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Why do Men Earn more than Women? An Analysis Using British Household Panel Survey

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The analysis of pay gap across gender is sensitive to the use of specific econometric techniques. While the estimates may reveal upward bias in case of exclusion of significant covariates, the use of inappropriate estimation techniques results in underestimation. Although some analysis shows that gender pay differential has been declining over time, controlling for significant economic variables, this study does not find supporting evidence to this hypothesis. Wage differential varies positively with pay levels in case of weekly pay, but this pattern does not prevail in case of hourly pay which accounts more for the discrimination from the employer's side.

Key words: Gender pay gap, Oaxaca-blinder decomposition, Panel data, Quantile regression, wage differential

JEL Classification: C33, J31, J71

I. INTRODUCTION

Gender pay discrimination analysis—a widely addressed theme by labour economists throughout the world from the 1970s—is still receiving refinement in terms of use of quality data and advancements in econometric techniques. Almost all of the studies incorporated individual's productivity enhancing characteristics such as education, experience, occupation category and industry. Besides, there are factors like household division of labour–with future work expectations for relatively longer period married men have incentive to invest more in human capital compared to married women (and especially with children) resulting in greater pay gap between married men-women compared to singles (Polachek 1975, Weiss and Gronau 1981, Goldin and Polachek 1987, Kao, Polachek and Wunnava 1994). Studies considered unobserved heterogeneity among individuals

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that accounts for productivity differences (e.g. ability, long term career motivation) by applying fixed effects estimation techniques using panel data which yields consistent and efficient estimators compared to inconsistent OLS and between estimators and less efficient random effects estimator in presence of correlation of unobserved heterogeneity term to any of the covariates. However, this method can capture unobserved individual characteristics influencing only the level of individual earnings, not the rate of its growth (Polachek and Xiang 2006). Besides, as fixed effects model cannot estimate coefficient for time invariant variable, some studies used estimation of random effects model with instrumental variables suggested by Hausman and Taylor (1981) (e.g. Hausman and Taylor 1981, Kim and Polachek 1994) while others estimate male-female separate models and analyse gender pay differential using Oaxaca-Blinder decomposition method (1973) (e.g. Smith and Nielsen 1988, Meng 2004). Nevertheless, poor data quality and unavailability of hourly wages can result in biased estimates of discrimination using these models (Weichselbaumer and Winter-Ebmer 2005).

This study is an attempt to reinvestigate the gender pay gap analysis with some high quality data and different econometric techniques. The British Household Panel survey with its first 16 waves (1991-2006) is used to estimate basic and extended human capital models both for weekly and hourly real pay with a comparison of pooled OLS, between estimator, random effects and fixed effects coefficients, of which the latter is performed for male-female separate groups and Oaxaca-Blinder decomposition is used to estimate conditional differential. For the existence of endogeneity (suggested by Hausman test results), Hausman Taylor estimation method is also applied. Further, from the time interaction dummies with “male” dummy used in regression models an analysis is presented on the over time change of gender pay gap. A quantile regression model is also estimated to investigate discrimination among different levels of wages. Comparison of the results shows that in case of hourly real pay the gender pay differential of 0.284 log-points decreases to 0.2033 log-points applying Hausman Taylor estimation incorporating a set of relevant covariates, whereas the conditional differential from Oaxaca-Blinder decomposition remains as high as 0.28. In case of weekly pay these values are 0.637, 0.566 and 0.63 respectively. Therefore, using advanced econometric techniques applied in a high quality data helps to explain 28% of the raw differential which is a reduction from more than 100% unexplained differential of between and OLS estimates and 82% of random effects estimates in case of hourly pay. Though the raw differentials of 0.76 log-points (weekly pay) and 0.36 log-points (hourly pay) during the first wave (1991) have decreased over time to 0.53 log-points (weekly pay) and 0.23 (hourly pay) log-points in 2006, except for the basic fixed effects model, the extended models of fixed effects and Hausman Taylor estimations reveal that there is no significant reduction in gender pay gap over time, implying that the reduction in raw differential or basic fixed effects differences in differential can be explained by changes in other covariates over time. Besides, quantile regression results reflect that there are significant differences in gender pay differential within different levels of weekly pay, and it decreases with higher pay scales.

The paper is organised as follows. Section II presents the conceptual framework of the analysis reporting human capital relationship model in wage regression, section III provides a detailed data description with some summary statistics, section IV presents the econometric methods used to estimate gender pay gap, section V analyses the results of estimation and section VI concludes.

