The gender pay gap in UK universities 2004/5 to 2019/20

by

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Abstract

Using UK data supplied by universities, this paper confirms that women academics earn less than men, even after controlling for a range of covariates. Despite narrowing after 2004/05, the observed (unconditional) pay gap was still –0.089 in 2019/20, while the conditional pay gap was relatively unchanged remaining at around –0.050 in 2019/20. The results are consistent with the literature on why pay gaps might occur, with the key disparity occurring when women face a higher cost of investment and statistical discrimination, linked to bias, to achieve promotion. That is, the results presented here suggest that earnings gaps are significantly reduced when grade-balanced gender sub-groups are compared, suggesting conditional wage differences are more likely due to bias rather than any inherent differences in (research) productivity.

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Gender; pay gaps; UK universities.

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I. Introduction

In academia, women continue to face a gender pay gap compared to men, even after accounting for observable productivity-related characteristics (Ceci et al., 2014; Mumford and Sechel, 2020; Gamage et al., 2020). The existing literature highlights university demand-side differences in recruiting and promoting academics based on perceived productivity, as well as supply-side differences in investment activities that enhance productivity and lead to promotion. Such disparities between men and women are attributed to statistical discrimination and higher costs of investment linked to bias (Das and Joubert, 2023).

Longitudinal studies on the gender pay gap in UK universities are scarce, with most studies limited to a small number of subject areas and universities as well as relying on single-year cross-sectional surveys (with usually small sample-sizes) which are restricted in their ability to explain the determinants of changes in the pay gap over time. Cross-sectional data often is missing information on relevant variables such as how long an individual has worked as an academic (at different institutions, at different grades and on different contracts). Longitudinal studies using cross-sectional time-series data that cannot link individuals over time are unable to employ panel-data techniques (fixed- and random effects) which generally lead to better parameter estimates of the model estimated, since they help to control for heterogeneity across individuals. This study analyses sixteen years of population panel data from all UK universities provided by the Higher Education Statistical Authority (HESA) to determine the size of the pay gap and factors associated with it. The analysis reveals a persistent pay gap even after controlling for covariates. The unconditional (observed) pay gap was -0.089 in 2019/20, and the conditional (i.e., after controlling for covariates) pay gap remained around -0.050.

Significant variations were observed across different disciplines and academic grades. For instance, Veterinary Science had the largest conditional pay gap (-0.107), while Continuing Education showed the smallest gap (+0.1). The pay gaps in 2019/20 for Assistant through to full Professors were -0.025, -0.021, and -0.049, respectively. Our analysis further indicates that if earnings are compared based on comparable sub-groups of women and men within the same academic rank, the distribution of pay is similar, except at the highest earnings levels where men continue to dominate.

Addressing the gender pay gap is crucial as it signifies inefficiency and inequity in university employment practices. The results from this paper point to a need to lessen and/or remove the barriers hindering the promotion and retention of women throughout their careers.

II. Sources of bias

The extant literature on bias in higher education examines two main streams of factors, namely demand-side and supply-side, that contribute to bias.[1] Demand-side factors focus on statistical discrimination, which is particularly prominent in the work of economists (Arrow, 1998). This leads to a broader consideration of "stereotyping," which creates supply-side constraints and acts as barriers to women's progress in academia by impeding their investment in productivity-enhancing behaviours. These barriers

[1] Due to limitations on space, the broader literature on discrimination leading to gender pay gaps in the wider labour market are briefly touched on in the unpublished appendix, where there is also a more thorough discussion relating specifically to academics.

reinforce statistical discrimination (a feedback effect) and often result in women underinvesting in activities that could enhance their productivity.

Statistical discrimination occurs when limited and imprecise information about an individual's productivity is available, leading to the use of average productivity measures from the individual's group (Charles and Guryan, 2011). This average measure may underestimate women's actual productivity due to negative stereotypes associated with women. However, economists generally assume that the average measure is reasonably accurate, and over time, as more information on actual productivity becomes available, it receives higher weighting, reducing or eliminating statistical discrimination. Despite this, Lundberg and Startz (1983) and Coate and Loury (1993) demonstrate that statistical discrimination can still lower productivity-enhancing investment within affected sub-groups due to the perceived lower rewards, even when all gender groups possess similar underlying productivity levels. Thus, Della Giusta and Bosworth (2020) argue that the impact of statistical discrimination due to stereotyping, which involves exaggerating small differences between groups, may not diminish over time and is difficult to correct with new information.

Factors contributing to bias that hinder career advancement include women's reluctance to apply for positions (Nielsen, 2016; Ceci et al., 2014), the perception of women as more conscientious and compliant (Eswaran, 2014), and their lesser willingness to compete (Buser et al., 2014; Booth et al., 2019; Nicholls, 2022). In contrast, alpha men tend to be more assertive and ambitious (Coate and Howson, 2016), rate and cite their work more highly (King et al., 2017), and when women internalize these cultural norms and stereotypes, it often leads to negative outcomes, such as being perceived as "aggressive" (Monroe, 2013).

Consequently, research has shown that women publish less frequently than their male counterparts (Bird, 2011), face longer peer review times for their submissions (Branch and Kvasnicka, 2017), are less likely to be mentored (Buch et. al., 2011), and are often subjected to higher standards in top journals (Hengel, 2022). Academic prestige factors associated with career advancement are more likely to be established and acquired by male academics (Coate and Howson, 2016), resulting in slower and less frequent promotions for women (Winslow and Davis, 2016).

Differences in promotion likelihood may arise if family commitments reduce the quality time that female researchers allocate to research activities, especially during the early career years that coincide with peak family formation years (Probert, 2005; Mason, Wolfinger, and Goulden, 2013; Winslow and Davis, 2016). Goldin (2014) emphasizes that "…winner-take-all positions, such as … tenured professor at a university …are … positions for which considerable work hours leads to a higher chance of obtaining the reward". She concludes that the gender pay gap is primarily due to differences in the timing and continuity of work hours, rather than simply the number of hours worked.

