995, and 1998 to cover the pre-reform and transition period. The universe was obtained from a firm census administered by the Hungarian Central Statistical Office. The sample is nationally representative of all sectors and industrial activities. The sample sizes range from a low of 136,829 in 1992 to a high of 933,282 wage earners in 1989. The sample sizes for the three other years are all above 450,000 observations resulting in a pool of more than 2.9 million wage earners.

3.1. Sample design

For all five years the sampling units are wage earners and these are selected following a systematic, random selection procedure. The details of the procedures varied across the years in ways that affect the sample weights, but across all years the design is random and the estimates are representative of the sample frame. The sample frame for the years 1986, 1989, and 1992 includes all wage earners in private and public firms with more than 20

[10] In particular, we believe that issues of data quality and sample representativeness are important factors in explaining the lack of consensus. Supporting our belief that a lack of sufficiently representative sample data is a determinant of the conflicting empirical results, Munich, Svejnar and Terrell argue that "Depending on the number of individuals that one's sample contains from different age categories, one's estimates may reflect the concave or flatter parts of the wage-experience profile. This may account for some of the differences among the estimates obtained..." (2002, p. 25). Filer and Hanousek also lend support to this view by noting that "The bottom line is that it is even more important than usual in dealing with data from transition countries to pay careful attention to the details of how the data were collected and the exact wording of questions and sample design (2002, pp. 237–238)."

employees. The frame was supplemented in the 1995 and 1998 to also include smaller firms with more than 10 employees.[11]

In addition to this change in the sample frame, the procedure for sample selection changed on three occasions. In 1986 and 1989 wage earners were selected following a systematic, random design with a fixed interval of selection. From the list of all manual wage earners in each firm, one observation was randomly drawn and then every seventh employee thereafter was drawn. The same random selection procedure was used for all non-manual wage earners, except that the interval of selection was set to every fifth employee.[12] For the years 1992, 1995, and 1998, the selection procedure changed from a fixed-interval selection procedure to a systematic selection procedure based on date of birth. In the case of manual labourers, all workers born on the 5th or 15th day of each month were selected; and in the case of nonmanual labourers, all were selected who were born on the 5th, 15th, or 25th day of each month.[13] Rather than a random starting point and fixed interval of selection, this design is based on the fact that date of birth is randomly and approximately uniformly distributed across days of the month.

With the exception of the supplementation to the sample frame in 1995 and 1998, the sample design is a stratified, single-stage, systematic random draw that results in estimates which are representative of the sample frame population. The relevant issue is that the comparison across time suffers the slight problem that the frame changed for the last 2 years, 1995 and 1998. For the years 1986, 1989, and 1992, estimates are representative of all wage labourers who work in firms that have at least 20 employees. For the years 1995 and 1998, the estimates are representative of all wage labourers who work in firms that have at least 10 employees. If it were the case that firms with 10 to 20 employees reward education in a way that is systematically different from firms with 20 or more employees, then it is possible that observed changes in returns to education over time result in part from changing the sample frame in 1995.

One way to correct for this change in the sample frame is to exclude from our analysis those firms with 10 to 20 employees in years 1995 and 1998. Unfortunately, the variable which identifies firm size only indicates three types of firms: small firms with less than 50 employees, large firms with more than 300 employees, and mid-sized firms with 50 to 300 employees.[14] The strategy we follow in this paper is to report our results by these three types of firm size, and then for the entire sample. For the mid-size and large firms, the sample frame remains unchanged over the years. For the firms with less than 50 employees, the analysis suffers a potential bias resulting from the changing sample frame, and interpretations about change over time for the small firms needs to be interpreted with

[11] This supplementation was achieved following a two-stage selection process. In the first stage, 20% of the additional firms (10 to 20 employees) were selected and then in the second stage all wage earners in these firms were selected into the sample.

[12] Kish (1965) notes that systematic sampling is "perhaps the most widely known selection procedure" (p. 113) and suggests its simplicity reduces the potential for introducing error in the selection procedure.

[13] This change in the design reduced the sample size starting in 1992. Survey non-response in 1992 also led to a decline in sample size. Table 2 lists the number of sample observations and the weighted sample size for each year.

[14] To put it differently, we are unable to identify those firms with fewer than 20 employees separately from those firms with fewer than 50 employees.

Table 1
Comparison of wage estimates from WES and other data sources

	1986	1989	1992	1995	1998
Monthly gross earnings (Forint)					
Wage and Employment Survey (WES)[a]	6716	10,756	22,465	40,190	69,415
Central Statistical Office-Census[b]	6260	10,461	22,133		
Central Statistical Office-Survey[c]			22,294	39,854	68,718
Fazekas and Koltay[d]		10,571	22,294	38,900	67,764
Female–male wage ratio					
Wage and Employment Survey (WES)	73%	74%	82%	81%	80%
Central Statistical Office-Survey			81%	80%	79%
Fazekas and Koltay	74%	75%	83%	81%	85%

[a] Wage and Employment Survey (WES), National Labor Center, Hungary. All industrial sectors.
[b] Central Statistical Office, Labor-related Establishment Census. Data provided by International Labour Organization, available at: http://laborsta.ilo.org. Estimates are restricted to industry codes 2–9 of ISIC, revision 2 (not directly comparable to WES estimates). 1986 estimates are net earnings.
[c] Central Statistical Office, Labor-related Establishment Survey. Data provided by International Labour Organization, available at: http://laborsta.ilo.org. All industries included and estimates are gross earnings.
[d] Fazekas and Koltay (2002, Tables 7.1 and 3.1).

this caveat in mind. Analysis for the full sample also suffers this potential bias, but it is likely mitigated by the presence of the mid-sized and large firms.

