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IZA DP No. 13635

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AUGUST 2020

ISSN: 2365-9793

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ABSTRACT

Pay Transparency Initiative and Gender Pay Gap: Evidence from Research-Intensive Universities in the UK*

Given the ongoing efforts to close the gender pay gap across different sectors in the UK, this paper investigates the impact of a pay transparency initiative on the gender pay gap in the university sector, focusing on the Russell Group of top-tier universities. The initiative, introduced in 2007, enabled public access to mean salaries of men and women in UK universities. Using a rich individual-level administrative dataset and a difference-in-differences approach comparing men and women, we document several key findings. First, following the pay transparency intervention, the log of salaries of female academics increased by around 0.62 percentage points compared to male counterparts, reducing the gender pay gap by 4.37%. The effect is more pronounced considering a balanced sample (1.27 percentage points increase in female wages or an 11.59% fall in the gender pay gap). This fall in the pay gap is mostly driven by senior female academics negotiating higher wages and female academics moving to universities with equal opportunity. We do not find any evidence of pre-existing wage gap or the gender composition associated with the fall in the gender pay gap.

JEL Classification: I23, J16, J31, J44

Keywords: gender pay gap, pay transparency, higher education sector, wage level

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* All statistics in this paper follow a level of aggregation to maintain the anonymity of individuals and ensures no personal data or personally sensitive data are identifiable. We follow the Higher Education Statistic Agency (HESA) standard rounding methodology to comply with HESA agreement. Rounding method implies that (i) counts of individuals are rounded to the nearest multiple of 5; (ii) percentages based on fewer than 22.5 individuals are suppressed; and (iii) averages based on seven or fewer individuals are suppressed.

1 Introduction

One of the most persistent and prominent features of labour markets around the world is that women earn less than men. In the UK, for example, a female employee typically makes about 81 pounds for every 100 pounds earned by a male employee (O'Reilly et al., 2015). Several contributing factors have been advanced as to why gender pay differences in the labour market arise, such as differences in job rank (Mumford & Sechel, 2019), variations in productivity (Euwals & Ward, 2005) and differences in wage negotiation (Bowles et al., 2007; Artz et al., 2018). The higher education sector is not an exception to the pay gap tendency, with several studies documenting such a tendency in the UK (Gamage et al., 2020; McNabb & Wass, 1997; Blackaby et al., 2005; Euwals & Ward, 2005; Schulze, 2015; Mumford & Sechel, 2019), the US (Ginther, 2001; Ginther & Hayes, 2003; Ginther & Kahn, 2014; Sutanto et al., 2014; Tao, 2018) and in Europe (Corsi et al., 2014).

Various interventions can be implemented in order to minimise (or abolish) such pay gaps. Examples include positive action (Gregory-Smith, 2018; Gamage & Sevilla, 2019; Healy & Ahamed, 2019); gender-neutral clock stopping policies (Antecol et al., 2018) and mentoring programs (Blau et al., 2010). Recent, efforts have also been made by governments to address the information asymmetry in wages through pay transparency policies to tackle the gender pay gap. For example, the US passed legislation which mandated firms with government contracts to report wages of employees by gender[1]. Similarly, the Danish government mandated firms with more than 35 employees to report salaries of employees by gender. In the UK, the Equality Act 2010 (Gender Pay Gap Information) Regulations came into force that mandated employers with 250 or more employees to publish gender pay gap in 2017. Moreover, countries including Australia, Germany, Canada and France have introduced some elements of pay reporting/transparency to their equal pay legislation. Nonetheless, there is limited evidence on the effectiveness of such policies. This study examines the case of a pay transparency intervention of academic salaries and its contribution to reducing the gender pay gap in the UK higher education sector.

A fundamental hypothesis recently discussed among academic and policy circles is that the gender pay gap persists partly because it is hidden. Organisations, such as Fawcett society (2018), believe that the culture of pay secrecy facilitates pay discrimination to thrive. They have launched the 'Right to Know' campaign to push for a new equal pay bill to modernise the law on equal pay.[2] We hypothesise that information asymmetry—i.e., not knowing what others earn—allow discriminatory practices to go undetected. Therefore, a pay transparency initiative acts as an 'information intervention' altering the bargaining power of female employees, if indeed paid less than their

[1] This policy was, however, recently retracted

[2] A survey by Fawcett Society (2018), a charity organisation, finds that 53% of women and 47% of men in work are reluctant to share information with colleagues on how much they earn. Further, 31% employees believe that the contracts prohibit them from talking about their pay. See https://www.fawcettsociety.org.uk/right-to-know.

male counterparts (Cullen & Pakzad-Hurson, 2019).

Against this background, in 2007 the THE started publishing average pay data separated by gender and academic rank, with around 99% of universities giving their consent to publish their pay data. Publication takes place in April of every calendar year and is publicly accessible through the THE website.[3] Our research suggests that this pay reporting is the only intervention occurring at that time aimed at the gender pay gap in the Higher Education sector. Therefore, we are interested in whether the pay transparency intervention has a causal impact on the gender pay gap. We focus our investigation on Russell Group Universities because they are considered to be the most research-intensive and competitive universities in the UK.

To empirically investigate the causal impact of this pay transparency initiative, we exploit the temporal variation of the gender pay publication by the THE using a difference-in-differences approach where we look at the within-individual changes in salaries of females before and after the pay transparency initiative as compared to males. We hypothesise that given a certain level of wage gap, female employees use the pay information to bargain higher wages. This setting allows us to consider females to be the 'treated group' and males to be the 'control group'. Whereas the evolution of wages may be determined by other factors unrelated to the pay transparency initiative, we compare the salaries of females to those of males to rule out other factors that may influence wages of females; such as, for example, sector-wide policies or university-specific policies. It is often challenging to investigate our research question empirically. It requires an exogenous implementation of the policy and individual level pay data. In our analysis we conduct suitable empirical tests suggesting that the intervention is indeed exogenous. For data, we draw on administrative-level panel data containing salaries of the entire population of academics between 2004-2016. The data consist of employment records of all academics employed in universities in the UK. Our regressions control for a rich set of additional variables determining academic wages over time, including employment-related factors (contract information, such as the basis of employment academic function and the mode of employment) and individual characteristics (including age, ethnicity and level of education).

We establish several key findings. First, following the pay transparency, we find a 4.37% decrease in the gender pay gap in Russell Group Universities (a figure based on the average pre-intervention male and female wages). This is resulting from an increase in log of female salaries by 0.617 percentage points holding male salaries constant. We find that the impact is higher when we consider a balanced sample. On average, female salaries increase by 1.27 percentage points reducing the gap by 11.59%. We find that the intervention is more pronounced two years after its implementation intervention due to the sticky pattern of wages.

We test several hypotheses to determine the main drivers of the decrease in the gender pay gap. We find that the effect is mainly driven by an increase in wages of senior female academics (academics earning above the median wage). The female

[3]See https://www.timeshighereducation.com/features.

salaries increase by 1.43 percentage points compared to male salaries, thus reducing the wage gap by 25.9%. We also find that one standard deviation decrease in the gender pay gap (equivalent to £1,982) increases the likelihood of a female academic moving to a university by 0.42 percentage points compared to a male counterpart. We do not find gender composition or pre-existing university level wage gap to influence the results.

Our paper adds to the general literature on the effect of pay transparency. Several studies show that pay transparency can influence employee well-being (Perez-Truglia, 2015), job satisfaction (Akerlof & Yellen, 1990; Card et al., 2012; Breza et al., 2018), work effort, output and employee relation (Cullen & Perez-Truglia, 2017). Further, it also influences the female representation in above median wage occupations (Duchini et al., 2020). These studies do not, however, focus on the gender pay gap *per se*. We specifically contribute to a limited literature that examines the impact of pay transparency on the gender pay gap. Backer et al. (2019) investigate a pay transparency policy in the Canadian education sector and find that following the intervention the gender pay gap decreases. Similarly, Bennedsen et al. (2019) also find the pay gap reducing following a gender pay transparency policy in Denmark. Kim (2015) reports similar findings when investigating the US States that outlaw pay secrecy. These results are mainly driven by the unionisation of workers (Backer et al., 2019), level of education (Kim 2015) or changes in compensation within firms (Bennedsen et al., 2019) where employees put pressure on firms to reduce their pay gap (Cullen & Perez-Truglia, 2017, 2018). Equally, Mas (2017), argues that the fall in gender pay disparity can also be driven due to public pressure and public aversion after investigating public disclosure of municipal managers' wages. In contrast, Burn & Kettler (2019) conclude that pay secrecy bans have no impact on the gender pay gap where females fail to bargain higher wages after the passage of the law. On the contrary, after pay transparency, if authorities monitor and punish organisations with high pay gap, this can be an effective strategy aimed at reducing the gender pay gap (Vaccaro, 2018).