Regarding gender pay studies in the UK, we are aware of only four cross-sectional studies that have included individual productivity measures.[2] Ward (2001) found that publication productivity did not significantly affect earnings for Senior Lecturers and Professors in five major Scottish universities for the 1995/6 period. For economists,

[2] For the U.S. there are more studies which have access to periodic surveys that includes productivity measures (e.g., Kelly and Grant, 2012, use the National Study of Post-Secondary Faculty); as well as subject specific surveys (e.g., Ginther and Hayes, 1999, that use data collected by the American Economic Association) or individual university data (e.g., Binder et. al., 2010). Generally, these studies find gender differences in salaries are determined by rank, and that even after controlling for productivity sizeable conditional pay gaps remain.

Blackaby et al. (2005) found that while publications and grant capture were statistically significant, they were not important when considering earnings by academic rank. However, using similar data to Blackaby et. al. (op. cit.), Mumford and Sechel (2020) found that publications were an important determinant of the gender pay gap. Lastly, Bandiera et al. (2016) examined the gender pay gap at the LSE using internal research productivity scores, concluding that controlling for predicted REF scores had minimal effect on the pay gap, indicating lower pay for women with the same level of research productivity. Thus, as noted by Kim et. al. (2023) "… productivity is an important determinant of wages but it explains little of the gender pay gap" (p. 1).[3]

III. Data and method

The dataset used comprises information on the population of individual staff supplied annually by UK universities to the Higher Education Statistical Authority (see HESA, 2022). This dataset offers a novel perspective on the dynamics of the higher education sector. Observations for each academic member of staff on a teaching and/or research

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[3] For example, Blackaby et. al. (op. cit.) reported a 11 log percentage points gender pay gap after controlling for ethnicity, marital status and age, which declines to 9.8% when productivity and workforce covariates are also included. Separately, there is a parallel literature on gender gaps in academic promotions which confronts the issue of whether controlling for research productivity in empirical work 'explains away' gender-gaps. The overwhelming evidence (including for the UK) is that research productivity is a strong determinant of academic rank but it does not explain much of the gender-gap (e.g., Santos and Dang Van Phu, 2019; Brower and James, 2020).

contract covering all universities in the UK (excluding those listed in Table A.1) were used to estimate the following baseline Mincer-type panel-data model:

$$\ln W_{it} = \beta_j(gender_i \times year_t \times \boldsymbol{X}_{it}) + \alpha_i + \varepsilon_{it} \qquad (1)$$

where W refers to full-time equivalent (FTE) real annual earnings for individual *i* in year *t*;[4] *gender* is a dummy coded 1 for women;[5] *year* covers the academic years 2004/05 to 2019/20; $\boldsymbol{X}$ is a vector of covariates comprising characteristics such as age (and age-squared), ethnicity, nationality, the proportion of a full-time equivalent contract worked (and its squared term), and length of time working in the university system (and its squared term)[6,7]; and α_i, ε_{it} denote different intercepts for each individual *i* and a random error term, respectively. Each of the covariates is allowed to vary by year and by gender sub-group, and therefore overall there are *j* parameters to be estimated. A full list of variables (and how they were constructed) that enter Equation (1) is provided in Table A.2 in the Supplementary Appendix. Note, in common with most of the extant literature, academic grade is omitted from Equation (1), as in the UK higher grades equate to generally non-overlapping higher pay scales. That is, once appointed to a particular grade, an individual is usually placed at the bottom of the pay scale, securing annual pay increases in line with national pay awards as well as automatic incremental increases

[4] HESA staff returns record earnings as that which would be earned if full-time; there is a separate measure of the actual FTE of each individual. Data is not collected on hours worked, as universities assume full-time academic staff typically work 36.5 contracted hours over the work week.

[5] The very small number of staff classified as 'other/non-binary' are omitted from the analysis.

[6] FTE and age were also allowed to interact. Note, all continuous variables (except % female) were logged in Equation (1) – see Table A.2 for details.

[7] Note, not all of the covariates vary over time, such as ethnicity and nationality.

until the top of the scale is achieved (above automatic increases, and increases above the pay scale ceiling, can occur if progression panels deem performance is 'above average'). For Professors, who are on spot salaries, pay increases are also dealt with by progression panels who may award higher pay linked to performance. Thus, including academic grade in Equation (1) is likely to significantly bias downwards the size of the gender wage-gap (as well as reduce the importance of other determinants particularly age).[8]

In line with nearly all large-scale studies of university pay, there is no direct measure of (research) productivity available in the HESA dataset, as such information is not collected annually but rather is assessed periodically in the Research Assessment Exercise (RAE) and the Research Excellence Framework (see REF, 2021, for details of the current procedures used). The RAE/REF grade point average (GPA) results for units of assessment covering 2001, 2008 and 2014 have been merged into the HESA dataset to provide some indication of differences across units and universities of average research productivity – further details are provided in the discussion of Table A.2.

Estimating Equation (1) produces unconditional (i.e., estimating the model excluding X) and conditional estimates (including covariates) of the gender pay gap. For comparison purposes, OLS, matching estimators, and random effects (RE) were each applied, the latter in principle having the additional benefit of capturing (via the α_i) individual-specific differences that should help control for other individual productivity effects. It is not relevant to estimate Equation (1) using a fixed-effects model as key variables (especially gender) do not vary over time.

[8] The unpublished appendix contains a sub-section with robustness checks that also confirms this downward bias that results when adding in academic grade to Equation (1).

Given the potential importance of differences in hours worked for men and women (here proxied by differences in FTE status), and how this may impact on productivity, promotion prospects and thus pay, Equation (1) was also re-estimated with ln FTE_{it} as the dependent variable (and this variable omitted from the right-hand-side of the model). The purpose for doing this was to test whether women are more likely to have lower FTE than men (and especially whether they have relatively lower FTE status during the years typically associated with child-bearing and child-rearing) and, if so, the impact on earnings (using Equation 1) of relative differences in FTE for women and men. Note, HESA data for 2015/16 onwards does have a variable that records whether maternity/paternity leave was taken, but over 97% of women aged 27 to 46 years in the data are returned as 'unknown' which is unlikely to reflect the actual uptake of maternity leave.