II. CONCEPTUAL FRAMEWORK

According to well established economic theory labour market discriminations lower the wage of minority group as well as pay a premium to the majority (Madden 1975, Bergmann 1971). However, over time female participation in labour force has increased considerably along with their human capital development which makes the analysis of still prevailing gender pay discrimination an interesting field of investigation. In doing so, it becomes important to take into account that part of wage differential which can be explained by observed (and unobserved) heterogeneity among individuals and their changes over time. The human capital model (based on Becker's (1964) human capital theory) is therefore the one that conceptually captures these issues.

In this study, the basic human capital model (an extended version of Mincer 1974 model) has been used along with its extended version in terms of including a number of economically significant covariates. It is assumed that wages are determined according to the following equation:

$$\log w_{it} = \gamma m_i + x_{it}\beta + \delta_t + a_i + \varepsilon_{it}, \text{ t=1, 2,....16, } \varepsilon_{it} \sim iid(0, \sigma_{\varepsilon}^2) \quad (1)$$

where, log w_{it} is log real weekly gross pay or log real hourly gross pay, m_i is a male dummy, x_{it} is a vector of covariates, δ_t is a year-specific intercept shift, a_i is a person-specific time-invariant heterogeneity term, and ε_{it} is an idiosyncratic error term which is, conditioned to x_{it}, a_i, independently and identically distributed with mean zero and constant variance.

III. DATA

The British Household Panel Survey (BHPS) is a nationally representative survey that covers residents of Great Britain at multiple time points corresponding to the waves of the data. The first wave was in 1991 consisting of an equal-probability clustered sample of 10,300 individuals (5,500 households, where all members over 16 years of age are interviewed) and from then they are interviewed each year (until their death and with some addition of new adults reaching 16 years). The survey follows a core questionnaire covering household composition, housing condition, residential mobility, education and training, labour market behaviour, income from employment, benefits and pension, health and socioeconomic values along with a variable component comprising questions to get panel member's lifetime history, e.g. marriage, children and job history. BHPS is conducted by the Institute for Social and Economic Research (ISER) and it is one of the longest running panel surveys in the world with 18 years of panel data up to 2009.

For the present analysis of determinants of gender pay gap, first 16 waves of BHPS (covering 1991-2006) are used comprising observations of 35,199 male-years and 36,362 female-years. Adult individuals (over 16) up to 65 years of age are considered to focus on the labour force participants. Real weekly pay (lrwkpay) and real hourly pay (lrhrpay) variables are constructed using monthly nominal gross usual pay deflated by annual retail price level and usual hours worked per week.[1] Key covariates of the analysis include '*male*' a male dummy, "*qual1 to qual6"* 6 qualification dummies with *qual1* referring to the highest degree qualification and "*qual6"* to no qualification and "*agebelow20 to age61to65"* 10 age categories as a proxy of *experience.* Besides some other covariates are used to extend the basic model : "*north*" to refer to a region dummy including North West, Yorkshire, North East and Scotland with a value 1, "*married*" a dummy for whether married or not, "*nchild*" number of own children in household, "*white"* dummy to classify ethnic group–whether white or not, "*manual"* a dummy to distinguish between manual job and others, "*covered*" a dummy to refer to whether covered by union agreement or not, "*services"* dummy including broad service sectors-distribution, hotels and catering, transport and communication, and banking, finance, insurance, business services and leasing, and four farm size categories "*sz1_24 to sz500"* based on number of employees.

[1]Log real weekly pay=log(((monthly nominal gross pay*12)/ Price Index)/52) and Log real hourly pay =log((((monthly nominal gross pay *12)/ Price Index)/52)/hours worked per week).

The unbalanced panel data used here constitutes 49.19% male and 50.81% female individuals on the whole with average monthly gross nominal earnings of 1,680.12 and 995.66 pounds respectively. In case of weekly real pay, the wage differential is 0.637 log-points (89.08%) and considering hourly real pay men get 0.284 log-points (32.84%) more than women. However, these differentials vary from 0.342 to 0.899 log-points in case of weekly real pay and 0.199 to 0.337 log-points in case of hourly real pay from higher degree education to no qualification groups respectively and from 0.254 to 0.972 log-points in case of weekly real pay and 0.102 to 0.296 log-points in case of hourly real pay from the young (21-to-25 years) age group to the old (61-to-65 years) age group. These raw differentials are consistent to the conventional findings of basic human capital relationship models that women with higher qualification are less discriminated and their experience does not add much to their pay as compared to men.

Raw pay differential if married is much higher compared to any other marital status (0.859 versus 0.334 log-points for weekly real pay and 0.395 versus 0.132 log-points for hourly real pay). Besides, women's participation in the labour force is affected by the number of children they have. For example, where ratio of male to female participation in the labour force is less than 1 for women with 1 or no child, it is more than tripled for women with 5 children compared to their male counterparts. Raw differential of gender pay also shows an upward trend with increasing number of children.