3.2. Descriptive statistics

The monthly value of wages used in our analysis is the sum of the official base wage received and other payments that the employee receives monthly (rewards given in the reference month, provisions, overtime work, shift work, other special payments, e.g. in mining). In addition, the value of wages includes a pro-rated estimate of irregular payments (1/12 of irregular payments in the previous year).[15]

To assess the data quality, we show in Table 1 that the WES wage data match reasonably well with other available data sources. In particular, we compare average wages and the female–male wage ratio from the WES with data from the Hungarian Central Statistical Office (CSO) and from Fazekas and Koltay (2002). The WES data used in this paper are based on all industrial sectors and provide estimates of gross wages. The first set of CSO estimates, available from 1986 to 1992, are from a subset of industries and in 1986 are for net earnings.[16] The second set of CSO estimates and the Fazekas and Koltay estimates are gross wage estimates based on all sectors. WES average wages are slightly higher than all of the other estimates. The worst match is in 1986 where the CSO average wage estimate is approximately 7% less than the WES estimate. We assume that part of the difference in the estimates is because the CSO estimate is based on a subset of industries and note that when the WES is compared with the other data sources, the differences are

[15] It should be noted that our sample is restricted to full-time workers. In the WES data set, unfortunately, there is no information on the total number of hours worked. It must be said, however, that we are unaware of any existing results covering both pre and post-transition using information on hours worked.
[16] Estimates are restricted to ISIC (revision 2) industry codes 2–9.

Table 2
Descriptive statistics by sex, 1986–1998

	1986	1989	1992	1995	1998
Full sample					
Wages (Forint/month), Male	7604	12,181	24,639	44,438	77,283
	(5.39)	(13.56)	(62.46)	(127.12)	(265.08)
Wages (Forint/month), Female	5544	9035	20,088	35,879	61,607
	(3.967)	(9.349)	(48.910)	(84.557)	(185.210)
Years of Schooling, Male	9.8	10.0	11.3	11.1	11.1
	(0.005)	(0.006)	(0.011)	(0.010)	(0.009)
Years of Schooling, Female	9.6	10.3	11.2	11.3	11.4
	(0.005)	(0.006)	(0.011)	(0.008)	(0.008)
Potential Experience, Male	22.7	22.6	21.8	22.3	22.2
	(0.022)	(0.027)	(0.044)	(0.040)	(0.042)
Potential Experience, Female	22.2	22.1	21.5	21.7	21.9
	(0.024)	(0.024)	(0.041)	(0.033)	(0.033)
Proportion Male	0.57	0.55	0.52	0.50	0.50
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of observations	831,407	933,282	136,829	529,928	487,160
Weighted number of observations	3,342,962	3,092,818	2,858,445	2,211,040	1,984,667

Wage and Earnings Survey (WES) of the National Labor Center in Hungary. Standard errors are in parentheses.

much smaller. In terms of the female–male wage ratio, the WES estimates are within a percentage point of the other sources for all years except 1998. For this most recent year, the WES estimate is close to the CSO estimate but differs substantially from Fazekas and Koltay.[17]

The measure of schooling is a vector of six dummy variables that denote the highest type of completed schooling. The school types include primary, three types of secondary (vocational, technical, and gymnasium or general), college, and university.[18] In 1998, 22% of wage earners had only primary schooling or less, while 19% had college or university education. Of the remaining 59% who completed some form of secondary schooling, slightly less than half attended vocational school (28% of the total).

Table 2 lists means and standard errors for several of the relevant variables by gender. To allow for ease of comparison, school attainment is presented as total years of schooling where degrees have been assigned specific years.[19] It is immediately apparent that not only is there a large difference in the mean level of wages, but also that the male–female wage gap appears to be declining during transition. In 1986, the ratio of mean female to male wages was 73%, and by 1998 this ratio increased to 80%. A difference in average wages is certainly no indication of discrimination since it could simply be due to different economic

[17] It should be noted that although the total number of observations vary from year to year, the variation in *weighted* number of observations mimics Hungarian labour force developments over time. As noted, the sample starts including smaller firms only after 1995, which is 6 years after the demise of central planning when a buoyant private sector has already started taking root. Although we are able to insulate our results from these changes, it would be valuable for future research to look into the behaviour of the private sector in more detail, in particular, during the early transition years (1989 to 1992) when major changes actually took place.

[18] The omitted category is those individuals with less than primary schooling.

[19] For details on how the different types of schooling are mapped into years of school attainment, see Campos and Žlábková (2001).

attributes of men and women wage earners. The data on years of schooling and experience, though, appear to provide little explanation for the wage gap. While average levels of schooling are slightly lower for women in 1986 and 1992, female wage earners have higher levels of education in 1989, 1995 and 1998.[20] In contrast, there is a consistent gap in years of experience with male wage earners having approximately one-half year more experience on average than females.