More specifically, we offer two key contributions to this literature. First, this study provides the first evaluation of a pay transparency intervention in the UK and its effect on the gender pay gap. As far as we are aware, there is only one other study (Duchini et al., 2020) that investigates the impact of the UK mandated pay reporting (occurring in 2017) on hourly wage rate and female employment but not on the gender pay gap. Second, it utilises high-quality administrative panel data—thus allowing us to look at career trajectories and wage growth over time—with information on, nearly, the entire population of academics in the Russell Group universities in the UK.

The rest of the study is structured as follows. Section 2 outlines the institutional background; Section 3 describes the data and empirical approach; Section 4 presents the results including results on robustness and identification tests; in Section 5 we explore possible channels through heterogeneity analysis; Section 6 concludes.

2 Background

2.1 The Times Higher Education (THE) Pay Publication

The Times Higher Education was established in 1971 as part of The Times newspaper in England. It was later re-launched as an independent publication in 2008. THE provides information about the global higher education sector and, as part of its activities, it reports news and issues related to the higher education sector in the UK. In 2007, THE began publishing university level pay data to inform the public on gender pay disparities within the sector. At that time gender pay gap gained much attention following the standardisation of the higher education pay structure in 2006 introduced by the Framework agreement to address equal pay for equal value.[4]

The first THE pay publication reported the average nominal pay of male and female full-time academics for the 2005/2006 academic year at the university level. The report included 121 universities including all the Russell Group universities. Over the years, the number of universities included in the list continued to increase, reaching 166 universities by 2009. This represents almost all universities and university colleges in the UK. By default, the THE report publishes all university pay data; a university can, however, request the THE to refrain from publishing their data in their annual publications. According to the THE pay report, although only London Metropolitan University and Liverpool Hope University appear to have explicitly opted out from the publication list, the number of universities reported in the first year is less than the total number of universities. The universities who publish this data increased until 2009, suggesting that the first pay publication took place over three years. The pay information for reporting is collected from the Higher Education Statistical Agency (HESA).[5]

The structure of the pay report has been amended several times. Whereas the first year of pay publication is aggregated at all academic ranks, in the following years (2008 and 2009), the pay data is disaggregated by broad academic ranks, namely Professor, Senior Lecturer (Associate Professor)/Researchers, Lecturer (Assistant Professor), researcher, other grades and all grades. From 2009 onwards, the pay reporting is only disaggregated by Professors and non-Professors and is available for full-time academic staff only. Although not explicitly stated in the reports, disaggregation of pay data by Professor and non-Professors may be influenced by the differences in wage determination, which we discuss in the following section.

[4]See https://www.ucu.org.uk/framework.

[5]See 2015 report https://www.timeshighereducation.com/features/times-higher-education-pay-survey-2015/2019360.article.

2.2 The UK Academic Sector

2.2.1 University setting

The UK Higher Education sector encompasses 158 institutions that have degree-awarding powers. Many of these institutions are not-for-profit organisations, though the charity commission does not regulate them. All institutions conduct research and teaching activities, but the weight applied to these activities varies by institution (Mccormack et al., 2014). Institutions are mainly divided into two main types: 'old universities' and 'new universities'. Old universities are found pre 1992 whereas the new universities are the ones that were awarded university status post-1992 through the Further and Higher Education Act 1992.[6] Within these two main groups, there are further divisions. Old universities are categorised into Russell Group and other old universities. Russell Group institutions (comprised of 24 universities[7]) form 74% of the research income among UK universities and are considered the most research-intensive universities in the UK.[8] New universities are categorised into former polytechnic and other new universities that were previously higher education colleges.

Throughout our study, we focus on Russell Group universities because, according to the World University Rankings, these institutions perform better compared to other universities in the UK and Europe and are comparable to US universities that have typically been the focus of studies on gender pay inequalities. Similar to the US, UK universities, in general, have a high level of autonomy over budget and hiring practices (Aghion et al., 2010). For example, less than 30% of the UK higher education expenditure come from public spending, which is the lowest share among the OECD countries.[9] Therefore, there is a high level of competition for resources from students, and for research funds. Besides, the Research Excellence Framework, an exercise that ranks each department's quality of research output, adds new level of competition to the British Higher Education sector.[10] We can hypothesise that, in principle, a high degree of competition should reduce the degree of gender discrimination, conditional on objective evaluation of research quality. In contrast, research has shown that British Universities have autonomy over the hiring of academics and setting salaries, in particular at senior levels such as professorial ranks (Aghion et al., 2010). As a result, we can argue that a high level of autonomy can increase the degrees of gender

[6]See http://www.legislation.gov.uk/ukpga/1992/13/contents.

[7]These are: University of Birmingham, University of Exeter, University of Bristol, University of Liverpool, University of Cambridge, King's College London, Cardiff University, University of Nottingham ,Durham University, University of Southampton, University of Edinburgh, University of York, University of Glasgow, Imperial College London, , University of Leeds, London School of Economics, University of Manchester, Newcastle University, University of Oxford, Queen Mary University of London, University of Sheffield, Queen's University Belfast, University College London and University of Warwick.

[8]See https://www.russellgroup.ac.uk/media/4997/profile-of-the-russell-group-of-universities.pdf.

[9]See https://data.oecd.org/eduresource/spending-on-tertiary-education.htm OECD (2020), Spending on tertiary education (indicator). doi: 10.1787/a3523185-en (Accessed on 17 January 2020).

[10]Research Excellence Framework is the UK system of assessing the quality of research output. It was first carried out in 2008. It focuses on the following three dimensions: the quality of outputs, their impact beyond academia, and the environment that supports research. For more information see https://www.ref.ac.uk/.

discrimination.

Within the UK, the degree of competitiveness and autonomy varies by Universities. For example, McCormack et al. (2013) show that research-intensive universities are more likely to compete in the international and national markets compared to less research-intensive universities that compete mainly in the international markets for the hiring of staff and students. Therefore, by focusing on Russell Group institutions, we are considering a set of universities that are highly competitive with autonomy over hiring and salaries, similar to the US research-intensive universities.

2.2.2 Pay structure

In 2004, the UK moved away from a nationally determined pay scale to a more flexible pay structure implemented by the Framework Agreement.[11] The framework agreement was designed to promote salary and career progression to attract and retain academic staff. The convention introduced two distinct divisions in the pay structure of academics. While non-professorial salaries are determined by sector-wide collective bargaining between the university and the University and College Union, the professorial salaries are determined individually between the academic and the university via individual bargaining.

The non-professorial salaries are governed by negotiated fixed salary structure known as the pay spine system. The recommended pay spine system consists of 51 spinal points that correspond to a particular salary. Multiple pay spines form the salary scale for a specific academic grade. For example, grade 6 relates to a position encompassing assisting teaching or research activity. This corresponds to the pay spine scale between 22-32 that translates into a salary between £19,068-£25,626 based on the 2003/2004 pay spine point system. Depending on the qualification and years of experience in the higher education sector, academics are placed onto a particular spinal point. Consider, for example, an individual beginning his/her academic career as a research assistant (i.e., grade 6). He/she will be assigned to spinal point 22; the bottom of the scale. Every year the post holder moves up by one spinal point till they reach the maximum automatic increment point (we can identify this as the experience-based increment). The individual can apply for promotion from one grade to the next either on reaching the top of a salary scale or before this. The promotion decision is made at the discretion of the promotion panel. Although the Union recommends the structure, the pay structures for job ranks across universities can vary.

On the other hand, professorial salaries are not captured by the recommended pay structure. Generally, professorial salaries are above the highest spine point and are individually negotiated between the university and the staff member. The higher education (HE) providers set their contracts at the beginning of the academic year (generally between August/September) before teaching commences. The nature of contracts makes it difficult for wages to adjust immediately. For example, contracts typically run from the 1st of August to the 31^{st} of July of the following year. Any

[11] See https://www.ucu.org.uk/framework.

salary increment including the automatic increase and 'contribution' pay will come to effect at the beginning of the period (the 1^{st} of August).

On the other hand, an increment on the professorial salaries is based on the post review: The performance-based review allows professors to renegotiate salaries for the next academic year. Therefore, in our analysis, we hypothesise that wages take at least a year to adjust.