On the other hand, data shows that gender pay gap is lower in the services sector where female participation is higher than male, and in cases where there is coverage by union agreement. In general, small and large farms discriminate more in terms of real hourly pay. Raw pay differentials are high among 'white' ethnic group and low in Northern region.

These variations in raw gender pay gap according to various categories initiate extending the basic human capital relationship model incorporating these categories as covariates in addition to education and experience categories. It is therefore worth investigating what percentage of the raw differential can be explained by different characteristic effects other than unexplained discrimination.

IV. ECONOMETRIC MODELS AND ESTIMATION METHODS

Equation (1) is used to estimate panel data models with γ being the parameter of interest referring to the conditional wage differential between men and women ("*male*" dummy is with 1 if male, 0 if female). The basic human capital model is estimated with weakly exogenous covariates of 5 level of qualification dummies (*qual-qual5*) and 9 age categories (*age21 to 25– age 61 to 65*) in the first instance and then other covariates-whether married or not, no of children, whether covered by union agreement, whether doing manual job or not, whether employed in the services sector, three farm size dummies, whether belong to northern region and whether white or not- are included to extend the basic model. Additionally, the extended models include some interaction dummies with "*male"*–"*qual1-qual5*", "*age21 to 25-age61 to 65*", "*married*", "*no. of children*", "*covered*", "*manual"* and "*services"* based on their economic significance and summary statistics of data.

Among the panel data models, the fixed effects estimator is always consistent allowing for arbitrary correlation between a_i and x_{it}, while the random effects model is consistent and more efficient if there is no correlation of unobserved effects to any of the covariates. Here the two estimation techniques are compared using Hausman (1978) test which rejects the null hypothesis of no correlation between a_i and x_{it} and therefore indicates that random effects model is inconsistent. Though with the presence of unobserved heterogeneity OLS estimation is biased and inconsistent and between estimator ignores all time-varying information in the data, these two estimation techniques are also applied to get a complete comparison among different econometric model estimates.

However, the fixed effects estimation technique cannot estimate coefficient of any time invariant variable, in this case of the key variable "*male*" dummy. This can be tackled either by estimating the fixed effects model separately for the two groups-–male and female, or by applying the Hausman Taylor (1981) estimation technique. The former one is only used when a restricted model pooling the two is rejected using Chow (1960) test, and then the conditional differential can be estimated applying Oaxaca-Blinder (1973) decomposition, decomposing the raw differential into conditional differential (unexplained) and characteristic effects (explained). On the other hand, the Hausman Taylor (1981) estimation method is an instrumental variable estimation of the random effects model that uses residuals from fixed effects model as dependent variable to regress on exogenous variables used as instruments for time invariant endogenous and exogenous variables. Then using error variance estimators from the two step regressions, weight for feasible GLS estimation is formed and the transformed variables are then used to estimate a random effects model. In this study both these techniques—male-female separate regression and then Oaxaca-Blinder decomposition, and Hausman Taylor estimation–are applied.

Further to this analysis, quantile regression method is also applied to see whether gender pay gap varies within different pay levels. In line with the analysis of García, Hernandez and Lopez-Nicolas (2001) and Gardeazabal and Ugidos (2005), quantile regressions at 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} qunatiles are estimated with standard errors of parameters from bootstrapping with 100 replications. Then the coefficients of “male’ dummy of different quantiles are tested for equality using simple t-test.

V. RESULTS

The estimation results of the different econometric models can be presented in three broad groups—the conditional differential estimated from different models, over time changes in the differences in conditional differential and the extent of conditional differential within different pay levels.

FIRST, basic human capital regression models using qualification and age categories as covariates yield a relatively high conditional differential compared to the extended models including other covariates. For example, the parameters of “male” dummy are 0.60, 0.62 and 0.61 for between estimators, pooled OLS estimators and random effects estimators respectively in case of log weekly real gross pay and 0.25, 0.27 and 0.26 respectively for log hourly real gross pay in the basic models, whereas in the extended models these conditional differentials are reduced to 0.53, 0.52 and 0.49 log-points (weekly pay) and 0.31, 0.29 and 0.23 log-points (hourly pay) respectively (Tables I and II). From the Hausman test results fixed effects model come out to be better than random effects model, though the former cannot be used to estimate the conditional gender pay differential pooling male and female groups together. Using the variables with significantly different coefficients between fixed effects and random effects models as endogenous, Hausman Taylor regression model is estimated to get consistent and efficient results. Conditional differential in gender pay gap using this model come out to be 0.566 (weekly pay) and 0.203 log-points (hourly pay).

