Workforce Wage Gap in Space, Labour Market Transformations and Structural Inequality*

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Abstract

This paper studies within space structural variations on wage inequality and the workforce wage gap in the UK. I first analyse the factors contributing to the workforce wage gap across geographical regions and the causes affecting wage inequality along the lines of vertical segregation, horizontal segregation and labour market transformations. I then examine the causal effects of the Gender Wage Gap Reporting Policy−a policy reform enacted in the Equality Act 2010 (Specific Duties and Public Authorities) Regulation 2017 in the UK−on the workforce wage gap. Using data from the British Quarterly Labour Force Survey, I implement a synthetic control method to examine the effects of the policy across geographical regions. Synthetic control method estimators estimate the treatment effects by finding a weighted combination of units for the control group that best resembles the characteristics of the treated group in the absence of the policy. I find a positive impact effect of the policy and after the policy implementation the average treatment effect on treated is 2.32%. The result is robust to a wide variety of synthetic control method model specifications.

Keywords: Occupational segregation, gender pay gap, wage inequality, labour markets, causal inference, synthetic control method.
JEL Classification: J22, J31, J38, C32, C54.

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1 Introduction

The workforce wage gap based on gender differences has been the focus of investigation over the last decades since the figures underlying its pattern remain striking. In the UK, the gender wage gap decreased by a quarter to 13.1% in April 2024.[1] The occupation of skilled trades is the occupation with the highest gender wage gap in the UK accounting for 24% of wage discrepancies in 2024, by contrast the gender wage gap in professional occupations has been increasing over time and stabilising to 17% in 2024. Even though a considerable part of the gender wage gap can be explained by occupational segregation and the gap has been narrowing over time among all occupations and sectors, the high within occupations wage gaps and the implementation of recent policies aimed at tackling the gender wage gap both from a supply side and demand side perspectives require further analysis that delineates the effectiveness of these policies.

On average women still earn 83p for every £1 pound earned by men in 2024. In the South of England, 20.21% of male workers are in high wage occupations such as managers and senior officials, that is almost double the percent of female workers in the same occupation, for a wage that is also 14.53% higher than female workers. The South East of England records the highest gender wage gap of 25.4% followed by the Easter with 24.8% and the South West with 23.5%. The lowest gender wage gap is present in the region of Northern Ireland of about 11.2% and Wales of about 16.5% indicating that female and male hourly wages are relatively almost of the same magnitude. But how do within space structural variations affect wage inequality and the gender wage gap? How different industrial and job structures impact the geography of the gender wage gap? To what extent do geographical labor market characteristics contribute to the observed workforce wage gap? What is the effect of the Gender Wage Gap Reporting Policy in the UK?

In this paper, I offer an answer to these questions based on geographical variations and I provide causal estimates of occupational choices, spatial choices and the effects of the Gender Wage Gap Reporting Policy in the UK on the gender wage gap. My primary focus of investigation is the study of the impact of the Gender Wage Gap Reporting Policy regarded as the Equality Act 2010 (Specific Duties and Public Authorities) Regulations 2017 and examining the geographical nature of the policy in the UK.[2] The hypothesis I test focusses on the interaction between industrial and job structures to examine the impact of the policy on the gender wage gap across geographical regions.

The analysis is motivated by the rich in space descriptive evidence on the gender wage gap provided in this paper along the lines of in space vertical and horizontal segregation where I explore the factors contributing to the gender wage gap across in space sectors, geographical occupations, age bands over the lifecycle, spatial labour market transformations over full-time and part-time, permanent and not permanent, flexible and not flexible working arrangements,

[1] More details are available at ONS estimates website: ONS gender wage gap estimates.

[2] I provide details on the contextual framework of the Gender Wage Gap Reporting Policy in Appendix B.

as well as the role of education on the in space gender wage gap. These are factors that shape the structure of the labour market and over time define the industrial structure across regions.

I document that London and Midlands and the South of England have the largest participation of female workers in the public administration sector, education and health sector, however in London and Midlands the highest wage is brought by the energy and water sector, whereas in the South of England banking, finance and insurance is the sector with the highest wage. The highest wage in the North of England for female is in the professional occupations (£18.21), however only 17.76% of females work in this occupation. Horizontal segregation obtain a portion of the gender wage gap across all sectors, and in particular, the manufacturing sector and energy and water maintain a gender wage gap of about 12% and 10%, respectively. Along the lifecycle, I document a high gender wage gap in the age band 45-49 of 38% in 2003 and reaching approximately 17.15% in 2024.