3 Data and Empirical Strategy

The data for this study come from the Higher Education Statistical Agency (HESA), spanning over the period 2004-2016. This is an administrative dataset compiling academic data from all HE Institutes that include all publicly and privately funded institutions and also other organisations that offer HE courses, including those that are not publicly funded. The data are collected as of the 31^{st} of July each calendar year. The dataset includes information about staff members who are employed on an academic contract, such as only teaching staff, only research staff, and teaching and research staff employed in any type of employment (part-time and full time). It excludes administrative and support staff, and librarians. HESA is a body set up to act as the intermediary between the higher education funding councils and the higher education providers to accomplish the statutory requirements set out by the Further and Higher Education Act 1992 and the White Paper–'Higher Education: A new framework'.

The unit of observation in the dataset is the individual academics and information on the individual and employment characteristics of staff—including pay—are obtained from university databases. The following sample restrictions are imposed throughout the analysis. First, individuals are included if they hold full time, permanent teaching and research contract. We consider these as the standard academic contracts, thus allowing us to have a clearer understanding of salary determination for this type of contracts. For example, research-only contracts may be funded by a body outside the HE provider and may not necessarily follow the academic pay structure. Second, we exclude academics employed in clinical departments as their salaries are partly determined by the National Health Services (NHS) in the UK and follow different pay structure to HE providers. Third, the sample is—by definition, given the nature of our research question—restricted to the 24 Russell Group Universities, as discussed in section 2 above. Our final sample thus consists of 64,772 observations involving 10,769 female faculty, and 173,145 observations of 25,207 male faculty in 24 universities over 13 years.

While there are many measures of gender pay differences, such as hourly wages, we use annual full-time equivalent (FTE) salaries of faculty as the primary dependent variable. Using FTE annual salaries to measure the gender pay gap only reflects the differences in hourly wages and not the working hours. We use age, age squared, highest educational qualification as our primary independent variables in the wage equation, available in HESA. Table A1 in the Appendix lists and defines the variables used in the analysis.

Our research question seeks to estimate the effect of the pay transparency initiative on the gender pay gap among academics in Russell Group universities. To achieve this, we exploit the temporal variation of male and female salaries to an exogenous change driven by the THE pay publication initiative. We use a difference-in-differences approach to investigate the within-individual change in wages of female academics before and after pay transparency initiative relative to that of males given by the following equation:

$$Y_{itj} = a + \beta_1 D_t + \beta_2 (D_t \times F_i) + X_{it} + \theta_i + \eta_j + \delta_t + \gamma_{jt} + \epsilon_{itj} \quad (1)$$

Where Y represents log-wages using 2016 as the base year for individual i in university j in year t. D_t is the pay transparency variable taking the value 1 for years after the publication of the first pay report in university j in year t; and the value of 0 otherwise. Our key regressor is $D_t \times \mathrm{F}_i$ which captures the effect of the relative impact on females compared to males following the intervention. A positive coefficient would indicate a fall in the gender pay gap.

The vector X accounts for socio-demographic factors that may be correlated with wages, including age, age squared and highest qualification held. We also control for university fixed effects, η_j, to account for unobservable and time-invariant university-specific characteristics that may correlate with wage and not correlated to the pay transparency intervention such as university rank. For example, due to competition within the Russell Group, some universities are likely to offer higher salaries compared to others to attract the best academics. The specification controls for time fixed effects, δ_t, to account for economic conditions that vary over time; for example, the 2008 economic downturn which arguably influenced wages across sectors. Finally, we include university-specific time fixed effects, γ_{jt} that capture unobservable factors by university-year cells. We use a fixed-effect to estimate equation 1, θ_i, and thereby control for unobserved individual-level time-invariant characteristics. All standard errors are clustered at the individual level.

A compelling aspect of estimating the impact of pay transparency reporting on the gender pay gap is that there was virtually no room for anticipated effects. Given that the THE did not make an official announcement before the first report, universities could not have possibly anticipated the intervention. Arguably, even if universities were informed, say, a few months in advance, university contracts are sticky and can not be adjusted swiftly (see discussion in section 2). Nevertheless, we check for any anticipated effects by testing for parallel trends. Our validity of the identification strategy relies on whether the trends of male and female wages are identical before the intervention. We also test whether the intervention is endogenous to the prevailing gender pay gap before the intervention.

4 Results

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics of our sample by gender. On average, male academics earn £7,162 (circa 11%) more compared to their female peers. There are in total 237,917 observations in our sample and 72.7% of which are male. Although there is presently about a 3:1 higher representation of male to female academics, this is a definite improvement over the years. In the 1970s, only 10% of academics were females, a percentage which has been consistently increasing ever since (Mcnabb & Wass, 1997). On average, male academics in our sample are more likely to have a doctorate and are older by two years compared to female academics. In terms of ethnicity, male and female academics are generally similar, with around 90% of academics coming from white ethnic background.

Figure 1 plots the average annual trend in the gender pay gap in the Russell Group Universities in the UK. We plot the raw gender pay gap (left) and the gender pay gap separately after controlling for individual characteristics (right), both of which produce similar trends. In particular, we observe the upward trend up until 2007—the intervention year—and a gradual fall in the subsequent years. There is also a steep fall in the gap around 2009.

4.2 Regression Results

Table 2 presents the estimates of Equation 1, using a fixed-effect model on the sample of academics in Russell Group Universities. We estimate several specifications (columns 1-5) by adding controls progressively. We use column 5 as our benchmark specification with a full set of controls. According to this benchmark estimate, on average, following the pay reporting, the log of female salaries increased by 0.62 percentage points. This corresponds to an increase in average female salaries by £323 relative to men. Based on average pre-intervention wage levels of male and female academics, the results translated to a 4.38% fall in the gender pay gap.[12] We do not find a significant change in the overall wage levels of academics. The remaining coefficients in Table 2 are as expected. For example, on average, an increase in age increases log of wages by 8 percentage points, diminishing as an academic gets older. Academics with doctorates and postgraduate qualifications are earning significantly more than academics with other levels of qualification.

4.3 Robustness and Identification Tests

4.3.1 Robustness tests

We perform robustness checks to assess the sensitivity of our findings. In particular, we investigate: (a) alternative samples by including only academics observed over the

[12]Pre-treatment average female salary is £52,274 and average male salary is £59,646.

whole sample period in Russell Group Universities (i.e., a balanced sample); and (b) using the treatment two years after the pay transparency. Overall these reveal that our results are robust.

Table 3 presents the finding of estimating the same specification given in equation 1 using a balanced sample of academics observed over the entire 13-year period. Focusing on the complete specification, we find our main results are in line with the balanced sample. Moreover, we see a more substantial influence of the pay reporting on the gender pay gap where log female salaries increase by 1.27 percentage points. This is a fall in the gender pay gap of 11.43% based on average male and female wage gap before the intervention.[13] We also do not find a significant change in the overall wage levels. This is in line with our main findings. We also test for parallel trend assumption to validate our identification strategy for the balanced sample in Table A2 in the Appendix.

We also experiment with changing the timing of the intervention. In particular, we treat the year of first pay publication as the 'announcement' and two years after as the 'implementation'. In essence, we assume that full time permanent academic contracts are sticky, and they are likely to take at least a year to change in light of the first pay report. To that extent, we estimate the following specification:

$$Y_{itj} = a+\beta_1 A_{t=2007}+\beta_2(A_{t=2007}\times F_i)+\beta_3 I_t+\beta_4(I_t\times F_i)+X_{it}+\theta_i+\eta_j+\delta_t+\gamma_{jt}+\epsilon_{itj} \quad (2)$$

Where variables hold the same definition as above. Here, the treatment variable is split into two: for variable $A_{(t=2007)}$ we are taking value 1 for year equals 2007 when the first report is published and zero otherwise, and variable T_t takes value 1 from 2009 onwards and zero otherwise. We interact the female dummy with each treatment variable to separate the effect on female wages relative to male wages.

Table 4 presents the estimation results of equation 2. We only report the coefficients of the intervention terms and their interaction with the female dummy. We estimate several specifications (columns 1-5) by adding controls progressively. We use column 5 as our benchmark specification with a full set of controls. As expected, the results show that wages take time to adjust. The intervention is more pronounced two years after. Following 2009 the log female salaries increase by 0.87 percentage points compared to males salaries, which is 0.25 percentage points (40.3%) higher than our main results (0.62%). This confirms our hypothesis that wages take time to adjust and after accounting for the adjustment period, our results are similar but large in magnitude compared to our main estimates.