An examination of the ratio of mean female to male wages by firm size reveals that the most change occurred in large firms: in 1986, the mean female wage was equal to 68% of the mean male wage, which was the lowest ratio across the three firm sizes. By 1998, this ratio increased to 93%, which was the highest ratio across the firm sizes. In contrast, the pattern for experience by firm size is fairly similar, with men having slightly more experience on average than women in firms of all sizes. One notable exception is in 1986, when men working in large firms had an average of 3 years more experience than their female counterparts. Similarly, men had higher mean levels of schooling in 1986 across all firm sizes, but in 1995 and 1998 women working in medium- and large-sized firms had significantly more schooling.

3.3. The wage equation

Wage equations are estimated using a standard Mincer equation, taking the form:

$$\ln(w_i) = \beta_1 S_i + \beta_2 E_i + \beta_3 E_i^2 + \beta_4 \mathbf{X}_i + \varepsilon_i \tag{1}$$

where the i subscript denotes the individual, w is wages, S indicates the highest level of schooling attained, E is potential experience, and $\mathbf{X}$ contains a set of variables to control for institutional and demographic characteristics as well as spatial price differences. More specifically, $\mathbf{X}$ includes a set of eight dummy variables to control for potential differences across industries.[21] The set of controls also includes dummy variables for the size of the firm, and $\mathbf{X}$ also contains a dummy for each of the 19 counties of Hungary and for the capital, Budapest. These spatial-specific, binary variables control for any variation that is specific to Budapest or some particular county. In particular, these dummy variables control for spatial variation in prices, which are likely to be significant with wages and prices in Budapest higher than other regions. The county dummy variables also control for region specific differences in labour markets, which might affect wages. For example, unemployment rates are relatively lower in Budapest, the counties along the Budapest–Vienna highway, and the counties along the Hungarian–Austrian border. Similarly, the county dummies will control for the potential measurement issue that a year of schooling may result in different levels of human capital accumulation over different regions if there are differences in schooling quality across regions.

[20] While all the differences are statistically significant due to the small standard errors, the largest gap in mean school attainment is 0.3 years in 1998.

[21] The eight classifications are: industry, construction, transportation and telecommunications, trade, water, services, health and social services, and public services. The excluded classification is agriculture.

The controls for firm size, industry and county fixed effects, greatly reduce the potential for omitted variable bias in our estimation of Eq. (1).[22] Having data that has been collected using the same survey instrument over the years of 1986 to 1998 also significantly improves the credibility of measured changes. Frequently, comparisons over time come from different data sources and one is left with the question of whether the change over time observed by the data analyst results from actual changes in the population, or is simply the result of changing the survey instrument. These are important advantages to using the WES data.

The disadvantage of using the WES data is that the choice of variables is small and our ability to empirically address violations of the OLS parametric assumptions is limited accordingly. One well-known violation of the classical assumptions occurs if education is correlated with the regression residual. One candidate cause of correlation is that there is some omitted variable, such as innate ability, that is both correlated with education and with wages. Failing to include ability in the regression results in correlation between education and the residuals and biased point estimates. One way to correct this type of bias is to use instrumental variables to purge education of that component which is correlated with the residuals. This approach though, requires that there is some variable that is both correlated with schooling but also reasonably excluded from the wage equation. We argue that there is no such variable in the WES data that allows us to credibly instrument education, and we caution that one should keep this potential bias in mind when interpreting the results. A mitigating factor is that our analysis focuses on how returns have changed over the communist and transition years. If the magnitude of these potential biases has not changed over time, then their impact on drawing inferences about change over time is limited.

Another potential cause of correlation between education and the regression residual can occur if people select in and out of the sample based on some characteristic that is correlated with the return to schooling.[23] For example, if persons with high returns are more likely to be wage earners and those with expected low returns opt out of the sample, then this induces correlation and results in sample-selection bias. This source of bias is typically corrected by explicitly modelling the selection decision, but this requires that there exists at least one variable that explains the decision to work in the wage sector but does not explain the wage level.[24] Again, we believe that no such variable exists in the WES data, but we argue that the unique features of the labour market in 1986 will help us to control for sample-selection bias.

[22] Though, we should note, these controls also do introduce the potential for endogeneity bias. For example, if highly educated people move to high-wage counties to earn better wages, then the estimated return to education is biased. While we believe there is little evidence of labour mobility sufficiently large to create this sort of bias, we did estimate the model with industry and county controls omitted as an alternate specification and found qualitatively similar results.

[23] For East Germany from 1990 to 1994, Hunt (2002) finds that the 10-point improvement in the gender wage gap is a result of the reduction of participation of low wage women in the labour market.

[24] Just to make this point clear: this data set does not contain observations for those individuals not in the wage market. The standard Heckman correction can therefore not be made because it is not possible to estimate a participation equation.