The economic inequality and wage distribution unfairness are also highlighted in the metric of kurtosis for East Midlands, Easter, Yorkshire and Humberside, Northern Ireland and South East with all exceeding a value of 4 which can therefore be denoted as less egalitarian regions in terms of wage distribution. The South East, South West and Eastern are the regions with the highest workforce wage gap at an average of 24.57%. By contrast, Northern Ireland, Wales and London appear among the geographical regions with the relatively lowest workforce wage gap ranging between 11.2%-17.6%.

By analysing wage inequality across geographical regions, the majority of wage inequality between female and male is within each group accounting for 14.5% in 2003 and 13.9% in 2024, and a level of structural inequality in wage that decreased by 11.54% and 8.19% for male by 2024. For female and male the region with the highest wage inequality is the South East, despite the wage inequality for male has decreased by 0.65%.

After having laid out the in space descriptive evidence, I contribute to the literature of wage inequality in the UK by performing a Blinder-Oaxaca decomposition between female and male wages across British regions. To this aim, I group British regions in three spatial bands consisting of North of England, London and Midlands, and the South of England. The analysis reveals that in the North of England 19.44% of the wage inequality between female and male is due to observable characteristics, whereas in in London and Midlands and the South of England observable individual characteristics account for 33.31% and 42.36% of wage inequality between female and male, respectively. The remaining part of inequality that cannot be attributed neither to observable characteristics nor to coefficient effects is the inequality due to discrimination effect.

This paper is concerned with the evaluation of the effectiveness of the Gender Wage Gap Reporting Policy in the UK designed to reduce the gender wage gap and examines the extent to which industrial job structures expose regions to the policy. The policy introduces for all organisations with 250 or more employees a mandatory annual publication of reports on the gender wage gap within each organisation. The policy aims at addressing disparities in pays and promotions between females and males by raising transparency in pay structures with objective criteria for promotions and allowing females to progress with career progressions and pays, similarly to men. The policy was implemented nationwide however some areas experienced a delay in its implementation. I therefore use the areas with an implementation delay to identify the effect of the programme and a suitable control group by adopting a synthetic control method that deals with individual data to provide robust causal estimates of the policy on the gender wage gap, taking into account the industrial structure of each region.

To investigate the plausibility of the assumptions surrounding the synthetic control method I rely on the availability of data over time prior to the policy implementation and I use inferential methods to test the robustness of the significance of the estimates in space and in time. Since I document that the South West of England is one of the regions with the highest gender wage gap, the treated unit is regarded as the South West of England. I use then a data driven procedure to select a reasonable comparison group. The validity of the synthetic control method rests on how close the control group resembles the observable characteristics of the treated units in the absence of the policy prior to the policy intervention to obtain a reasonable conterfactual (Heckman, 1979; Heckman and Robb, 2013; Blundell et al., 1998; Bell et al., 1999).

Under this synthetic control methodology, I first assess the reliability of the method by analysing the impact of the policy on female wage only. I show that the synthetic control group reproduces the path of female wage of the treatment group in the pre-intervention period 2003-2017 extremely well with an important impact effect for the period 2017-2024. I then implement the synthetic control method for the gender wage gap first with a nested optimisation technique to compute the weights of the regressors and second, with an efficient weighting scheme optimisation technique. I include in the set of regressors variables that can shed lights on industrial structures and wage impacts based on a more equal sharing of work and childcare responsibilities between female and male such as dummies for occupations, sectors, flexible and part-time working arrangements that I denote as labour market transformation variables, and career progressions. The reason for choosing these variables in this analysis is because different industrial and job structures across regions, in particular in the pre-intervention period, may lead geographical regions to be exposed differently to the policy, thereby delivering different gender wage gaps.