4.3.2 Identification tests

The validity of our results depends on several assumptions. In this section, we test each assumption and investigate whether they are fulfilled.

[13] Pre-treatment average female salary is £51,520 and average male salary is £57,161.

Test for parallel trend assumption

The validity of the causal interpretation of our main results rests on the parallel trend assumption where we assume that the relative trends in female wages to male wages before the pay transparency initiative are the same. To validate the causal impact of the pay transparency, we demonstrate that the trend in wages of the 'treated' group (female) do not differ from the 'untreated' group (male) in the years preceding the initiative. If wages of females are growing at a different rate than males, the difference-in-differences estimator is not a consistent estimator of the treatment effect.

To address this, Figure 2 plots the trends in wages of males and females. Visually, wage patterns are similar before the intervention. Following Autor (2003) and Kavetsos et al. (2020), we also estimate the following equation to establish the parallel trend observed in Figure 2:

$$Y_{itj} = a + \sum_{\tau=-3}^{\tau=9} \theta_\tau D_\tau + \sum_{\tau=-5}^{\tau=9} \beta_\tau (D_\tau \times F_i) + X_{it} + \theta_i + \eta_j + \delta_t + \gamma_{jt} + \epsilon_{itj} \qquad (3)$$

We include a vector of year dummies, D_τ, for the τ_{th} year before and after the pay reporting. This will capture the general trends both common to men and women before and after the intervention. To separate the gender differences in the trends, we interact the time dummies with the female dummy, $D_\tau \times \mathrm{F}_i$. In the absence of any pre-existing differences in wage trends between males and females, the coefficient of the interaction term before intervention should be statistically insignificant. We use the first observation in our sample, year (-3), as the reference year.

Figure 3 plots the estimated coefficient of the interaction term (see Table A2 in the Appendix for the values). The coefficients of the interaction term two years before the intervention is statistically insignificant relative to the third year before the intervention. This result suggests a lack of any anticipated effect before the pay reporting and that our difference-in-differences model is identified.

Addressing endogeneity concerns

Another potential concern of our main result is the endogeneity of the intervention concerning existing gender pay gap. In most policies, the endogeneity can arise from two sources, the non-random implementation of the intervention and the non-random choice of universities to authorise the pay publication. In both cases, the pay reporting intervention would not be exogenously determined. Given that all the Russell Group universities authorised THE to publish their pay information in the first round, we do not anticipate a selection bias at the university level. On the contrary, the implementation of pay reporting may not be random. The university-level gender pay gap may drive the adoption of the intervention. We follow a similar methodology to La Ferrara et al. (2012) whereby we aggregate the data at the university level to estimate the following model using a linear probability model.

$$ReportYear_t = \sum_{\tau=-3}^{\tau=-1} \theta_\tau Gap_{j,t-\tau} + \eta_j + \epsilon_{itj} \tag{4}$$

Where $ReportYear_t$ takes value one for the first year of pay reporting and zero otherwise. $Gap_{j,t-\tau}$ is the average gender pay gap in university j, τ years before the pay intervention. The specification also controls for university-level fixed effects.

Table 5 reports these results where we first regress year of pay report on the average lagged gender pay gap at university level without any controls (column 1). We do not see a significant correlation between the gender pay gap and the intervention. Including university fixed effect (column 2) again suggests that pay reporting is not correlated with the gender pay gap. In all, these estimates indicate that the intervention is not endogenous.

5 Heterogeneous Effects

Our main specification shows that following the pay transparency, the gender pay gap narrows. Next, we investigate potential channels that may have driven the fall in the gender pay gap. In particular, we consider the following four hypotheses.

5.1 Academic Ladder

First, we test whether the impact on the wage gap is different across the wage distribution. Professorial academics are likely at the top of the pay distribution while junior non-professorial academics to be at the bottom of the pay distribution. Given the distinct differences in the wage determination whereby professorial salaries are individually negotiated, and a sector-wide standardised structure determines non-professorial salaries, it is plausible to assume that professorial pay is relatively sensitive to pay transparency initiative compared to non-professorial pay. And that senior academics mainly drive the fall in the pay gap. Although, the data does not allow us to distinguish between professorial and below professorial academics, investigating the impact of pay transparency below and above the median wage can be useful to proxy occupational hierarchy. To that extent, we run equation 1 on academics below the median wage and above the median wage separately. Table 6 presents these results.

The results show that on average female academics earning below the median wage experience an increase in log wages by 0.50 percentage points (a nominal fall of £223 or 22.8% fall in the gender pay gap).[14] More importantly, academics earning above the median wage also experience a fall in gender pay gap by 1.43 log percentage points (a nominal fall of £980 or 25.9% fall in the wage gap) almost three times the fall experienced by academics earning below the median wage.[15] The difference in the

[14]Pre-intervention average female salary below the median wage is £44,440 and average male salary below the median is £45,419. The wage gap is £979.

[15]Pre-intervention average salary of a female earning above the median wage is £68,517 and average male salary earning above the median wage is £72,300. The wage gap is £3,783.

impact between academics below and above the median is statistically significant at the 95% significance level. We also test for the parallel trend assumption for the two samples separately to confirm our causal interpretation. Trend estimates are given in Table A3 in the Appendix. The results confirm that there are no differences in trends of male and female wage before the intervention in our two samples. The evidence suggests that senior academics mostly drive the fall in the gender pay gap.

5.2 Pre-Existing Gender Gap

Next, we follow Bennesden et al. (2019) to examine the role of the pre-existing gender pay gap in reducing the pay gap following pay transparency. High-status organisations such as the Russell Group institutions are aware of their status in the industry and are concerned in maintaining that status. These organisations are likely to be more vigilant about potential reactions associated with their behaviour that could damage the status (Rhee & Haunschild, 2006; Graffin et al., 2013; McDonnell et al., 2015).

Therefore, we test whether universities with high gender pay gap react more aggressively compared to universities with lower gender pay gap to maintain their status. To do so, we use the pre-intervention gender pay gap at the university level, measured by taking the difference between the male and female log wages at the university-year level and averaged over the pre-treatment period. We standardise the pre-intervention wage gap to have a mean zero and a standard deviation of one. The standardised variable is interacted with the intervention and female interaction term $D_t \times \mathrm{F}_i$ given in equation 1.

Table 7 presents the results. We do not find any significant evidence that universities with gender pay gap before the intervention reacts differently compared to universities with low gender pay gap before the intervention. This is consistent throughout with the different specification estimated in Table 7 (columns 1-5).

5.3 Gender Composition

In this section we test whether gender composition at the university level influences the average impact of pay transparency on the gender pay gap. Given a level of the gender pay gap, universities with high female representation may face pressure from academics to address the gender pay gap compared to universities with lower female representation. To test this hypothesis, we calculate the average proportion of female at the university-year level before the intervention and standardise the variable to have a mean of zero and a standard deviation of one. We interact with the standardised female representation variable with $D_t \times \mathrm{F}_i$ given in equation 1.

Table 8 presents the results. Although the coefficient of the triple interaction term is positive, it is not statistically significant. This implies that university-level gender composition does not influence the gender pay gap following the intervention.

5.4 Female Labour Supply

Research has shown organisations that provide fair compensation attract more female employees (Bennesdsen et al., 2019). If we assume low gender pay gap indicates an 'equal opportunity' employer, females do not accept job offers with a lower salary relative to what they earn. Outside offers from 'equal opportunity' employers may help female academics to increase their wages and reduce the gender pay gap. We exploit the panel nature of the data to investigate whether female academics are more (less) likely to supply labour to universities with low (high) gender pay gap following the pay transparency.

To that extent, we estimate the following specification using a linear probability model.

$$\begin{aligned} Y_{itj} = a + \beta_1 D_t + \beta_2 Gap_{jt} + \beta_3(F_i \times D_t) + \beta_4(D_t \times Gap_{jt}) + \beta_5(F_i \times Gap_{jt}) + \\ + \beta_6(D_t \times F_i \times Gap_{jt}) + X_{it} + \theta_i + \eta_j + \delta_t + \gamma_{jt} + \epsilon_{itj} \end{aligned} \tag{5}$$

As before, D_t is the intervention variable taking the value of one for the years after pay publication. Gap_{it} measures the average university-year level wage gap standardised to have a mean of zero and a standard deviation of one. The primary variable of interest is the triple interaction given by $D_t \times \mathrm{F}_i \times \mathrm{Gap}_{it}$, which indicates the probability of a female academic moving to a university j to standard deviation change in the university level gender pay gap following pay publication.