In both basic and extended models, the coefficients of other covariates are consistent to economic reasoning. For example, both weekly and hourly log real gross pay increases with qualification and the level of influence of high qualification is much higher than low qualification levels. In case of age categories, the conventional non-linear relationship (quadratic form) is implicitly reflected here with higher increment to experience during young ages compared to old ages. Wage is lower in Northern region, for married individuals, with increasing number of children, for manual job and in services sector, whereas higher if covered by union agreement, if white and in case of larger farms.

Besides, fixed effects estimate is used to run separate wage models for male and female and then Oaxaca-Blinder decomposition is calculated to get conditional differential and characteristic effects. As reported in Table III, higher qualification has higher return for female compared to male, whereas women are not paid as much as their male counterparts for increased experience. Wage decreases significantly for married women and with number of children they have. Working in larger farms is more beneficial for women and union coverage significantly improves their pay.

TABLE I

GENDER PAY GAP USING HUMAN CAPITAL RELATIONSHIP MODELS

(WEEKLY PAY), 1991-2006#

Variable	Between Estimator	Pooled OLS Estimator	Random Effects Estimator	Fixed Effects Estimator	Hausman Taylor Estimator
			Basic Human Capital relationship Models§		
Male	0.6010*** (0.0113)	0.6212*** (0.0047)	0.6116*** (0.0112)	♣	♣
No of observations	69788	69788	69788	69788	♣
Sigma_a		0	0.54013557		
Sigma_u	0.5809326 (+)	0.61174	0.34967609		
Theta		1	0.70466783		
Hausman Test Statistic			$\chi^2(29) = 793.35$***		
			Extended Human Capital relationship Models♠		
Male	0.3799***	0.3986***	0.3332***	♣	0.4383***
	(0.0551)	(0.0248)	(0.0297)		(0.0389)
Male × qual1	-0.4536***	-0.4377***	-0.3418***	-0.1363*	-0.1324*
	(0.0749)	(0.0294)	(0.0461)	(0.0623)	(0.0596)
Male × qual2	-0.3633***	-0.3930***	-0.2501***	-0.0618	-0.0581
	(0.0478)	(0.0196)	(0.0319)	(0.0468)	(0.0448)
Male × qual3	-0.2254***	-0.1999***	-0.1105***	-0.0076	-0.0072
	(0.0399)	(0.0163)	(0.0244)	(0.0316)	(0.0303)
Male × qual4	-0.1173**	-0.1085***	-0.0406	0.0247	0.0248
	(0.0418)	(0.0174)	(0.0268)	(0.0347)	(0.0333)
Male × qual5	0.0152	0.031	0.0996**	0.0404	0.0391
	(0.0446)	(0.0193)	(0.0308)	(0.0430)	(0.0413)
Male × age21to25	0.1596** (0.0537)	0.0965*** (0.0228)	0.0973*** (0.0173)	0.0635*** (0.0183)	0.0641*** (0.0175)
Male × age26to30	0.1931*** (0.0545)	0.1109*** (0.0227)	0.1522*** (0.0190)	0.0999*** (0.0207)	0.1008*** (0.0199)
Male × age31to35	0.1779** (0.0615)	0.1231*** (0.0233)	0.2014*** (0.0208)	0.1264*** (0.0232)	0.1272*** (0.0223)
Male × age36to40	0.2715*** (0.0636)	0.1528*** (0.0236)	0.2191*** (0.0219)	0.1106*** (0.0250)	0.1115*** (0.0240)
Male × age41to45	0.2889*** (0.0658)	0.2168*** (0.0237)	0.2366*** (0.0225)	0.0860** (0.0264)	0.0869*** (0.0253)
Male × age46to50	0.3433*** (0.0657)	0.2937*** (0.0240)	0.2585*** (0.0233)	0.0645* (0.0280)	0.0653* (0.0269)
Male × age51to55	0.5342*** (0.0685)	0.3817*** (0.0250)	0.3024*** (0.0246)	0.0722* (0.0300)	0.0726* (0.0288)
Male × age56to60	0.4372*** (0.0718)	0.3993*** (0.0269)	0.3033*** (0.0264)	0.043 (0.0325)	0.043 (0.0312)

(Cont. Table I)