In addition, a Kitagawa-Oaxaca-Blinder (KOB) decomposition (Kitagawa, 1955; Oaxaca and Ransom, 1994; Blinder; 1973) is applied to the panel data (using the STATA 'xtoxaca' routine written by Kröger and Hartmann, 2021) to estimate the contribution of 'endowment' and 'other' factors to the difference in mean (ln) earnings between women and men in 2004/05, 2019/20 and the change in this difference between these two dates. Using this decomposition provides some guidance of whether gender pay gaps were due to a different (observable) 'mix' of characteristics (i.e., differences in $\overline{\boldsymbol{X}}_{it}$) as opposed to (i) different relationships for women and men in how the $\boldsymbol{X}_{it}$ in Equation (1) determined earnings (i.e., differences in $\hat{\beta}_j$ across genders) and (ii) differences in the distribution of unobservable characteristics, (ε_{it}), such as effort. Specifically, rewriting Equation (1) for any period t as the expected difference between earnings for women (F) and men (M), assuming $\varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^2)$, and rearranging gives:

$$E\left(\ln \widehat{W}^F\right) - E\left(\ln \widehat{W}^M\right) =$$

$$[E(\boldsymbol{X}^F) - E(\boldsymbol{X}^M)]'\boldsymbol{\beta}^M + E(\boldsymbol{X}^M)'(\boldsymbol{\beta}^F - \boldsymbol{\beta}^M) + [E(\boldsymbol{X}^F) - E(\boldsymbol{X}^M)]'(\boldsymbol{\beta}^F - \boldsymbol{\beta}^M) \quad (2)$$

The first term shows that part of the difference in $E\left(\ln \widehat{W}\right)$ between women and men that is predicted by differences in observed individual characteristics. This is referred to as the 'endowments' or 'explained' component. The second term in Equation (2) measures that part of the difference in $E\left(\ln \widehat{W}\right)$ that is attributable to differences in coefficients, i.e., the 'unexplained' component which shows the hypothetical difference in $E\left(\ln \widehat{W}\right)$ if women had the same characteristics as men. The third component in Equation (2) is an interaction term that allows for the effect of differences in both individual characteristics and coefficients across genders. In the results presented below, this third term is relatively small.[9] Estimates of $\boldsymbol{\beta}^{F,M}$ are obtained by estimation of Equation (1). Note, this use of the KOB decomposition has led some to interpret the 'unexplained' component as causal evidence of bias invoking the methods and arguments put forward in the treatment effects literature; for Fortin et. al. (2011) this is unlikely to be valid because (i) 'treatment' (here gender) is generally not a choice or manipulable; and (ii) the $\boldsymbol{X}_{it}$ (and unobservables ε_{it}) are unlikely to be pre-treatment variables – instead they can assume different values as a consequence of treatment (e.g., anticipation of bias will lead to

[9] The decomposition in Equation (2) is formulated from the viewpoint of men such that the endowment effect is based on the group differences weighted by $\boldsymbol{\beta}^M$. Equation (2) could be expressed from the viewpoint of women; however, the stated formulation is preferred because, as stated by McNabb and Wass (1997) "… it shows what would happen if women were treated the same way as men. Since this is a male-dominated labour market this is the most appropriate comparison" (p. 339). In any event the interpretation of the results obtained here do not change substantially whichever approach is taken. See supplementary appendix for more details.

different levels of, for example, effort, hours or investment in other factors that impact on promotion and progression).

Decomposition of changes in the gender pay gap over time is undertaken using an expanded version of Equation (2) that compares two time periods (see section 4 of Kröger and Hartmann, 2021). There are various approaches that can be taken, with the 'interventionalist' approach preferred since it takes as given the initial differences in levels between gender groups at a reference date and then decomposes the change in the difference into changes in 'endowments' and unexplained changes in 'coefficients'.

IV. Results

Unconditional and conditional pay gaps are obtained from estimating Equation (1) are analysed for different sub-groups and over time.[10] The wage setting process is then examined to determine if there are differences by gender, particularly in terms of salary increases with age and hours worked. The KOB decomposition approach is used to explore the contribution of 'coefficients' and 'endowments' to the pay gap.[11]

Figure 1 and Table 1 around here

[10] Note, Equation (1) – and subsequently Equation (2) – were also re-estimated excluding outliers identified using the 'bacon' routine in STATA (deleting the top 5% of ± outliers) with very little change to the results obtained. Additionally, including 133 dummies representing each university had only a minor effect on the results obtained (see footnote 16 below).

[11] There is also a preliminary, initial analysis (presented in the unpublished appendix) that points to promotion and retention, known as the 'leaky pipeline,' significantly contributing to gender pay differences.

(a) Gender pay gaps

The unconditional and conditional pay gaps obtained from estimating Equation (1), using data for all UK universities, are reported in Figure 1.[12] The raw pay gap was –0.138 in 2004/05, narrowing to –0.089 by 2019/20. After conditioning on covariates, the gap was estimated between –0.060 to –0.031 at the start of the period covered, and –0.055 to –0.047 by 2019/20, with the OLS results suggesting a small increase in the gap over time while there was a slight narrowing based on the results using random effects. These overall pay gaps hide differences across different types of universities, faculties within universities, academic grades and especially across 45 cost centres equating to broad academic disciplines (see Figures A1 and A2 in the unpublished appendix).[13]

Table 1 reports the results from estimating Equation (1) for all academics and separately by academic grade.[14] It shows that unconditional gender-pay gaps by 2019/20 were only –0.007 for Assistant Professors, –0.019 for Associate Professors, and much larger at

[12] Note, Equation (1) is estimated using panel data e.g., the unconditional pay gap (i.e., dropping the $\boldsymbol{X}_{it}$ and replacing α_i with a constant α_0) produces separate parameter estimates of the β_j for women in each year.