A fundamental characteristic of the centrally planned economies was that workers had very limited ability to select in or out of the wage market. All persons of working age were required to work, official unemployment was close to zero, and the opportunity to choose to work in non-wage employment was highly limited. An implication of this lack of freedom to select out of the wage market means that the pre-transition, 1986 WES estimates of the wage Eq. (1) will not suffer from sample-selection bias.[25]

Access to the 1986, pre-transition data is a unique feature of our analysis that allows us to control for selection bias in the later, post-1989 years. Our principal assumption is that the decision to participate in the wage market is correlated with age, sex and schooling demographics.[26] The change that is empirically observed in these characteristics in the post-1989 WES data comes from either people selecting in and out of the wage market or true population changes. If we assume that any change of these characteristics in the sample after 1989 is due to people choosing to leave and enter the wage market, then we can control for selection bias by re-weighting the WES data to have the same demographic composition as the 1986 data.[27]

More specifically, we partition each of the WES samples into six age categories (under 30, 30–34, 35–39, 40–44, 45–49, 50 and over), the seven school types described above and sex; for a total of 84 age–sex–education categories. We then define the proportion of the population that belongs to each of these categories in year t as:

$$v_k^t \equiv \sum_i^{j_k} \omega_{i,k}^t \Big/ \sum_i^{j_k} \sum_k^K \omega_{i,k}^t \tag{2}$$

where the k subscripts runs from 1 to K and represents the 84 age–sex–education categories, i subscripts the individual observation and runs from 1 to j_k for each of the k categories, and $\omega_{i,k}$ represents the weight or expansion factor for individual i in category k. To re-weight the data such that the demographic composition in later years matches the composition from 1986, we construct new weights for each year:

$$\varpi_{i,k}^t = (v_k^{86}/v_k^t)\omega_{i,k}^t \quad \forall k \in K \tag{3}$$

The v^{86} term in the numerator adjusts the weights to reflect the demographic composition in 1986, and the v^t in the denominator normalises the adjustment to ensure

[25] Munich et al. (2002) note that “In addition to regulating wages, the central planners regulated employment and admissions to higher education. With minor exceptions, all able-bodied adults were obliged to work. Jobs were provided for everyone and employment security was assured” (p. 6). Further, Horvath et al. (1999) argue that the registered unemployment rate in Hungary increased rapidly with the launching of reforms reaching 1.4% in 1990.

[26] Svejnar (1999) and Boeri and Terrell (2002) observe that early retirement schemes, youth unemployment and the reduction of female labour force participation rates are stylised facts of the transition.

[27] This methodology is conceptually similar to that proposed by DiNardo et al. (1996). They propose a semi-parametric methodology to answer questions such as “what would the density of wages have been in 1988 if worker’s attributes, such as their union status, had remained at their 1979 level? One methodological contribution of this paper is to show that the estimation of such counterfactual densities can be greatly simplified by the judicious choice of a reweighting function” (1996, p. 1009). In this paper, we generate a baseline density by treating our 1986 sample as one in which sample-selection bias is negligible and re-weighting all the other four samples according to the demographic distribution of the 1986 sample, in terms of age–gender–education.

that the sum of unadjusted weights equals the sum of adjusted weights. For example, if low-educated, young males comprise a larger proportion of the sample in 1986 than in 1995, we adjust upwards the 1995 weights to ensure that they represent the same proportions across both years. One difficulty with this approach is that it does not allow for any true population changes in the age, sex and education composition of the sample. Since there has been change in the population characteristics of these variables, this assumption does bias the estimates, but our assumption is that this bias is smaller in magnitude than the sample-selection bias.[28] While reweighting the data to match the 1986 demographic characteristics of the sample affects the interpretation of the results, it is in some ways a desirable characteristic. Changes in returns to say education can result from changes in the composition of the labour market and from how the labour market rewards education, conditional on the characteristics of the labour market. By re-weighting the data to the 1986 demographic composition, we purge from our analysis changes in labour supply and focus on market changes in the demand for wage labour. This focus allows us to examine whether firms are responding to liberalisation by providing greater returns to investment in human capital.

4. Results

4.1. Wage regressions

In this section, we first discuss our results from estimating male and female wage regressions, as specified in Eq. (1), and then we study the Oaxaca decomposition. Panel A of Table 3 presents the industry and county fixed-effects estimates of Eq. (1) for males, and Panel B lists these estimates for female wage earners. The standard errors listed in this table are corrected for heteroskedasticity of unknown form through use of the 'sandwich variance estimator' (Huber, 1967; White, 1980). While the estimates for the male and female wage equations differ, there are no clear patterns in their difference over time and few stark differences in a given year.[29]

4.2. Oaxaca decompositions

Using the separate regression estimates for the male and female wage functions, Oaxaca (1973) proposed a method to decompose the observed gender wage gap into two

[28] The Hungarian Central Statistical Office reports that the Hungarian population declined by about 2% between 1990 and 1998, but the population proportion of men and women has remained constant. The changes have been much more significant for the population of wage earners. Fazekas and Koltay (2002, Table 3.1) note that registered unemployment increased more than tenfold from 47,700 in 1990 to 507,700 in 1995. Similarly, the WES data indicate that there has been a significant change in the gender composition of the labour force with the proportion of male wage earners dropping from 57% in 1986 to 50% in 1998.

[29] A slight pattern that can be noticed is that the returns to schooling appear to be modestly higher for women. In particular, over all five years examined, the return to the female graduates of secondary vocational school and secondary general school are higher than for their male counterparts.