Variable	Between Estimator	Pooled OLS Estimator	Random Effects Estimator	Fixed Effects Estimator	Hausman Taylor Estimator
Male × age61to65	0.5966*** (0.0776)	0.4827*** (0.0343)	0.3608*** (0.0324)	0.0523 (0.0391)	0.0518 (0.0375)
Male × married	0.2714*** (0.0287)	0.2241*** (0.0103)	0.1132*** (0.0110)	0.0623*** (0.0119)	0.0631*** (0.0114)
Male × nchild	0.2568*** (0.0155)	0.2718*** (0.0054)	0.2450*** (0.0053)	0.2421*** (0.0056)	0.2435*** (0.0054)
Male × manual	0.0668* (0.0298)	0.0477*** (0.0111)	0.0151 (0.0114)	-0.0006 (0.0123)	-0.0011 (0.0118)
Male × covered	-0.2901*** (0.0240)	-0.2255*** (0.0087)	-0.0855*** (0.0088)	-0.0529*** (0.0094)	-0.0528*** (0.0090)
Male × services	0.0146 (0.0279)	0.0363*** (0.0100)	0.0387*** (0.0093)	0.0367*** (0.0099)	0.0384*** (0.0094)
Conditional Differential	0.5257	0.5224	0.4884	♣	0.5659
No. of observations	67,855	67,855	67,855	67,855	67,855
Sigma_a	0.4986279 (+)	0	0.45805156		0.81651895
Sigma_u		0.546	0.33301932		0.33285232
Theta		1	0.65420225		0.85750284
Hausman test statistic			$\chi^2(57) =$ 1,092.58***		

Notes: **#**Estimation based on British Household Panel Survey 1991-2006. Dependent variable is log real weekly pay (lrwkpay). Figures in the parentheses refer to respective standard errors.
♣ Cannot be estimated.
§ Basic models include male dummy, qualification dummies, age categories and time dummies, among which only the variable of interest "male" is reported.
♠ Extended models include region, ethnicity, marital status, union coverage, no. of children, manual job, service sector and farm size dummies in addition. Only "male" dummy and its interactions are reported.
\+ 0.5809326 and 0.4986279 refer to sd(u_i + avg(e_i.))
***, **, and * indicate that the parameters are significant at 0.1%, 1% and 5% levels.

TABLE II
GENDER PAY GAP USING HUMAN CAPITAL RELATIONSHIP MODELS (HOURLY PAY), 1991-2006#

Variable	Between Estimator	Pooled OLS Estimator	Random Effects Estimator	Fixed Effects Estimator	Hausman Taylor Estimator
			Basic Human Capital relationship Models§		
Male	0.2519*** (0.0079)	0.2709*** (0.0034)	0.2609*** (0.0078)	♣	♣
No. of observations	68,653	68,653	68,653	68,653	♣
Sigma_a	0.4045372 (+)	0	0.3691		
Sigma_u		0.44163	0.2699		
Theta		1	0.6517		
Hausman Test Statistic			$\chi^2(29) =$ 2933.36***		
			Extended Human Capital relationship Models♠		
Male	0.3029*** (0.0405)	0.2797*** (0.0189)	0.1742*** (0.0231)	♣	0.1489** (0.0560)

(Cont. Table II)

Variable	Between Estimator	Pooled OLS Estimator	Random Effects Estimator	Fixed Effects Estimator	Hausman Taylor Estimator
Male × qual1	-0.2472***	-0.1898***	-0.0663	0.0805	0.0835
	(0.0549)	(0.0225)	(0.0359)	(0.0507)	(0.0482)
Male × qual2	-0.2323***	-0.2146***	-0.0885***	0.0303	0.0332
	(0.0351)	(0.0149)	(0.0245)	(0.0378)	(0.0360)
Male × qual3	-0.1291***	-0.0950***	-0.0182	0.0608*	0.0617*
	(0.0293)	(0.0124)	(0.0189)	(0.0255)	(0.0243)
Male × qual4	-0.0750*	-0.0436***	0.0104	0.0733**	0.0739**
	(0.0307)	(0.0132)	(0.0208)	(0.0281)	(0.0267)
Male × qual5	-0.0248	-0.0275	0.0663**	0.0923**	0.0924**
	(0.0327)	(0.0147)	(0.0237)	(0.0347)	(0.0331)
Male × age21to25	0.0942*	0.0633***	0.0630***	0.0432**	0.0433**
	(0.0394)	(0.0173)	(0.0138)	(0.0147)	(0.0140)
Male × age26to30	0.1114**	0.0660***	0.0858***	0.0568***	0.0569***
	(0.0400)	(0.0172)	(0.0151)	(0.0167)	(0.0159)
Male × age31to35	0.0794	0.0708***	0.1144***	0.0730***	0.0731***
	(0.0450)	(0.0177)	(0.0165)	(0.0187)	(0.0178)
Male × age36to40	0.1497**	0.1209***	0.1512***	0.0872***	0.0874***
	(0.0465)	(0.0180)	(0.0174)	(0.0202)	(0.0192)
Male × age41to45	0.2286***	0.1642***	0.1705***	0.0775***	0.0777***
	(0.0482)	(0.0180)	(0.0178)	(0.0213)	(0.0203)
Male × age46to50	0.1427**	0.1758***	0.1639***	0.0445*	0.0447*
	(0.0481)	(0.0183)	(0.0183)	(0.0226)	(0.0215)
Male × age51to55	0.2772***	0.2010***	0.1594***	0.0151	0.0153
	(0.0503)	(0.0190)	(0.0193)	(0.0242)	(0.0230)
Male × age56to60	0.2150***	0.1648***	0.1105***	-0.0524*	-0.0522*
	(0.0528)	(0.0205)	(0.0208)	(0.0262)	(0.0250)
Male × age61to65	0.079	0.0649*	0.0316	-0.1501***	-0.1499***
	(0.0573)	(0.0263)	(0.0257)	(0.0317)	(0.0302)
Male × married	0.1134***	0.1001***	0.0360***	0.0004	0.0006
	(0.0211)	(0.0078)	(0.0088)	(0.0096)	(0.0092)
Male × nchild	0.0588***	0.0707***	0.0515***	0.0500***	0.0500***
	(0.0114)	(0.0041)	(0.0043)	(0.0045)	(0.0043)
Male × manual	-0.0516*	-0.0332***	-0.0145	-0.0036	-0.0041
	(0.0219)	(0.0085)	(0.0090)	(0.0099)	(0.0095)
Male × covered	-0.1022***	-0.0942***	-0.0311***	-0.0144	-0.0143*
	(0.0176)	(0.0066)	(0.0070)	(0.0076)	(0.0072)
Male × services	-0.0766***	-0.0555***	-0.0300***	-0.0299***	-0.0291***
	(0.0205)	(0.0076)	(0.0075)	(0.0080)	(0.0076)
Conditional Differential	0.3107	0.2968	0.2326	♣	0.2033
No. of observations	66,762	66,762	66,762	66,762	66,762
Sigma_a	0.3643047	0	0.3281488		2.2839241
Sigma_u	(+)	0.41234	0.26669613		0.26656231
Theta		1	0.60221779		0.98656127
Hausman test statistic			$\chi^2(57) =$ 1656.45***		