[13] Figures A.1 and A.2 in the unpublished appendix show unconditional gender pay gaps are much larger in the 24 Russell group research-intensive sector and least prevalent in the post-1992 'new' university sector. Gaps are also much larger in medicine and health faculties, followed by science and business faculties, and relatively smaller in arts and humanities.

[14] For completeness, results by cost centre are reported in Table A.3 in the unpublished appendix.

–0.057 for Professors.[15] However, after conditioning on covariates, the gap was estimated to have been –0.025, –0.021 and –0.049, respectively for Assistant through to full Professor (based on the RE estimates). Thus, whilst the conditional gap was twice as large for Professors, it remained important for other academic grades.

Table 2 around here

(b) Wage setting process across genders

The elasticities obtained from estimating Equation (1) using OLS and Random Effects are provided in Table 2.[16] Although similar to the OLS results, the RE results would normally be preferred, given the large (significant) value of ρ obtained, signifying the proportion of the variation in the overall random error term ($\alpha_i + \varepsilon_{it}$) due to differences in the α_i. In what follows both the OLS and RE results are discussed, recognising that if the α_i are correlated with $\boldsymbol{X}_{it}$ then both OLS and RE both produce biased results.[17]

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[15] See also the additional analysis presented in the unpublished appendix in the sub-section 'unconditional gender pay gaps adjusting for academic grade', which reinforces the point that wage-gaps largely disappear after accounting for academic grade (except for Professors).

[16] The results based on using propensity-score matching (Table A.4), to ensure women and men were compared on the basis of 'balanced' samples, are similar to the those using the full sample, and so are not discussed further. Other robustness checks are provided in Table A.5 including adding academic grade as a regressor, organisational fixed effects (university dummies) and excluding outliers. These are discussed in the supplementary appendix and essentially confirm the results in Table 2 are robust.

[17] For completeness, Table A.6 in the Supplementary Appendix shows the results from estimating Equation (1) using a fixed-effects (FE) estimator *separately* for men and women while including only those variables that vary over time (and therefore omitting the variable $gender_i$); comparing the results with the comparable estimates from the RE model shows that the difference between the parameter estimates for men and women are consistent.

The first row of results in Table 2 show that the (conditional) impact on (*ln*) earnings of being female differs depending on which gender results are considered. This occurs because the marginal effects were calculated separately for men and women (following the estimation of the pooled panel data using Equation 1), and therefore use only the characteristics of each sub-group rather than averaging across all individuals (with the marginal effect from the female equation is more relevant).[18] One of the most important differences across genders is that earnings for women increase at a slower rate with age; this is discussed in more detail below. Men experience larger increases in earnings when they move institutions (cf. Blackaby et. al., 2005), benefit more from working in units that did better in the RAE/REF (in line with De Fraja et. al., 2019), have relatively better earnings if they worked in more than one HEI in any year and benefit from not working in teaching-only roles. However, they experience a larger negative impact if they worked in the post-1992 university sector, where research productivity is generally lower and there is more concentration on the teaching of students below PhD level (cf. Figure A.1). The number of years employed in the HEI sector has a larger positive impact for women. Black, mixed- and other-race men rather than women have (relatively) lower pay vis-à-vis whites; there is some evidence that male US-nationals do (relatively) better than UK

[18] That is, the gender elasticity in the 'male' column is the conditional wage elasticity of being female using the average characteristics of just the male sub-group. The fact that the gender elasticities differ indicates that there are differences in endowments (characteristics) across gender. In all other results reported separately by gender (including the 'average' elasticity reported in the second row of Table 2), marginal effects are based on averaging across all individuals. The difference in the marginal effects resulting from using the different approaches is minimal, except for the discrete variable *gender*. The second approach was also used to calculate whether differences in marginal effects between genders was statistically significantly different in Table 2 (reported in the footnote to the table).

men (the impact for women is smaller), while those originating in other countries do (relatively) less well. An important result is that (cet. par.) the larger the proportion of academics who were women (by cost centre, university and year, measured by "%female") the relatively higher (lower) was female (male) pay, presumably reflecting the strength of cultural norms – and thus the prevalence of stereotyping and bias – operating in different academic disciplines and universities. [19] The OLS results suggest that doubling the proportion of women, cet. par., reduces male earnings by 1.1% and increases female earnings by 0.5%, suggesting men get lower wages in disciplines that are female dominated compared to other disciplines. Overall, the results in Table 2 support previous findings that men, especially in more research-intensive environments, benefit from (statistically significant) different relationships than women in how the $\boldsymbol{X}_{it}$ in Equation (1) determined earnings (i.e., differences in $\hat{\beta}_j$ across genders).

Figures 2 and 3 around here

The large impact of age on earnings, taking into account the non-linearities in Equation (1), is shown in Figure 2. Early on there is little difference, but with seniority men experience higher earnings, with a (conditional) gap of some £5,260 by aged 70 (i.e., men earning some 14.6% more than women). Figure 3 helps to explain the relationship. There is a U-shaped relationship with initially a larger gender wage-gap in favour of men but

[19] Table A.7 in the supplementary appendix shows a significant and systematic increase in the proportion of academics who were women after 2004/05; it also shows that the cost centres with the average highest proportions were Nursing & allied health professions; Education; Modern languages; Health & community studies; Social work & social policy; and Continuing education. Those with the lowest proportions were: Electrical, electronic & computer engineering; Mechanical, aero & production engineering; Physics; General engineering; and Civil engineering.

after 10% FTE status female earnings catch-up. The right-hand-side panel shows the marginal effect on (*ln*) FTE of being female as (*ln*) age varies; again there is a U-shaped relationship. Thus, Figure 3 confirms that women tend to lower their hours relative to men in the early years of their academic careers, and this lower FTE status coincides with in relatively lower earnings for women. This confirms the arguments of Goldin (2014) set out in section 2 that if women face higher barriers to providing the same (quality-related) hours as men in the earlier stages of their careers, they will underinvest relative to men and, cet. par., receive lower earnings.