Table 3
Returns to school by sex, 1986–1998, fixed-effects estimates of wage Eq. (1)

Dependent variable: log of wages, full sample by sex	1986	1989	1992	1995	1998
Panel A: male wage earners					
Primary schooling	0.104	0.020	0.109	0.095	0.160
	(0.0023)	(0.0038)	(0.0095)	(0.0128)	(0.0186)
Vocational (secondary school)	0.190	0.088	0.228	0.208	0.307
	(0.0023)	(0.0039)	(0.0120)	(0.0129)	(0.0189)
Technical (secondary School)	0.317	0.400	0.247	0.461	0.590
	(0.0026)	(0.0051)	(0.0098)	(0.0134)	(0.0192)
General (secondary school)	0.238	0.201	0.458	0.422	0.525
	(0.0033)	(0.0047)	(0.0102)	(0.0148)	(0.0201)
College	0.516	0.424	0.786	0.822	1.015
	(0.0034)	(0.0053)	(0.0118)	(0.0145)	(0.0199)
University	0.690	0.718	0.992	1.042	1.277
	(0.0034)	(0.0057)	(0.0119)	(0.0147)	(0.0199)
Potential experience	0.034	0.020	0.031	0.028	0.023
	(0.0002)	(0.0003)	(0.0009)	(0.0008)	(0.0011)
Potential experience squared	− 0.051	− 0.030	− 0.047	− 3.835	− 0.029
	(0.0004)	(0.0006)	(0.0020)	(0.1794)	(0.0026)
Number of observations	434,224	387,278	67,440	161,106	148,966
R-squared	0.31	0.23	0.37	0.36	0.40
Panel B: female wage earners					
Primary schooling	0.079	− 0.012	0.117	0.047	0.175
	(0.0024)	(0.0040)	(0.0083)	(0.0125)	(0.0169)
Vocational (secondary school)	0.207	0.061	0.307	0.168	0.301
	(0.0029)	(0.0046)	(0.0111)	(0.0131)	(0.0177)
Technical (secondary school)	0.359	0.310	0.253	0.470	0.628
	(0.0028)	(0.0045)	(0.0094)	(0.0130)	(0.0173)
General (secondary school)	0.290	0.220	0.476	0.425	0.597
	(0.0029)	(0.0046)	(0.0088)	(0.0132)	(0.0176)
College	0.583	0.412	0.770	0.795	0.911
	(0.0042)	(0.0049)	(0.0093)	(0.0129)	(0.0172)
University	0.786	0.747	1.005	1.065	1.236
	(0.0037)	(0.0057)	(0.0113)	(0.0142)	(0.0187)
Potential experience	0.026	0.017	0.022	0.024	0.019
	(0.0002)	(0.0003)	(0.0006)	(0.0009)	(0.0011)
Potential experience squared	− 0.035	− 0.031	− 0.029	− 0.033	− 0.022
	(0.0004)	(0.0007)	(0.0015)	(0.0022)	(0.0027)
Number of observations:	397,183	546,004	69,389	368,822	338,194
R-squared:	0.35	0.27	0.37	0.37	0.38

Dependent variable is the log of monthly wages in Forint. Estimates are corrected for sample selection bias. Standard errors, in parentheses, are robust to heteroscedasticity of unknown form. The remaining results from estimation of Eq. (1) are suppressed for the sake of brevity. The firm-size and industry dummies are jointly significant as well as the county, fixed effects.

components: (1) that which results from differences in education and experience levels (and any other explanatory variable) of men and women; and (2) that which cannot be explained from the model and is often interpreted as resulting from labour-market discrimination.

The Oaxaca decompositions rests on the fact that the OLS regression line runs through the mean and the difference in the mean of log wages between men and women can be written as:

$$\overline{\ln(w_{\rm m})} - \overline{\ln(w_{\rm f})} = (\bar{X}_{\rm m} - \bar{X}_{\rm f})\beta^* + [(\hat{\beta}_{\rm m} - \beta^*)\bar{X}_{\rm m} + (\beta^* - \hat{\beta}_{\rm f})\bar{X}_{\rm f}] \tag{4}$$

where β^* is the hypothetical wage structure that would exist in the absence of discrimination. The first term on the right-hand side of Eq. (4) represents the portion of the wage difference that is explained by differences in endowments across men and women. The second term on the right-hand side, in square brackets, represents the portion of the wage difference that is due to the different wage structures for men and women. This is the part of the wage differential that cannot be explained by the model and is potentially due to discrimination.

Interpreting the model residual as discrimination needs to be done with caution. If there is any sort of omitted variable that has a positive effect on wages, and if men are more highly endowed with this characteristic, then the results from the decomposition would overestimate discrimination. Alternatively, if some of the factors that are in the model are themselves affected by discrimination, then the analysis could well underestimate discrimination. For example, if women are more likely to be fired in economic downturns, or if they have less access to the types of schooling deemed more valuable by the market, then the decomposition may well underestimate discrimination.[30]

The selection of β^*, the hypothetical non-discriminatory wage structure, poses a known index number problem that has been extensively discussed in the literature.[31] We follow Neumark (1988) who shows that the non-discriminatory wage structure can be given by the OLS estimate from the pooled sample of male and female wage earners. One way to approach the problem of different candidate estimates of the non-discriminatory wage structure is to use several different estimates of β^* to verify the robustness of results. In our case, though, we are examining the level of discrimination at five different points in time and believe that it is helpful to choose one estimate of β^* in order to more easily interpret the results.[32]

Panel A of Table 4 provides Oaxaca decompositions of the log wage gap for the five years of 1986, 1989, 1992, 1995, and 1998 using the pooled-sample, OLS estimate as the non-discriminatory wage structure. We refer to this panel as our preferred estimates because they are corrected for sample-selection bias and control for firm size, industry and

[30] In terms of examining the welfare of women workers during the transition period, the Oaxaca analysis does not capture the many other activities that women frequently are required to undertake, such as childcare and housework. For a full discussion of the impact of transition on females, see Grapard (1997).