Notes: # Estimation based on British Household Panel Survey 1991-2006. Dependent variable is log real hourly pay (lrhrpay). Figures in the parentheses refer to respective standard errors.

♣ Cannot be estimated.

§ Basic models include male dummy, qualification dummies, age categories and time dummies, among which only the variable of interest "male" is reported.

♠ Extended models include region, ethnicity, marital status, union coverage, no. of children, manual job, service sector and farm size dummies in addition. Only "male" dummy and its interactions are reported.

+ 0.4045372 and 0.3643047 refer to sd(u_i + avg(e_i.))

***, **, and * indicate that the parameters are significant at 0.1%, 1% and 5% levels.

TABLE III

FIXED EFFECTS ESTIMATION: MALE-FEMALE SEPARATE REGRESSION RESULTS 1991-2006

Variable	Weekly Pay		Hourly Pay	
	Male	Female	Male	Female
Constant	0.6670*** (0.0266)	0.1817*** (0.0341)	-2.9210*** (0.0249)	0.1817*** (0.0247)
qual1	0.2536*** (0.0368)	0.4379*** (0.0494)	0.2196*** (0.0347)	0.4379*** (0.0362)
qual2	0.1769*** (0.0291)	0.2826*** (0.0344)	0.1076*** (0.0273)	0.2826*** (0.0250)
qual3	0.0075 (0.0192)	0.0583* (0.0238)	0.0078 (0.0180)	0.0583* (0.0172)
qual4	-0.0339 (0.0216)	-0.0186 (0.0257)	-0.019 (0.0202)	-0.0186 (0.0187)
qual5	-0.0672* (0.0270)	-0.0286 (0.0326)	-0.0337 (0.0253)	-0.0286 (0.0237)
age21to25	0.3318*** (0.0117)	0.2777*** (0.0159)	0.2609*** (0.0110)	0.2777*** (0.0115)
age26to30	0.4507*** (0.0155)	0.3716*** (0.0209)	0.3728*** (0.0146)	0.3716*** (0.0152)
age31to35	0.4773*** (0.0203)	0.3833*** (0.0269)	0.4022*** (0.0190)	0.3833*** (0.0195)
age36to40	0.4527*** (0.0251)	0.3876*** (0.0331)	0.3765*** (0.0236)	0.3876*** (0.0240)
age41to45	0.3721*** (0.0302)	0.3456*** (0.0393)	0.2992*** (0.0283)	0.3456*** (0.0286)
age46to50	0.2803*** (0.0353)	0.2880*** (0.0458)	0.2190*** (0.0331)	0.2880*** (0.0333)
age51to55	0.1501*** (0.0407)	0.1624** (0.0527)	0.0981* (0.0382)	0.1624** (0.0383)
age56to60	-0.0241 (0.0462)	0.0318 (0.0597)	-0.0349 (0.0434)	0.0318 (0.0434)
age61to65	-0.3173*** (0.0522)	-0.2586*** (0.0682)	-0.2276*** (0.0491)	-0.2586*** (0.0496)
north	-0.0625** (0.0197)	-0.0081 (0.0266)	-0.0427* (0.0187)	-0.0081 (0.0194)
married	0.0225** (0.0075)	-0.0384*** (0.0091)	0.0185** (0.0070)	-0.0384*** (0.0066)
nchild	0.0116*** (0.0033)	-0.2299*** (0.0046)	0.0130*** (0.0031)	-0.2299*** (0.0034)
manual	-0.0289*** (0.0069)	-0.0304** (0.0104)	-0.0240*** (0.0065)	-0.0304** (0.0076)
covered	0.0630*** (0.0058)	0.1079*** (0.0076)	0.0690*** (0.0055)	0.1079*** (0.0055)
services	-0.0429*** (0.0058)	-0.0796*** (0.0083)	-0.0328*** (0.0054)	-0.0796*** (0.0060)
sz25_99	0.0776*** (0.0058)	0.1069*** (0.0073)	0.0590*** (0.0055)	0.1069*** (0.0053)
sz100_499	0.1032*** (0.0065)	0.1467*** (0.0085)	0.0839*** (0.0061)	0.1467*** (0.0062)
sz500	0.1192*** (0.0076)	0.1667*** (0.0100)	0.1045*** (0.0071)	0.1667*** (0.0073)
Constant	0.6670*** (0.0266)	0.1817*** (0.0341)	-2.9210*** (0.0249)	0.1817*** (0.0247)
No. of Observation	33,183	34,672	32,588	34,174
Chow Test Statistic	F(38, 67777)= 90.383418***		F(38, 66684)= 13.292236**	