Table 3 around here

(c) KOB decompositions

Turning to the KOB decomposition (Equation 2) results, Table 3 shows that in both 2004/05 and 2019/20 some 42-49% of the observed (i.e., unconditional) pay gap in favour of men was because they experienced a more favourable wage-setting process than women with the same underlying characteristics (i.e., differences in $\hat{\beta}_j$ across genders in Equation 1), as well as there being differences in unobservable characteristics, such as effort. This confirms the results discussed in Table 2 and suggests women experience significant levels of bias in the wage-setting process. The rest of Table 3 provides more information on the relative impacts of the underlying differences in endowments, with academic function (whether teaching, research or both activities) accounting for the biggest influence on the overall endowments gap of –0.091 (–0.062) in 2004/05 (2019/20). In 2019/20, the next most important influence was the proportion of women present by academic discipline and university; and then the impact of women on average being younger.

Table 4 around here

Table 4 shows that nearly 120% of the narrowing over 2004/05 to 2019/20 of the wage-gap was due to average female endowments associated with higher earnings becoming more favourable. The influence of the wage-setting process changing (linked more to bias) was relatively small. The detailed results in Table 4 indicate that women benefited most from a relative improvement in endowments associated with length of time in HEI's, more research-oriented academic roles, and increases in relative age profiles, as well as more disciplines across universities employing relatively more women.

V. Summary and Conclusion

The literature on gender pay provides a range of examples of how and when women face bias that leads to relatively lower earnings relative to men. On the demand-side there is statistical discrimination where the lack of individual information on productivity leads to employers using an average, expected measure that underestimates actual productivity because of negative stereotypical attributes applied to women, and which can lower productivity-enhancing investment because of the perceived lower reward to women, even when men and women have the same underlying, unobserved productivity levels. This stereotyping may lead to long-term bias because of what psychologists label as 'confirmation' and 'belief' bias.

On the supply-side, there are a range of 'bias' factors which can be summarised by the prevalence of an alpha-male culture that dominates much of academia. Consequently, there are negative impacts on female research productivity, from publishing to networking and mentoring. Overall, prestige factors are more likely to be established and acquired by male academics and consequently women are promoted at a slower rate and less often than men. Additionally, a major factor determining productivity differences put forward by Goldin (2014) is that hours of work (and the quality of such hours) have a significant impact on wage setting.

The results from the empirical modelling showed a sizeable, but narrowing, unconditional pay gap which was still –0.089 in 2019/20, while the conditional pay gap was relatively unchanged and/or worsened remaining at around –0.050 in 2019/20. A major result was, cet. par., that earnings for women increased at a relatively slower rate with age. This was shown to be linked to women earning relatively less if they worked less than 100% of a full-time equivalent work year, coupled with women working on lower FTE contracts especially as women enter the age range where having and caring for young children is most likely. Other results supported previous findings that men, especially in more research-intensive environments, benefit from different wage-setting relationships than women. This included the larger the proportion of academics who were women present, the relatively higher (lower) was female (male) pay, presumably reflecting the prevalence of stereotyping and bias operating in different academic disciplines. The KOB decompositions also confirmed that a major and consistent explanation of the observed (unconditional) pay gap was because men experienced a more favourable wage-setting process than women when both had the same underlying characteristics, although the closing of the pay gap over time was dominated by female endowments associated with higher earnings becoming more favourable. This more favourable wage-setting process, together with the impact of working fewer hours during key (mid-career) periods when human capital investment is likely crucial, also point to the strong likelihood that women experience bias helping to explain pay gaps.

We also show (based on some preliminary analysis presented in the unpublished appendix) that the distribution of earnings is broadly similar when grade-balanced gender sub-groups are compared, and this increases the likelihood that conditional wage differences are more likely due to bias (i.e., if there were relatively more women in higher grades the earnings gender gap would be reduced significantly). However, to fully undertake an analysis of promotions and exiting requires a different, follow-up, paper involving specific modelling of who gets promoted and survival models of promotion and exiting. Additionally, and specifically relating to measuring gender pay gaps in HEIs, without an adequate, unbiased measure(s) of individual research productivity (and the ability to control for factors such as the age of children, number of children and marital status), it is not possible for the present study to reach any definitive conclusion that gender pay differs predominately because of bias and the barriers that women face in obtaining promotion to higher grades. If, as likely, bias is the main problem, the important research issue becomes how to get relatively more women promoted to full professor. And this requires more understanding of how to mitigate against bias arising from culture and stereotyping, that limits productivity and career advancement. Thus, better mentoring, better advice on how to compete, as well as improving understanding on what causes (unconscious) bias have all been advocated. Overall, it is recognised that there exists the need for greater equity (i.e., not just equal opportunity and access but also equal outcomes – cf. Barrow and Grant, 2019; Angervall and Beach, 2020). Some advocate the need for short-run policies such as the adoption of gender quotas in promotions processes where the percentage of women promoted should at least equal the percentage of women at the grade below. Of course, this approach to fixing "… a dysfunctional system that disadvantages women" comes up against the meritocracy argument that "… perceives preferential treatment as a threat to the stability of a well-functioning, objective, promotion system, where only the 'best' and 'brightest' succeed" (Nielsen, 2016, p. 386).