Table 9 presents these results in estimating equation 5. We find that following pay transparency females are more (less) likely to move to universities with low (higher) gender pay gap compare to males. In other words, following pay transparency, one standard deviation fall (increase) in the gender pay gap (one standard deviation is equivalent to £1,982) increases (decreases) the likelihood of a female academic moving to a university by 0.42 percentage points compared to a male counterpart.

6 Conclusion

The gender pay gap is a prominent discussion among policymakers and academics. Various governments use pay transparency policies as an instrument to address gender pay inequality. Our paper examines, for the first time, the impact of pay transparency initiative on the gender pay gap in the higher education sector in the UK. Although we focus on one sector, efforts taken by many governments to increase pay transparency in other sectors potentially allow researchers to understand whether our findings are comparable in other sectors.

An important significance of pay transparency policy is that it changes the information environment and it informs agents the wage levels of the employees and of any pay disparities within the organisation. In light of this information, employees earning less than their peers are prone to negotiate higher salaries to match the salaries of their peers or move to organisations that offer fair compensation. The extent to which pay transparency intervention affect gender pay gap depends on the bargaining power between employee and employer and between men and women.[16] Alternatively, pay transparency can lead to employers adjusting salaries to reduce the gender pay gap. Specifically, to avoid public scrutiny, organisations with high public status are, therefore, more likely to react to preserve their status.

Against this backdrop, we find that on average following the introduction of the pay transparency initiative, the gender pay gap narrows significantly. An increase in female wages drives the fall. Our results are consistent with the existing literature. We also demonstrate that senior academics in the upper half of the wage distribution mostly drive this fall. We do not find pre-existing gender wage gap or the gender composition at university level influencing the impact on pay inequality. Moreover, we show that following pay transparency, female academics are more likely to move to universities with a low gender pay gap. Taken together, we conclude that the fall in the gender pay gap is mostly driven by senior female academics negotiating higher salaries within the universities and female academics obtaining outside offers from universities with a low gender pay gap.

We cannot, however, rule out any spillover effects that may limit the impact of pay transparency policy on gender pay gap whereby men take advantage of pay disclosure to increase their salaries. In addition, there are concerns about the accessibility and awareness of such transparency policies. If individuals are unaware of policies or if accessibility is difficult or costly, the impact on wage levels and in particular on gender pay gap will be sub-optimal (Backer at al., 2019).

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[16]Some research suggests that men are better negotiators than females (Bowles et al., 2007; Fortin, 2008; Card et al., 2013). Also, see Marianne (2011) for a relevant overview.

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Tables

Table 1: Descriptive statistics

	Female		**Male**		**Difference (Male - Female)**	
Variables	Mean	S.D.	Mean	S.D.	Mean	S.D.
Log-Wages	55,420	15,084	62,582	19,321	7,162***	200.6117
Nominal Wages (2016 prices)	10.89	0.244	11.00	0.268	0.109***	0.003
Ethnicity						
White	0.899	0.302	0.909	0.287	0.0107***	0.0039
Black	0.0047	0.0683	0.0058	0.0762	0.0011	0.0009
Asian	0.0652	0.247	0.0620	0.241	-0.0032	0.0033
Other	0.0314	0.174	0.0227	0.149	-0.0086***	0.0022
Age	44.26	8.937	46.85	9.355	2.596***	0.1109
Highest Qualification						
Doctorate	0.811	0.392	0.880	0.325	0.0694***	0.0047
Postgraduate, equivalent	0.134	0.341	0.0768	0.266	-0.0574***	0.004
First Degree, equivalent	0.04	0.196	0.0287	0.167	-0.0112***	0.0023
Below Undergraduate Level	0.0025	0.0499	0.0025	0.0494	-0.0001	0.0007
Other Qualification	0.012	0.109	0.0115	0.107	-0.0005	0.0013
No Qualification	0.0006	0.0248	0.0004	0.0202	-0.0002	0.0002

Notes: HESA dataset from 2004-2016. There are of 64,772 observations consisted of 10,769 female faculty and 173,145 observations of 25,207 male faculty in 24 universities over 13 years. The sample consists of full time permanent and research and teaching academics. Log real annual wages and nominal wages are adjusted using 2016 CPI index. Annual wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries.

Table 2: Impact of pay transparency on wages

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Log-Wages	Model 1	Model 2	Model 3	Model 4	Model 5
Pay Transparency	0.152***	0.0789***	0.0788***	0.0303	-0.0172
	(0.0011)	(0.0009)	(0.0009)	(0.115)	(0.114)
Pay Transparency × Female	0.0174***	0.0043**	0.0048**	0.0065***	0.0062***
	(0.0021)	(0.0019)	(0.0019)	(0.0019)	(0.0018)
Age		0.0674***	0.0676***	0.0776***	0.0798***
		(0.0008)	(0.0007)	(0.0096)	(0.0095)
Age^2		-0.0006***	-0.0006***	-0.0006***	-0.0006***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Postgraduate		0.0041	0.0043	0.0032	0.0022
		(0.0036)	(0.0036)	(0.0033)	(0.0032)
First Degree		-0.0172***	-0.0175***	-0.012**	-0.0077
		(0.0058)	(0.0057)	(0.0054)	(0.0047)
Below Undergraduate Level		-0.0027	-0.0001	0.0059	0.0071
		(0.022)	(0.0229)	(0.0225)	(0.0177)
Other Qualification		-0.0328***	-0.0326***	-0.0157**	-0.0192***
		(0.0067)	(0.0066)	(0.0062)	(0.006)
Constant	10.86***	9.061***	9.086***	8.677***	8.632***
	(0.0007)	(0.018)	(0.0209)	(0.382)	(0.377)
Individual Controls	No	Yes	Yes	Yes	Yes
University FE	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes
Uni×Year FE	No	No	No	No	Yes
N	237,917	237,917	237,917	237,917	237,917
N of Individuals	35,976	35,976	35,976	35,976	35,976
R^2	0.351	0.504	0.507	0.568	0.628

Notes: Source HESA dataset. Sample: Full-time permanent academics on teaching and research contracts observed over 13 years from 2004-2016. The table presents estimates from equation 1. Dependent variable is log real annual wages adjusted using 2016 CPI index. Annual wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries. All estimates include individual fixed effects. Individual controls include age, age squared, the highest level of education. Robust standard errors are clustered at the individual level are shown in parentheses.
*** $p < 0.01$, ** $p < 0.05$

Table 3: Impact of pay transparency on wages —Balanced sample

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Log-Wages	Model 1	Model 2	Model 3	Model 4	Model 5
Pay Transparency	0.17***	0.0838***	0.0839***	0.245	0.147
	(0.0017)	(0.00014)	(0.0014)	(0.164)	(0.137)
Pay Transparency $\times$ Female	0.0238***	0.013***	0.0133***	0.0144***	0.0127***
	(0.0039)	(0.0036)	(0.0036)	(0.0036)	(0.0033)
Age		0.0689***	0.0688***	0.0548***	0.0619***
		(0.0015)	(0.0015)	(0.0138)	(0.0115)
Age^2		-0.0006***	-0.0006***	-0.0005***	-0.0006***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Postgraduate		-0.0091	-0.011	-0.006	-0.0007
		(0.0082)	(0.0082)	(0.0077)	(0.0071)
First Degree		-0.0303**	-0.0317**	-0.0211	-0.0143
		(0.013)	(0.013)	(0.0126)	(0.01)
Below Undergraduate Level		-0.0881**	-0.0876	0.065	0.0504
		(0.0431)	(0.045)	(0.0551)	(0.0395)
Other Qualification		-0.0309***	-0.0307***	-0.0113	-0.0199**
		(0.0115)	(0.0116)	(0.011)	(0.0099)
Constant	10.91***	9.068***	9.091***	9.541***	9.303***
	(0.0011)	(0.0376)	(0.0448)	(0.57)	(0.474)
Individual Controls	No	Yes	Yes	Yes	Yes
University FE	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes
Uni$\times$Year FE	No	No	No	No	Yes
N	67,912	67,912	67,912	67,912	67,912
N of Individuals	5,224	5,224	5,224	5,224	5,224
R^2	0.433	0.531	0.537	0.586	0.667

Notes: Source HESA dataset. Sample: Full-time permanent academics on teaching and research contracts observed over 13 years from 2004-2016. The table presents estimates from equation 1 using a balanced sample. The dependent variable is log real annual wages adjusted using 2016 CPI index. Annual wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries. All estimates include individual fixed effects. Individual controls include age, age squared, the highest level of education. Robust standard errors are clustered at the individual level are shown in parentheses.
*** $p < 0.01$, ** $p < 0.05$