[31] See Oaxaca (1973), Reimers (1983), Cotton (1988), Neumark (1988) and Appleton et al. (1999).

[32] We did also use $\beta_{\rm f}$ and $\beta_{\rm m}$ as estimates of β^*, and found that the qualitative nature of the changing pattern of discrimination over time was similar to the results from using the pooled estimate of β. One of our primary results is that the male–female log wage difference declined by 0.12 and the large majority of this decline is due to a similar drop in the discrimination component of the Oaxaca decomposition. When β^* is proxied by the pooled estimate of β, the discrimination component declines by 0.11 between 1986 and 1998. When proxied by $\beta_{\rm f}$ the decline is 0.12 and using $\beta_{\rm m}$ results in a decline of 0.14 in the discrimination component of the decomposition.

Table 4
Oaxaca decomposition of gender wage gap, full sample comparisons, 1986–1998

	Log wage gap	Standard error wage gap	Part of gap explained by the model			Unexplained 'discrimination'	Standard error
			Total	Education	Experience		
Panel A: corrected for sample selection bias preferred model, controlling for industry and county							
1986	0.31	(0.0009)	0.09	0.03	0.01	0.21	(0.0007)
1989	0.30	(0.0012)	0.09	0.01	0.00	0.22	(0.0010)
1992	0.21	(0.0027)	0.03	− 0.02	0.00	0.18	(0.0022)
1995	0.21	(0.0027)	0.10	0.02	0.01	0.11	(0.0024)
1998	0.19	(0.0029)	0.09	− 0.01	0.00	0.10	(0.0030)
Panel B: not corrected for sample selection bias							
1986	0.31	(0.0009)	0.09	0.03	0.01	0.21	(0.0007)
1989	0.30	(0.0011)	0.09	0.02	0.00	0.22	(0.0009)
1992	0.20	(0.0027)	0.04	− 0.01	0.00	0.16	(0.0019)
1995	0.19	(0.0024)	0.10	0.02	0.01	0.09	(0.0020)
1998	0.18	(0.0023)	0.09	− 0.01	0.00	0.08	(0.0021)

Standard errors are bootstrap estimates from 200 replications. The last column lists standard errors for the unexplained component of the model, or discrimination.

county.[33] The first column of this panel shows that the male–female difference in log wages has declined by 39% from 0.31 in 1986 to 0.19, and the second column provides standard errors which indicate that the difference is highly significant.[34] How do our results compare? Our estimate of the male–female difference in log wages for 1992 is 0.21, which is fairly close to the estimate of 0.23 found by Pailhé (2000) for 1993.

The column labelled 'Part of the Gap Explained by the Model, Total' provides an estimate of the first term on the right hand side of Eq. (4). The estimates from Panel A of Table 4 indicate that in 1986, the male–female log wage difference would have been 0.09 if males and females were paid according to the same wage structure. In other words, 29% of the actual log wage difference of 0.31 can be explained by factors in the model. This estimate fluctuated over the 13-year period, but the data indicate that by 1998 the male–female log wage difference would once again have been 0.09 if males and females were paid according to the same wage structure. A noteworthy difference, though, is that in 1998 the estimate of 0.09 implies that the proportion of the actual log wage difference that can be explained by factors in the model increased to 47%.

As noted above, it is possible that some of the factors in the model may themselves be affected by discrimination, which makes interpreting the decompositions in terms of discrimination somewhat difficult. For example, the decomposition for 1998 indicates that 47% of the log wage gap of 0.19 is explained by the model, which is sometimes interpreted as meaning that this portion of the gap is not resulting from discrimination. In addition to measures of education and experience, though, the model also includes controls

[33] Panel B of Table 4 provides estimates without the correction for sample selection. By 1998, the uncorrected log wage gap is slightly greater than the corrected gap indicating that a small amount of the observed differences in wages is due to selection. The results also indicate that the decline in the 'discrimination' component between 1986 and 1998 is slightly dampened by the correction for sample selection.

[34] Given the large samples sizes it is not that surprising that this decline in the log wage gap is highly, statistically significant with a p-value of 1.3e − 47.

for county fixed effects as well as dummies for firm size and type of industry. If it were the case that the level of discrimination varied systematically by county, then some of this variation would be picked up in the county fixed effect.

With this caveat in mind, it is useful to examine the estimates in the columns labeled 'Education' and 'Experience' that measure what portion of the log wage gap is explained by the male–female differences in these particular human capital characteristics. The decomposition for 1986 indicates that about 10% (or 0.03 points) of the log wage gap of 0.31 is explained by differences in educational outcomes. Only 3% (or 0.01 points) of the male–female log wage gap is due to differences in average levels of experience. Together, the education and experience variables explain 0.04 points, while the model in total explains 0.09 points. This is in stark contrast to 1998, when the differences in education and experience explain −0.01 points of the log wage gap. In other words, if men and women were paid according to the same wage structure, the market would value more highly the experience and education stock held by women.