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Table 1: Marginal effects[a] ($\partial ln\widehat{w}/\text{gender} = 1$) for *ln* earnings in 2004/05, 2019/20 and the average 2004/05 to 2019/20: all UK universities

	Unconditional pay gap			Conditional pay gap (OLS)			Conditional pay gap (RE)		
Academic grade	2004	2019	average	2004	2019	average	2004	2019	average
Professor	-0.055***	-0.057***	-0.061***	-0.023***	-0.049***	-0.043***	-0.057***	-0.049***	-0.057***
Associate Professor	-0.061***	-0.019***	-0.038***	-0.018***	-0.014***	-0.017***	-0.038***	-0.021***	-0.027***
Assistant Professor	-0.044***	-0.007***	-0.023***	-0.020***	-0.018***	-0.019***	-0.027***	-0.025***	-0.025***
Total	-0.138***	-0.089***	-0.111***	-0.031***	-0.047***	-0.040***	-0.060***	-0.055***	-0.056***

[a] Calculated using $e^{\widehat{\beta}} - 1$, and the "margins, dydx(gender)" command - see also footnote 18. The 'total' row is estimated using Equation (1) and data for all sub-groups.
*/**/*** denote significant at 10/5/1% levels

Table 2: Elasticities[a,b] $(\partial ln\hat{w}/\partial lnx)$ for *ln* earnings 2004/05 to 2019/20: all UK universities

	OLS		Random Effects (RE)	
	Male	Female	Male	Female
Gender	-0.044***	-0.035***	-0.061***	-0.050***
Gender (average across both groups)	-0.040***		-0.056***	
ln Age	0.494***	0.332***	0.468***	0.318***
>1 HEI in any year	0.009***	0.005***	0.002**	-0.001
>1 role in any year	*-0.022****	*-0.021****	-0.006***	-0.007***
ln FTE	0.037***	0.047***	0.030***	0.029***
ln years in HEI	0.031***	0.054***	0.067***	0.076***
REF equivalent GPA	0.018***	0.010***	***0.004****	***0.003****
Moved	0.021***	0.009***	0.032***	0.021***
% female	-0.011***	0.005***	-0.003***	0.007***
Fixed-term contract	-0.057***	-0.037***	-0.035***	-0.024***
Sector (benchmark: Russell Group)				
Old sector	-0.051***	-0.049***	***-0.036****	***-0.034****
New Universities	-0.131***	-0.102***	***-0.073****	***-0.059****
Ethnicity (benchmark whites)				
Asian	***-0.005****	***-0.003****	***0.000***	***0.003***
Black	-0.087***	-0.047***	-0.107***	-0.051***
Mixed	-0.015***	-0.008***	***-0.014****	***-0.007***
Other	-0.025***	-0.019***	***-0.026****	***-0.019****
Unknown	0.001	0.006***	***0.000***	***0.004***
Academic Function (benchmark teaching only)				
Research only	0.009***	-0.050***	0.013***	-0.017***
Teaching & research	0.249***	0.183***	0.107***	0.083***
National grouping (benchmark UK)				
USA	0.040***	0.021***	0.080***	0.038***
Canada	-0.003	0.003	***0.028****	***0.022****
English medium in HEI	0.003***	0.009***	**0.010*****	**0.015*****
EU pre-2004	-0.002**	-0.006***	0.010***	0.003**
EU accession	***-0.029****	***-0.030****	***-0.022****	***-0.027****
Muslim, Arabic countries	-0.054***	-0.041***	-0.069***	-0.049***
Rest of Africa	***-0.033****	***-0.025****	***-0.022***	***-0.026***
Central & S. America	-0.059***	-0.037***	-0.061***	-0.039***
China, HK, Taiwan, Macao	-0.050***	-0.040***	***-0.040****	***-0.036****
Japan, S Korea	***-0.048****	***-0.045****	***-0.048****	***-0.038****
Rest Europe	***-0.022****	***-0.021****	***-0.022****	***-0.013****
Russia, CIS	***-0.023****	***-0.024****	***0.006***	***-0.010***
Rest Asia	***-0.027****	***-0.032****	***-0.031****	***-0.035****
RoW, not known	-0.036***	-0.038***	***-0.054****	***-0.052****
44 Cost centre dummies	yes	yes	yes	yes
15 Year dummies	yes	yes	yes	yes
N	1,716,911	1,360,200	1,716,911	1,360,200
ρ-value in RE model			0.795***	
(overall) $\tilde{R}^2$	0.557		0.518	

[a] For discrete (dummy) variables the estimates need to be converted to $e^{\hat{\beta}} - 1$. Note also footnote 18 (and how separate as well as average wage elasticities are reported for gender). For the %female variable, margin effects were calculated as $(\partial ln\hat{w}/\partial x)$. Source: Equation (1)

[b] Figures in bold italics denote a failure to reject the null of no difference across gender sub-groups at the 5% significance level (or better).

*/**/*** denote significant at 10/5/1% levels

Table 3: Kitagawa-Oaxaca-Blinder decomposition of levels 2004/05 and 2019/20: all UK universities

Year	2004/05		2019/20	
	$\hat{\beta}$	$\hat{\beta}$ (%)	$\hat{\beta}$	$\hat{\beta}$ (%)
Observed (unconditional)	-0.138***		-0.090***	
Decomposition				
Endowments	-0.091***	65.8	-0.062***	69.2
Coefficients	-0.068***	49.4	-0.038***	42.1
Interactions	0.021***	-15.2	0.010***	-11.3
Total	-0.138***	100	-0.090***	100
Detailed decomposition of endowments				
Academic Function	-0.029***	21.0	-0.023***	25.9
% female	-0.003	2.2	-0.025***	27.8
ln Age	-0.028***	20.3	-0.012***	12.9
Sector	-0.003***	2.1	-0.008***	9.4
ln years in HEI	-0.010***	7.1	-0.006***	6.2
ln FTE	-0.006***	4.2	-0.002***	2.6
Contract	-0.012***	8.5	-0.002***	2.4
>1 role in any year	-0.000***	0.2	-0.001***	1.2
REF equivalent GPA	-0.002***	1.4	-0.001***	0.9
Moved	-0.000	0.0	0.000	0.0
>1 HEI in any year	0.000	0.0	0.000	-0.1
Ethnicity	0.000	-0.1	0.000	-0.3
National grouping	0.000***	-0.2	0.001***	-1.2
Cost centre	0.001	-1.0	0.017***	-18.5
Total (endowments)	-0.091***	65.8	-0.062***	69.2