Table 4: Timing of the intervention and gender pay gap

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Log-Wages	Model 1	Model 2	Model 3	Model 4	Model 5
Announcement$_{t=2007}$	0.048***	0.035***	0.0349***	0.064**	0.0421
	(0.0006)	(0.0006)	(0.0006)	(0.0287)	(0.0285)
Announcement$_{t=2007}$ × Female	-0.0031***	-0.0044***	-0.0042***	-0.0009	-0.0005
	(0.0012)	(0.001)	(0.001)	(0.001)	(0.0009)
Implementation	0.148***	0.061***	0.0609***	0.03	-0.0175
	(0.0011)	(0.0008)	(0.0008)	(0.115)	(0.114)
Implementation × Female	0.0185***	0.0064***	0.0068***	0.0092***	0.0087***
	(0.0022)	(0.002)	(0.002)	(0.0019)	(0.0018)
Constant	10.87***	9.036***	9.061***	8.68***	8.636***
	(0.0006)	(0.0182)	(0.0212)	(0.382)	(0.377)
Individual Controls	No	Yes	Yes	Yes	Yes
University FE	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes
Uni×Year FE	No	No	No	No	Yes
N	237,917	237,917	237,917	237,917	237,917
N of Individuals	35,976	35,976	35,976	35,976	35,976
R^2	0.337	0.484	0.487	0.569	0.628

Notes: Source HESA dataset. Sample: Full-time permanent academics on teaching and research contracts observed over 13 years from 2004-2016. The table presents estimates from equation 2. The dependent variable is log real annual wages adjusted using 2016 CPI index. Annual wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries. All estimates include individual fixed effects. Individual controls include age, age squared, the highest level of education. Robust standard errors are clustered at the individual level are shown in parentheses.
*** $p < 0.01$, ** $p < 0.05$

Table 5: Test for endogeneity of the intervention

	(1)	(2)
Dependent Variable: Year of Publication (takes value 1 in 2007)		
Wage Gap	-0.578	-1.472
	(0.618)	(0.789)
Wage Gap (t-1)	-0.296	-0.433***
	(0.757)	(0.806)
Wage Gap (t-2)	-0.244	-0.445
	(1.334)	(1.377)
Wage Gap (t-3)	0.0849	-0.489
	(0.948)	(1.093)
Constant	-0.0338	-0.143
	(0.0438)	(0.0841)
University FE	No	Yes
N	308	308
R^2	0.012	0.031

Notes: Source HESA dataset. Each observation is at the university year level. There are 23 Russell group universities observed for 13 years and 1 Russell Group University observed for 12 years. The table presents estimates from equation 4. The dependent variable is a dummy variable taking value 1 for the year 2007 and zero otherwise. Robust standard errors are clustered at the university level are shown in parentheses.
*** $p < 0.01$, ** $p < 0.05$

Table 6: Impact of pay transparency initiative above and below the median wage

Dependent Variable: Log-Wages	(1) Earning Below Median	(2) Earning Above Median
Pay Transparency	0.237***	0.0434
	(0.0709)	(0.111)
Pay Transparency × Female	0.005**	0.0143***
	(0.0021)	(0.0024)
Constant	9.209***	9.449***
	(0.204)	(0.411)
Individual Controls	Yes	Yes
University FE	Yes	Yes
Year FE	Yes	Yes
Uni×Year	Yes	Yes
N	111,849	113,007
R^2	0.719	0.567

Notes: Source HESA dataset. Sample: Full-time permanent academics on teaching and research contracts observed over 13 years from 2004-2016. The table presents estimates from equation 1 separate for academics below and above the median wage. The dependent variable is log real annual wages adjusted using 2016 CPI index. Annual wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries. All estimates include individual fixed effects. Individual controls include age, age squared, the highest level of education. Robust standard errors are clustered at the individual level are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$

Table 7: Effect of pre-existing gender pay gap on gender pay gap following the intervention

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Log-Wages	Model 1	Model 2	Model 3	Model 4	Model 5
Pay Transparency	0.152***	0.0789***	0.0787***	0.0326	-0.0266
	(0.0011)	(0.0009)	(0.0009)	(0.114)	(0.114)
Uni Gap	-0.0112	-0.0105	-0.0921**	-0.119***	-0.0905
	(0.0066)	(0.0057)	(0.0437)	(0.044)	(0.0533)
Pay Transparency × Female	0.0174***	0.0043**	0.0048**	0.0065***	0.0062***
	(0.0021)	(0.0019)	(0.0019)	(0.0019)	(0.0018)
Pay Transparency × Uni Gap	0.0016	0.0016	0.0017**	0.0012	-0.016
	(0.001)	(0.0008)	(0.0008)	(0.0008)	(0.0222)
Female × Uni Gap	0.0095	0.0082	0.0081	0.0095	0.0072
	(0.011)	(0.0089)	(0.0087)	(0.0087)	(0.0087)
Pay Transparency × Female × Uni Gap	-0.0008	-0.0017	-0.002	-0.0018	-0.0005
	(0.0019)	(0.0016)	(0.0017)	(0.0016)	(0.0016)
Constant	10.86***	9.061***	9.021***	8.601***	8.576***
	(0.0007)	(0.018)	(0.0302)	(0.379)	(0.374)
Individual Controls	No	Yes	Yes	Yes	Yes
University FE	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes
Uni×Year FE	No	No	No	No	Yes
N	237,917	237,917	237,917	237,917	237,917
N of Individuals	35,976	35,976	35,976	35,976	35,976
R^2	0.351	0.504	0.507	0.568	0.628

Notes: Source HESA dataset. Sample: Full-time permanent academics on teaching and research contracts observed over 13 years from 2004-2016. The table presents estimates from equation 1 after interacting average standardised university level pre-existing gender pay gap with the female and intervention interaction term. The dependent variable is log real annual wages adjusted using 2016 CPI index. Annual wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries. All estimates include individual fixed effects. Individual controls include age, age squared, the highest level of education. Robust standard errors, clustered at the Individual level, are shown in parentheses.
*** $p < 0.01$, ** $p < 0.05$

Table 8: Effect of gender composition on gender pay gap following the intervention

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Log-Wages	Model 1	Model 2	Model 3	Model 4	Model 5
Pay Transparency	0.152***	0.0789***	0.0787***	0.0302	-0.0131
	(0.0011)	(0.0009)	(0.0009)	(0.115)	(0.114)
Mean Rep.	0.0054	0.0079	0.0309**	0.0388***	0.04***
	(0.0061)	(0.0054)	(0.0125)	(0.0126)	(0.0149)
Pay Transparency × Female	0.0178***	0.0045**	0.0049**	0.0069***	0.0063***
	(0.0021)	(0.0019)	(0.0019)	(0.0019)	(0.0018)
Pay Transparency × Mean Rep.	-0.0003	-0.0009	-0.0011	-0.0018**	-0.0055
	(0.001)	(0.0009)	(0.0009)	(0.0009)	(0.0085)
Female × Mean Rep.	-0.0071	-0.004	-0.0145	-0.0144	-0.0135
	(0.0101)	(0.0082)	(0.0088)	(0.0087)	(0.0083)
Pay Transparency × Female × Mean Rep.	-0.0029	-0.0003	-0.0002	-0.0011	-0.002
	(0.0021)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Constant	10.86***	9.06***	9.07***	8.656***	8.61***
	(0.0007)	(0.018)	(0.0192)	(0.381)	(0.378)
Individual Controls	No	Yes	Yes	Yes	Yes
University FE	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes
Uni×Year FE	No	No	No	No	Yes
N	237,917	237,917	237,917	237,917	237,917
N of Individuals	35,976	35,976	35,976	35,976	35,976
R^2	0.351	0.504	0.507	0.569	0.628

Notes: Source HESA dataset. Sample: Full-time permanent academics on teaching and research contracts observed over 13 years from 2004-2016. The table presents estimates from equation 1 after interacting average standardised university-level female representation with the female and intervention interaction term. The dependent variable is log real annual wages adjusted using 2016 CPI index. Annual wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries. All estimates include individual fixed effects. Individual controls include age, age squared, the highest level of education. Robust standard errors, clustered at the Individual level, are shown in parentheses.