The penultimate column in Table 4 lists how much of the difference in male–female log wages cannot be explained by the model, and the last column lists the standard error of this measure. While Oaxaca and Ransom (1998) derive approximate standard errors (based on the delta method) for the components of the Oaxaca decomposition, we are not aware of any applied research that provides estimated standard errors. The reported standard errors are design matrix bootstrap estimates based on 200 replications. The advantage of resampling the design matrix (or resampling cases) rather than resampling simulated residuals, is that this method is more robust to heteroscedasticity.[35]

The estimate of the male–female difference in log wages that cannot be explained by the model is typically described as resulting from discrimination, and is the difference between the actual log wage gap and that part of the gap which is explained by the model. As such it is subject to the same caveats as described above. Nonetheless, it is revealing to examine how this measure has changed over time. In 1986, the unexplained component of the log wage differential was 0.21, or 68% of the difference. By 1998, the unexplained component dropped by more than half to 0.10, or 53% of the log wage difference. Another way to consider this is to note that from 1986 to 1998 the male–female difference in log wages declined by an amount of 0.12. This decline is almost fully matched by the drop in that part of the unexplained portion of the log wage differential. In other words, almost all of the decline in the log wage differential is due to the drop in the 'discrimination' component of the Oaxaca decomposition.

In addition to examining the Oaxaca decomposition over the full sample, it is also of interest to carry out this analysis by size of firm for two reasons. First, the sample frame for small firms changed over the time of the analysis and this potentially biases the results. This bias does not exist for medium and large firms since the definition of these firm sizes stayed unchanged between 1986 and 1998. Second, carrying out the analysis separately for

[35] The disadvantage of resampling the design matrix rather than residuals is that there is a loss of efficiency if the constant-variance assumption is correct. Given the large sample sizes of our data sets, the potential efficiency loss is not a concern, and our preference is to obtain estimates that are robust to heteroscedasticity. For a discussion of the various bootstrap methodologies for linear regression, see chapter 6 of Davison and Hinkley (1997) or chapter 7 of Shao and Tu (1995). For a general discussion of the bootstrap, see Efron and Tibshirani (1993).

firms of different sizes is also of potential interest because the extent of discrimination may be a function of firm size. For example, it might be that larger firms are more rigid in how they evaluate and reward their employees, following more written guidelines, and therefore are less likely to discriminate based on sex. Another, contradicting story might be that small firms are more likely the newer, more market-oriented firms, which act to reduce sex discrimination to improve their profitability.

Examining the results from Table 5 across Panels A, B and C reveals that in 1986 the male–female difference in log wages was greatest in the largest firms. Small and medium-size firms had approximately the same difference in log wages. By 1998, the picture is strikingly different. Large firms now have the smallest gap between men and women in terms of log wages with a difference of 0.06. The largest male–female difference in log wages in 1998 is found in the smallest firms, with a log differential of 0.27.

Another finding is that while the actual male–female difference in log wages diverged dramatically for the different firm sizes, that portion of the wage differential which cannot be explained by the model has followed a similar pattern across firms over time. In 1986, the log wage differential, which could not be explained by the model, was 0.18 for large firms and 0.21 for small and medium-size firms. By 1998, the 'discrimination' component of the Oaxaca decomposition fell significantly for all firms and ranges from 0.09 for the largest firms to 0.13 for the medium-size firms. From strictly examining the log wage gap,

Table 5
Oaxaca decomposition of gender wage gap, comparisons by firm size, 1986–1998

	Log wage gap	Standard error wage gap	Part of gap explained by the model			Unexplained 'discrimination'	Standard error
			Total	Education	Experience		
Panel A: small firms							
1986	0.31	(0.0011)	0.09	0.03	0.01	0.21	(0.0009)
1989	0.29	(0.0015)	0.07	0.00	0.00	0.22	(0.0014)
1992	0.21	(0.0033)	0.03	− 0.01	0.00	0.18	(0.0029)
1995	0.27	(0.0036)	0.14	0.02	0.01	0.13	(0.0032)
1998	0.27	(0.0040)	0.15	0.02	0.01	0.11	(0.0035)
Panel B: mid-size firms							
1986	0.30	(0.0022)	0.09	0.05	0.01	0.21	(0.0018)
1989	0.32	(0.0021)	0.11	0.04	0.01	0.21	(0.0018)
1992	0.17	(0.0051)	0.00	− 0.03	0.00	0.17	(0.0040)
1995	0.19	(0.0043)	0.07	0.03	0.01	0.12	(0.0042)
1998	0.19	(0.0044)	0.06	0.01	0.01	0.13	(0.0044)
Panel C: large firms							
1986	0.39	(0.0092)	0.21	0.18	0.04	0.18	(0.0074)
1989	0.33	(0.0038)	0.14	0.10	0.02	0.19	(0.0029)
1992	0.21	(0.0123)	0.04	0.01	0.00	0.17	(0.0098)
1995	0.15	(0.0045)	0.04	0.02	0.01	0.10	(0.0039)
1998	0.06	(0.0052)	− 0.04	− 0.04	0.00	0.09	(0.0049)

Standard errors are bootstrap estimates from 200 replications. Estimates corrected for sample selection bias. The last column lists standard errors for the unexplained component of the model, or discrimination. Small firms are less than 50 employees, mid-size firms are between 50 and 300 employees and large firms are more than 300 employees.