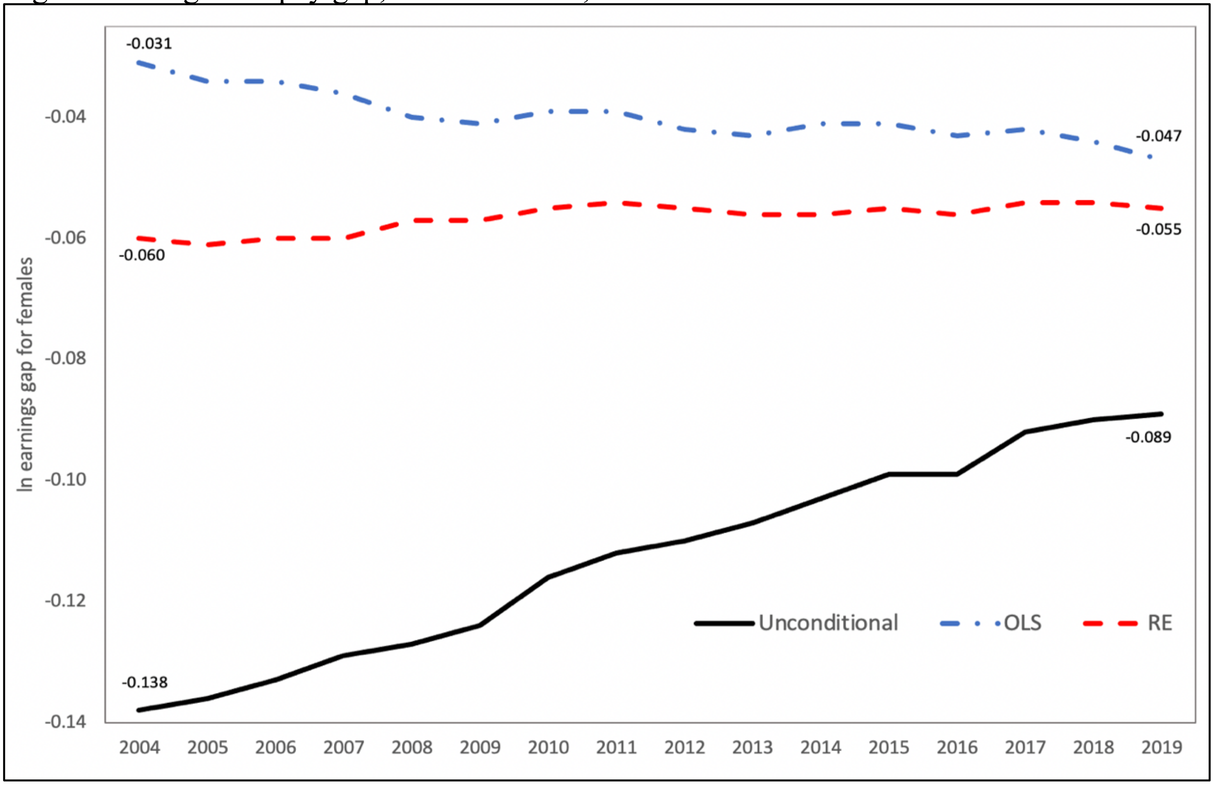
*** denote significant at the 1% level (bootstrapped standard errors based on 100 replications).
*/**/*** denote significant at 10/5/1% levels

Table 4: Kitagawa-Oaxaca-Blinder decomposition of change 2004/05 to 2019/20: all UK universities

	$\hat{\beta}$	$\hat{\beta}$ (%)
Observed (unconditional)	0.048***	
Decomposition		
Endowments	0.058***	119.9
Coefficients	-0.013***	-27.8
Interactions	0.004	7.9
Total	0.048***	100
Detailed decomposition of endowments		
ln years in HEI	0.018***	37.1
Academic Function	0.015***	31.1
ln Age	0.014***	28.6
% female	0.009***	19.5
Cost centre	0.003***	6.9
Contract	0.002***	5.1
ln FTE	0.002***	4.8
Ethnicity	0.001*	2.8
>1 role in any year	-0.000	-0.1
>1 HEI in any year	-0.000	-0.0
Moved	-0.001***	-1.3
Sector	-0.001***	-2.4
National grouping	-0.002*	-3.9
REF equivalent GPA	-0.004**	-8.1
Total (endowments)	0.058***	119.9

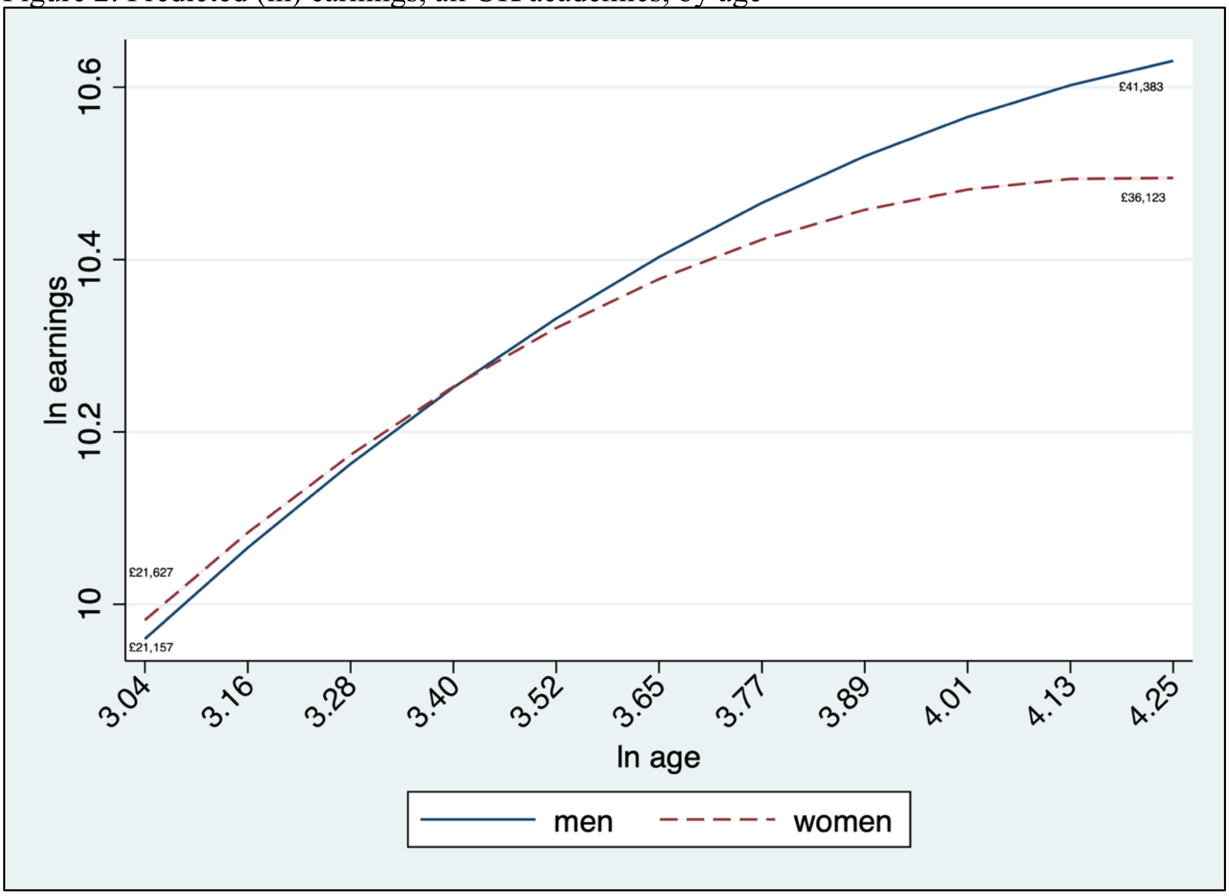
***/* denote significant at the 1/10% levels (bootstrapped standard errors based on 100 replications)
*/**/*** denote significant at 10/5/1% levels