*** $p < 0.01$, ** $p < 0.05$

Table 9: Movement of academics and university level gender pay gap

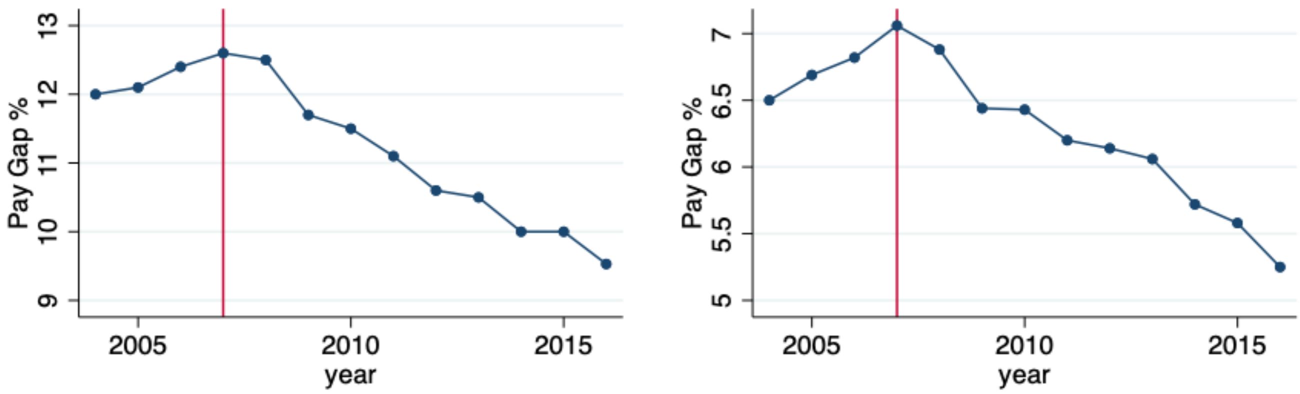
	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Pay Transparency	0.146***	0.0827***	0.0828***	0.0131	0.0058
	(0.0011)	(0.0009)	(0.0009)	(0.119)	(0.115)
Uni Gap	-0.0134***	-0.0044***	-0.0046***	-0.0138***	-0.0228***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0042)
Pay Transparency × Female	0.0111***	-0.0001	0.0005	0.0025	0.0024
	(0.0021)	(0.0019)	(0.0019)	(0.0018)	(0.0018)
Pay Transparency × Uni Gap	-0.0122***	-0.0008	-0.001	-0.0002	0.0466***
	(0.0009)	(0.0008)	(0.0008)	(0.0008)	(0.011)
Female × Uni Gap	-0.0128***	-0.0088***	-0.0087***	-0.0073***	-0.0084***
	(0.0025)	(0.0024)	(0.0024)	(0.0024)	(0.0022)
Pay Transparency × Female × Uni Gap	-0.0037**	-0.0044***	-0.0047***	-0.0048***	-0.0042***
	(0.0018)	(0.0016)	(0.0016)	(0.0016)	(0.0015)
Constant	10.86***	9.11***	9.131***	8.659***	8.64***
	(0.0007)	(0.0184)	(0.0211)	(0.394)	(0.382)
Individual Controls	No	Yes	Yes	Yes	Yes
University FE	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes
Uni×Year FE	No	No	No	No	Yes
N	237,917	237,917	237,917	237,917	237,917
N of Individuals	35,976	35,976	35,976	35,976	35,976
R^2	0.38	0.506	0.51	0.577	0.629

Notes: Source HESA dataset. Sample: Full-time permanent academics on teaching and research contracts observed over 13 years from 2004-2016. The table presents estimates from equation 5. The dependent variable is a dummy variable taking value 1 if an individual moves to university j. All estimates include individual fixed effects. Individual controls include age, age squared, the highest level of education. Robust standard errors, clustered at the Individual level, are shown in parentheses.

*** $p < 0.01$, ** $p < 0.05$

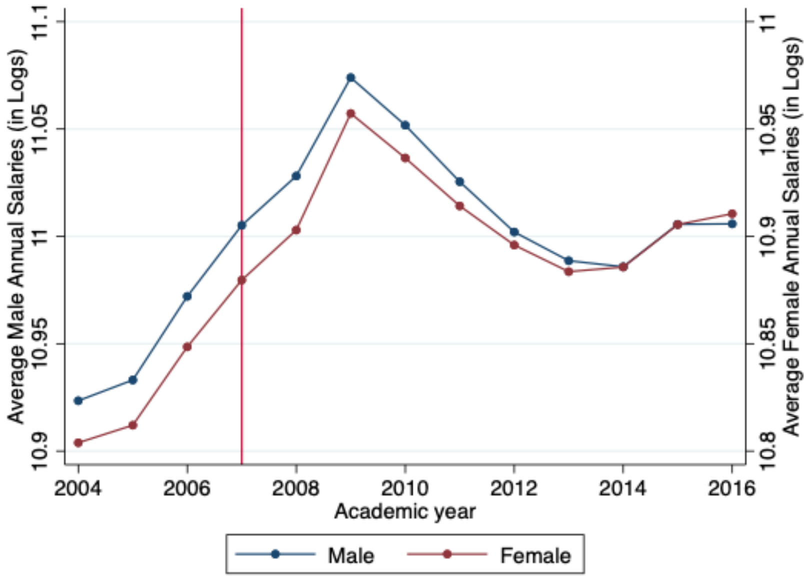
Figures

Figure 1: Trends in the gender pay gap, Russell Group Universities



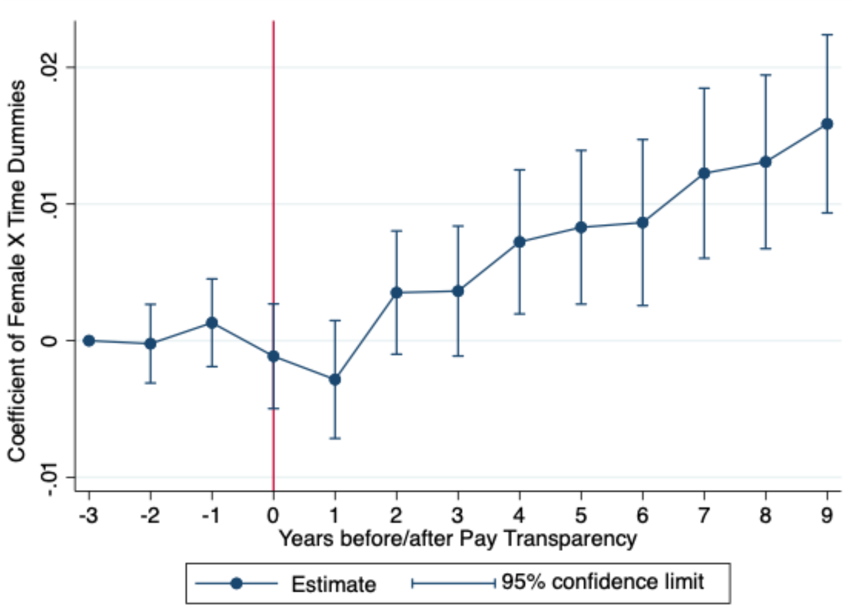
Notes: Source HESA 2004-2016. Left: raw data. Right: adjusted for controls (age, age squared, ethnicity, education and university FE).

Figure 2: Trends in wages before and after pay transparency



Notes: Source HESA dataset. Sample: Full-time permanent academics on teaching and research contracts observed over 13 years from 2004-2016. The figure presents the average log annual wages of female and male academics. Yearly wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries. Individual controls include age, age squared, the highest level of education.

Figure 3: Coefficient plot of estimates from Equation 3



Notes: Source HESA dataset. Sample: Full-time permanent academics on teaching and research contracts observed over 13 years from 2004-2016. The figure presents coefficient estimates of Female and year dummy interaction in equation 3. The dependent variable is log real annual wages adjusted using 2016 CPI index. Yearly wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries. Year(-3) is the reference year.

Appendix

HESA Data

This study uses administrative dataset collected and managed by the Higher Education Statistical Agency (HESA). The dataset contains data from academics year 2003/04-2015/16. Table A1 presents the main variables used in the study. HESA reports all variables. In 2013, the HESA reporting procedure changed, from an individual level to contract level. Due to this, an individuals can have multiple observations (multiple contracts) per year. We converted the 2012/13-2015/16 contract level data to individual-level, to have one observation per person per year. If an individual has only one contract per year, it is treated just as it is. Alternatively, if an individual has multiple contracts, we use a set criteria to identify the contract considered to be the 'main job'. We designed the criteria based on HESA variable, namely, the proportion in the cost centre, salary and terms of employment. The proportion of cost centre records the Full Person Equivalent (FPE), i.e. the proportion of a person's time allocated to a contract.[17] For example, if an individual has two contracts, the proportion in the cost centres indicates 70% and 30%, respectively, we select the contract with the highest proportion as the main job. If the proportions are equal (50/50), we use the Full Time Equivalent salary related to the contracts. Here we consider the contract with the highest salary as the main job. Finally, if the proportion in cost center and salaries are equal between the contracts, we use the terms of employment. Here we select the open-ended/permanent contract over the temporary/fixed-term contract to be considered as the main job.