Table 6
Oaxaca decomposition of gender wage gap, by legal status of firms, 1986–1998

	Log wage gap	Standard error wage gap	Part of gap explained by the model			Unexplained 'Discrimination'	Standard error
			Total	Education	Experience		
Panel A: private firms							
1992	0.19	(0.0034)	0.01	0.01	− 0.01	0.18	(0.0029)
1995	0.17	(0.0037)	0.00	0.01	0.0	0.17	(0.0028)
1998	0.14	(0.0046)	− 0.01	0.01	0.0	0.15	(0.0037)
Panel B: public firms							
1992	0.32	(0.0057)	0.14	0.10	0.01	0.18	(0.0038)
1995	0.21	(0.0029)	0.10	0.08	0.01	0.11	(0.0024)
1998	0.20	(0.0027)	0.09	0.07	0.01	0.11	(0.0024)

Standard errors are bootstrap estimates from 200 replications. Estimates corrected for sample selection bias. The last column lists standard errors for the unexplained component of the model, or discrimination. Indicator variable for private firms not available in WES data prior to 1992. Sample restricted to mid-size and large firms.

one would incorrectly infer that sex discrimination is much less of a problem in larger firms than in small firms. From the Oaxaca decomposition, one would infer that the magnitude of discrimination has declined dramatically over time, but the variation by firm size is not that large.

Another interesting finding refers to firms with 300 or more employees: in 1998, the male–female difference in log wages is low at 0.06, but the amount that is unexplained by the model is greater than this at 0.09. This means that if the men and women who worked in large firms were paid according to the same wage structure, and according to the model characteristics, then those women would earn more than men.

Table 6 provides the results from separate Oaxaca decompositions for public and private firms.[36] One candidate hypothesis is that the market punishes discrimination in private enterprises through loss of profit, but no such similar force exists in public firms. The results in Table 6 do not provide support for this hypothesis. In 1992, the male–female difference in log wages was 0.19 in private firms and about 68% greater in public firms. Between 1992 and 1998, the log wage differential declined significantly in both public and private firms and the gap between the two firm types narrowed. The 'discrimination' component of the log wage gap also suggests that the relative improvement of women's position in the labour market occurred in both public and private firms. In 1992 this 'discrimination' component of the Oaxaca decomposition was 0.18 in both firm types and declined for both over the next 6 years.

The results in Table 6 suggest that there were forces working in both private and public firms to reduce discrimination, a finding that is not necessarily inconsistent with Becker's theory of discrimination. Becker (1957, pp. 81–83) suggests that democratic forces could

[36] Public firms include state-owned enterprises, public services as well as public administration. Many firms are not clearly classified as public or private by the National Employment Office and are excluded from the analysis (for instance, the data includes wage earners in charities and non-governmental organisations). For this reason the results from Table 6 vary somewhat from those reported in Table 5. Finally, because central planning was still in force in 1986 and 1989, there are no firms classified as private for these years, and this is why this information is only available from 1992 onwards.

work in ways similar to market forces to punish discriminatory behaviour. Transition has not only allowed markets to function more freely, but has also brought new social freedoms that can change the behaviour of public institutions. Similarly, the desire to join the European Union may be motivating the government to make sure that remuneration practices of the whole public sector are as non-discriminatory as possible.[37]

5. Conclusions

Using data from the Wage and Earnings Survey (WES) for almost 3 million wage earners in Hungary, this paper examines the changes in the relative labour market positions of males and females wage earners after market liberalization, that is, before and during the transition from plan to market.

The available empirical evidence is highly inconclusive and we believe that this is driven in large part by data issues. Therefore, for this paper we use data that we believe is superior in various dimensions. With these data, separate regressions are estimated for males and females following a standard Mincer equation. The wage model controls for county fixed effects as well as industry specific effects and corrects for sample selection bias. We then apply the standard Oaxaca decomposition to examine how much of the male–female difference in the log wages cannot be explained by the model. This unexplained portion of the difference is normally interpreted as resulting from discriminatory differences in the male and female wage structures. The results from the full sample of data indicate that between 1986 and 1998, the male–female difference in log wages declined dramatically from 0.31 to 0.19. Quite remarkably, almost this entire decline resulted from a commensurate decline in "discrimination," or more precisely that component of the difference in log wages that cannot be explained by the model.

When examining these results by different firm sizes, we find that between 1986 and 1998 the largest firms had the greatest decline in the log wage difference between men and women. The log wage difference declined by 85% in the largest firms, compared to only a 13% decline in the smallest firms. This difference in declines is due to several factors, including the fact that the highest log wage difference in 1986 was found in the largest firms and also because the women who work in these firms possess education that is valued more highly.

The results presented in this paper show a large and statistically significant decline in the male–female difference in log wages through five points in time covering pre- and post-market liberalisation periods. The results also show a large and statistically significant decline in the amount of the log wage difference that cannot be explained by the econometric model, the so-called discrimination component. The Commission of the

[37] As a caveat to these findings, we again note that estimates for small firms may be biased because of the changes in the sample (smaller firms are only included after 1995). Since smaller firms may be disproportionately privately owned, this change in the sample could be bias in the estimates for private firms.

European Communities reports that Hungary has made significant progress in instituting a legal and institutional framework that is a necessary requirement for accession into the European Union. The results in this paper strongly suggest that the reform that took place in Hungary extend to actual improvement towards equitable wages for men and women.

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