Figure 1. UK gender pay gap, all universities, 2005/06 to 2019/20[1]



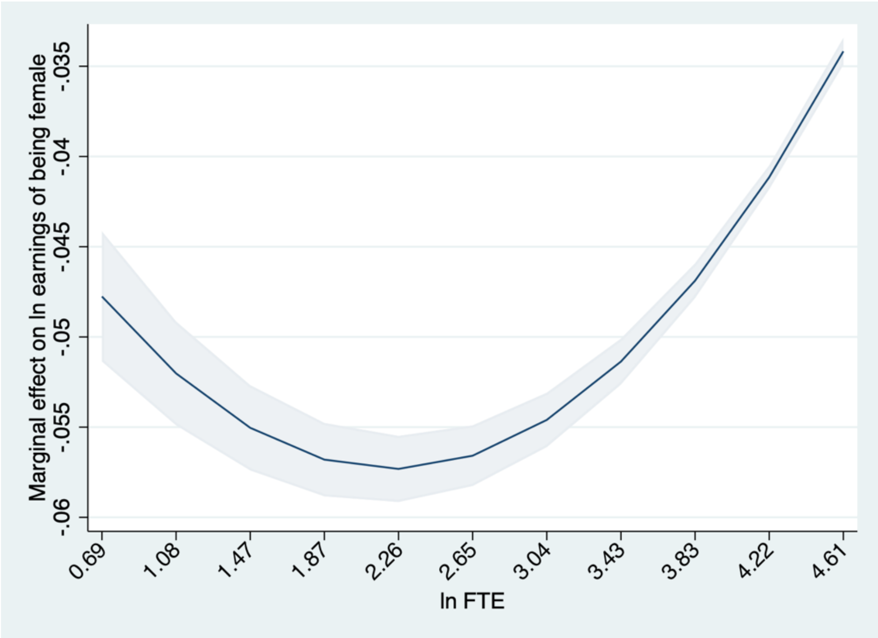
Source: based on Equation (1), with unconditional (OLS) omitting all $\boldsymbol{X}_{it}$ and replacing α_i with a constant α_0.

Figure 2: Predicted (ln) earnings, all UK academics, by age

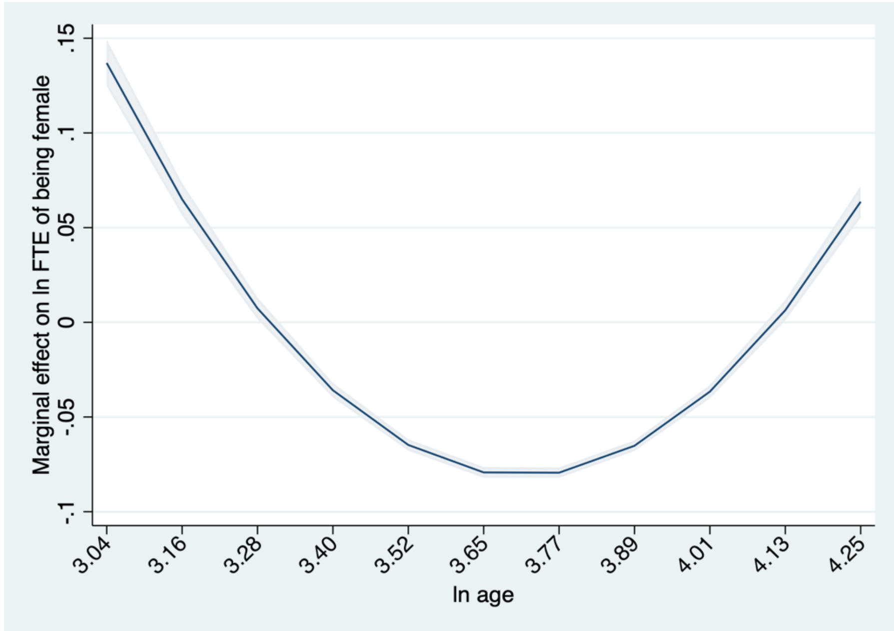


Source: based on Equation (1)

Figure 3: Impact of gender on earnings and FTE status, all UK academics, by age



Source: based on Equation (1)



Source: based on Equation (1) but with ln FTE_{it} on the left-hand-side.