Moreover, in our sample we excluded clinical departments, specifically, clinical medicine and clinical dentistry as they are more likely to follow a different pay structure. We use cost centres to identify these departments. Cost centres are defined groups used by university finance departments to allocate budgets. We include the following cost centres in our study, Anatomy & physiology, Nursing & paramedical studies, Health & community studies, Veterinary science, Psychology & behavioural sciences, Pharmacy & pharmacology, Biosciences, Chemistry, Physics, Agriculture & forestry, Earth, marine & environmental sciences, General engineering, Chemical engineering, Mineral, metallurgy & materials engineering, Civil engineering, Electrical, electronic & computer engineering, Mechanical, aero & production engineering, Architecture, built environment & planning, Mathematics, IT, systems sciences & computer software engineering, Business & management studies, Geography, Social studies, Media studies, Humanities & language based studies, Design & creative arts, Education, Modern languages, Archaeology, Sports science & leisure studies.

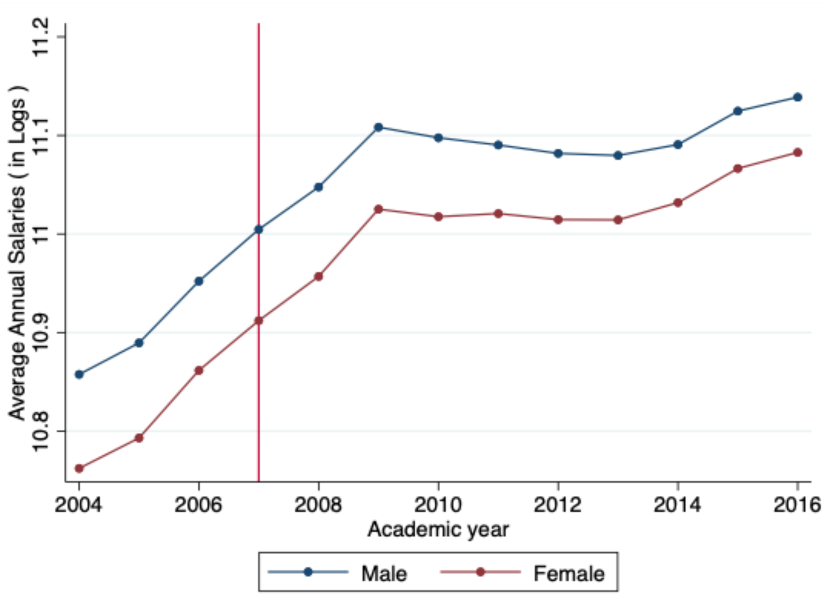
[17] See https://www.hesa.ac.uk/collection/c16025/fte$_v s_f pe$.

Table A1: Definition of Variables

Variable	Definition
Treatment Variable	
Pay Transparency Initiative	Dummy variable= 1 when the institution publishes their pay data in year t
Main Dependent Variable	
Salary	Continuous variable recoding log adjusted salary using CPI=2016 as the base year
Female	Dummy variable=1 if female
Age	Continuous variable measuring individual's age (in years)
Education	Categorical Variable recording levels of qualification
Ethnicity	Categorical variable recording ethnic origins of the individual. Classified into white/non-white
Employment Characteristics	
Institution	Categorical variable
Mode of Employment	Categorical variable taking values: 1 full time 2 full-time term-time only 3 Part-time 4-Part-time term-time only
Terms of Employment	Categorical variable taking values 1 for open-ended/permanent contracts; 2 for Fixed-term contracts
Academic Employment Function	Categorical variable taking values: 1 Teaching only; 2 Research only; 3 Teaching and Research

Notes: We use mode of employment, terms of employment and academic employment function to identify our sample of academics who are in full time permanent engaged in teaching and research activities.

Figure A1: Trends in wages before and after pay transparency balanced sample (Balanced Sample)



Notes: Source HESA dataset. Sample: Full time permanent academics on teaching and research contracts observed over 13 years from 2004-2016. Figure present the average log annual wages of female and male academics. Annual wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries. Individual controls include age, age squared, highest level of education.

Table A2: Parallel trend assumption

	(1) Unbalanced Sample	(2) Balanced Sample
Female × Year_{t-2}	-0.0002	-0.0022
	(0.0015)	(0.0023)
Female × Year_{t-1}	0.0013	0.0008
	(0.0016)	(0.0022)
Female × Year_{t}	-0.0011	-0.0019
	(0.002)	(0.0029)
Female × Year_{t+1}	-0.0028	-0.0015
	(0.0022)	(0.0034)
Female × Year_{t+2}	0.0035	0.0046
	(0.0023)	(0.0036)
Female × Year_{t+3}	0.0036	0.0058
	(0.0024)	(0.0038)
Female × Year_{t+4}	0.0072***	0.0128***
	(0.0027)	(0.0042)
Female × Year_{t+5}	0.0083***	0.0141***
	(0.0029)	(0.0045)
Female × Year_{t+6}	0.0087***	0.0133***
	(0.0031)	(0.005)
Female × Year_{t+7}	0.0123***	0.0196***
	(0.0032)	(0.0051)
Female × Year_{t+8}	0.0131***	0.0186***
	(0.0032)	(0.0051)
Female × Year_{t+9}	0.0159***	0.0202***
	(0.0033)	(0.0053)
Constant	8.64***	9.3***
	(0.377)	(0.472)
Individual Controls	Yes	Yes
University FE	Yes	Yes
Uni×Year FE	Yes	Yes
N	237,917	67,912
N of Individuals	35,976	5,224
R^2	0.629	0.667

Notes: Source HESA dataset. The table presents the estimates from equation 3 for the female and year dummy interaction. The dependent variable is log real annual wages adjusted using 2016 CPI index. Annual wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries. All estimates include individual fixed effects. Individual controls include age, age squared, highest level of education and ethnicity. Robust standard errors are clustered at the individual level are shown in parentheses.

*** $p < 0.01$, ** $p < 0.05$

Table A3: Parallel trend assumption estimates for sample split (above and below the median)

	(1) Adjusted Log Salary	(2) Adjusted Log Salary
Female × Year$_{t-2}$	0.0007	0.0024
	(0.0015)	(0.0021)
Female × Year$_{t-1}$	-0.0002	0.0059
	(0.0021)	(0.0031)
Female × Year$_{t}$	-0.001	0.0082**
	(0.0025)	(0.0035)
Female × Year$_{t+1}$	0.0011	0.0097***
	(0.0029)	(0.0037)
Female × Year$_{t+2}$	0.0031	0.0141***
	(0.0032)	(0.0038)
Female × Year$_{t+3}$	0.0034	0.0156***
	(0.0033)	(0.004)
Female × Year$_{t+4}$	0.0054	0.0183***
	(0.0033)	(0.0042)
Female × Year$_{t+5}$	0.0051	0.0216***
	(0.0035)	(0.0044)
Female × Year$_{t+6}$	0.0065	0.024***
	(0.0037)	(0.0046)
Female × Year$_{t+7}$	0.0093**	0.0312***
	(0.0038)	(0.0047)
Female × Year$_{t+8}$	0.0117***	0.0318***
	(0.0039)	(0.0048)
Female × Year$_{t+9}$	0.0133***	0.037***
	(0.004)	(0.0049)
Constant	9.215***	9.447***
	(0.204)	(0.414)
Individual Controls	Yes	Yes
University FE	Yes	Yes
Uni×Year FE	Yes	Yes
N	111,849	113,007
N of Individuals	23,618	18,537
R^2	0.719	0.568

Notes: Source HESA dataset. The table presents the estimates from equation 3 for the female and year dummy interaction. The dependent variable is log real annual wages adjusted using 2016 CPI index. Annual wages are censored at the top and the bottom 1% salaries earned to prevent extreme outliers affecting mean salaries. All estimates include individual fixed effects. Individual controls include age, age squared, highest level of education and ethnicity. Robust standard errors clustered at the individual level are shown in parentheses.

*** $p < 0.01$, ** $p < 0.05$