Notes: ***, **, and * indicate that the parameters are significant at 0.1%, 1% and 5% levels. Figures in the parentheses refer to respective standard errors. Time dummies are not reported.

In comparison to the Hausman Taylor estimates of conditional differential of gender pay, the Oaxaca-Blinder decomposition results are much higher. More than 95% of the raw differential remains unexplained in case of both weekly pay and hourly pay (Table IV).

TABLE IV

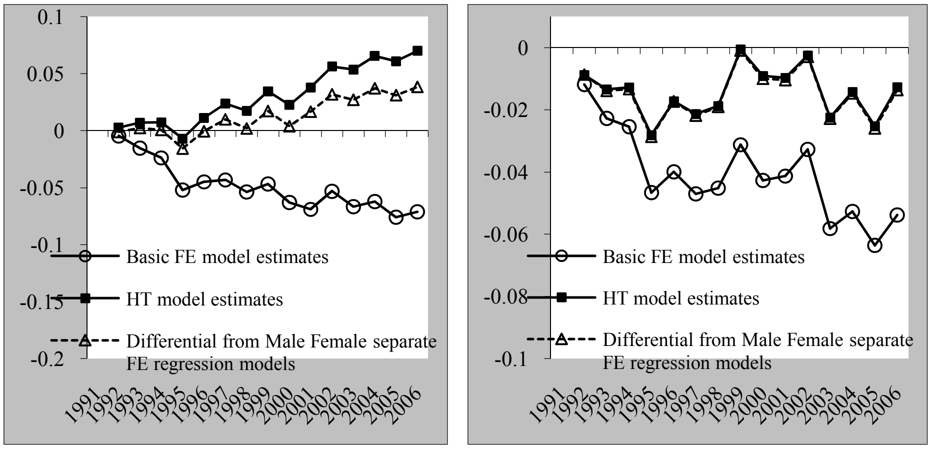
OAXACA-BLINDER DECOMPOSITION USING MALE FEMALE SEPARATE FIXED EFFECTS ESTIMATION MODELS

		Weekly pay	Hourly pay
Average Male wages		1.2994 (0.0011)	-2.3528 (0.0009)
Average Female wages		0.6494 (0.0013)	-2.6456 (0.0009)
Raw differential		0.6499 (0.0035)	0.2929 (0.0028)
Decomposition			
Using high outcome group (Male) coefficients as reference	Characteristic Effect ($(\bar{x}_1 - \bar{x}_2)\hat{\beta}_1$)	0.0168 (0.0034)	0.0128 (0.0031)
	Conditional Differential ($\hat{\Delta}_2 = \bar{x}_2(\hat{\beta}_1 - \hat{\beta}_2)$)	0.6332 (0.0039)	0.2800 (0.0032)
Using low outcome group (Female) coefficients as reference	Characteristic Effect ($(\bar{x}_1 - \bar{x}_2)\hat{\beta}_2$)	0.0242 (0.0045)	0.0040 (0.0033)
	Conditional Differential ($\hat{\Delta}_1 = \bar{x}_1(\hat{\beta}_1 - \hat{\beta}_2)$)	0.6258 (0.0047)	0.2889 (0.0035)

Note: Figures in the parenthesis refer to respective standard errors.

SECOND, the raw differentials over time are decreasing and using the basic fixed effects model with "male" interaction dummies to different waves, the difference in differential shows a decreasing pattern over time in case of both weekly pay and hourly pay models. However, estimation results show that this pattern is not significant if other covariates are incorporated. In case of weekly pay, Hausman Taylor estimates and differential from male–female separate fixed effects models show even an increasing pattern, though the results are insignificant as reported. For hourly pay, the magnitudes are very small and do not represent any pattern. Figure 1 shows over time differences in differential estimated using these models with wave1 (1991) being the base year.

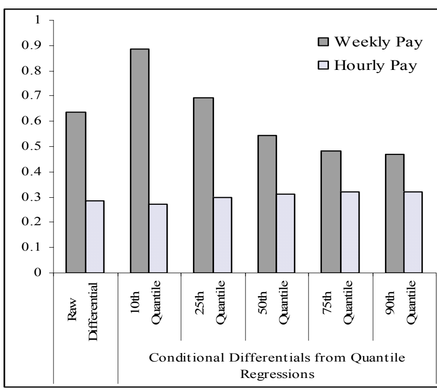
FIGURE 1: **Gender Pay Gap: Differences in Differential Over Time**



Weekly Pay **Hourly Pay**

THIRD, investigating gender pay differential within different pay levels, the quantile regression results show an interesting pattern in case of log real weekly pay. As reported in Figure 2, the conditional differential significantly decreases with increasing pay levels implying that gender pay discrimination is higher in case of low income groups. This is consistent to the earlier findings that improvement in women qualifications has significant influence in explaining gender pay gap. However, in case of log real hourly pay, the scenario is the opposite, though not significant.

FIGURE 2: **Gender Wage Differential in Different Wage Levels (Quantile Regression Results)**



	Weekly Pay		Hourly Pay	
	Conditional Differential	Difference between quantiles	Conditional Differential	Difference between quantiles
10th Quantile	0.887		0.272	
		0.1922*** (0.0095)		-0.0267*** (0.0048)
25th Quantile	0.695		0.299	
		0.1517*** (0.0057)		-0.0129*** (0.0038)
50th Quantile	0.5433		0.312	
		0.0600*** (0.0050)		-0.0058 (0.0043)
75th Quantile	0.4833		0.318	
		0.0141*** (0.0054)		-0.0038 (0.0054)
90th Quantile	0.4691		0.322	

*** indicates that the difference is significant at 0.01% level. Figures in the parenthesis are the respective standard errors.

A comparative analysis of estimates from different econometric techniques reveals that a well-specified econometric model, the Hausman Taylor model in this case, can reduce raw gender pay differential from 32.84% to 22.54% (a 31.31% reduction) in case of real hourly pay. However, there is no significant reduction of this differential over time and this prevails for almost all pay levels.

VI. CONCLUSION

Using BHPS 16 years panel data this study attempted to decompose the raw differential of gender pay into differential due to characteristic effects and unexplained (conditional) differential using different estimation techniques. Results are analysed from three main perspectives. First, gender pay gap analysis is considerably sensitive to econometric techniques used. While estimates are upward biased in case of exclusion of some significant covariates, use of inappropriate estimation techniques make it underestimated.

A well-specified econometric model, the Hausman Taylor model in this case, can reduce raw gender pay differential from 32.84% to 22.54% (a 31.31% reduction) in case of real hourly gross pay and from 89.08% to 76.12% (a 14.55% reduction) in case of real weekly gross pay. Estimates of conditional differentials using well known Oaxaca-Blinder decomposition, on the other hand, are much higher (more than 95% of the raw differential remains unexplained). However, it should be noted that the method has its own limitations in terms of not handling factors which are present for only one sex, or considers slope parameters of women in comparison to other women and men in comparison to other men, not across sex.

Second, although it is suggested in some literature (see, for example, Myck and Paull 2004) that there exists a declining trend of gender pay differential over time, using high quality panel data, sophisticated econometric techniques and controlling for significant economic variables, this study does not find supporting evidence to this hypothesis. Finally, wage differential varies positively with pay levels in case of weekly pay, but this pattern does not prevail in case of hourly pay (which accounts more for the discrimination from employer's side). In other words, given that hourly pay takes into account the usual hours worked per week, and that men tend to work longer hours than women, there is no significant pattern of discrimination in hourly pay at different wage levels.

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