I find that the synthetic control method provides a reasonable methodology to study the effect of the Gender Wage Gap Reporting Policy intervention on the gender wage gap. In particular, I estimate that the average treatment effect on treated is 2.32% overall since the gender wage gap effect is estimated to rise in the three years after the policy implementation before decaying. To assess the robustness of the estimates I implement a nested leave one out synthetic control methodology that ensures stability of the results and helps to control whether the procedure relies on one specific region. I find that the results are consistent with the nested full simultaneous optimisation, with a positive estimate of 2.43% of the average treatment effect on treated in the South West of England. The gender wage gap is not only a spatial phenomenon but also embedded in structural inequalities.

I conduct a series of iterative in space and in time Placebo tests to test the robustness of the analysis and I find a strong intervention effect through the mean squared prediction errors that support the uniqueness of the estimated gender wage gap effect. While the impact effect of the policy intervention is positive, this is suggestive that structural inequality, as highlighted in the descriptive evidence, can hinder the effect of the policy.

The analysis finds an increase in the gender wage gap three years after the policy intervention, therefore in the last part of the paper I investigate the mechanism that can lead to a fall of the gender wage gap. With a series of regressions analysis, I find that being in full-time employment accounts for most of the reduction in the gender wage gap ranging rom 0.227 to 0.675 decay. Additionally, I revert engineer the mechanism to investigate whether the presence of the workforce wage gap and wage disparities between female and male reduces the probability of being in full-time employment for female. I find that this probability decreases between 17.3% and 68.7% since wage inequality based on gender can make the job unattractive for female workers.

The results are informative to policymakers since the paper offers an analysis aimed at understanding the impact of the Gender Wage Gap Reporting Policy on the gender wage gap based on a counterfactual control group for each individual characteristic of the treated group. The synthetic control group is chosen so as to resemble each regressor of the treated units except for the missing intervention for these units. Given the persistent presence of structural inequality based on observable characteristics such as industries and jobs, the analysis calls for further studies and coordinated interventions to reduce the gender wage gap at all levels.

Outline. The paper is organised as follows. Section 2 presents the literature review on the gender wage gap and the synthetic control method used in this paper. Section 3 presents motivating descriptive evidence on the in space gender wage gap. Section 4 describes the empirical estimation, shows the associated results and explains the implications of the results on labour market outcomes. Section 5 analyses a mechanism able to show a reduction in the gender wage gap. Section 6 concludes. Appendices provide further descriptive evidence, empirical analysis and complementary robustness results.

2 Related Literature

This paper contributes to three strands of the literature: gender wage gap, interplay between gender wage gap, occupational segregation, industrial structures and labour market outcomes and, causal estimates on the gender wage gap provided with synthetic control methodology.

The main contributor of the gender wage gap is often referred to education and on the job training human capital attributing to the supply side of the labour market a preponderant role for the existence of gender differences in labour market outcomes such as wages between females and males. The groundbreaking studies by Becker (1975), Card and Krueger (1992) and Goldin (1994) document the years of schooling and lack of participation of women in the labour force as the main drivers to the gender wage gap. The landscape on the gender wage gap and educational attainments has recently changed, with women increasing their qualifications, commitment to work and participation in the labour market, thereby reducing the gender wage gap. By 2010 the most dominant factor that affects the gender wage gap has been documented to be the occupation and sector of employment (Blau and Kahn, 2017).[3]

Among the factors explaining the gender wage gap, the increase in female labour force participation has been defined as a "quiet revolution" in Goldin (2006) in counterbalancing the gender wage gap. While female labour force participation rose since 1950s, this participation in the labour market has come mainly from women married to high wage husbands further widening wage disparities (Juhn and Murphy, 1997; McGrattan and Rogerson, 2008; Autor et al., 2008). A strand of the literature has tried to explain the force underlying the rise in female labour force participation, documenting these factors from increasing returns to skills (Blau, 1998; Blau, 2025), to better technology for home work (Greenwood et al., 2005), to the introduction of the birth control pill (Goldin and Katz, 2002; Bailey, 2006) leading to a decrease in the gender wage gap (Goldin, 2014; Bick et al., 2022).

An issue affecting the gender wage gap, is that female tend to self select themselves into occupations characterised by low wages (Blau and Kahn, 2000; Levanon et al., 2009). Olsen and Walby (2004) document that labour market rigidities such as the self selection of women into low paid occupations account for 18% of the gender wage gap in the UK until 2003. According to their study, they find that 38% of the gender wage gap is due to direct discrimination and 8% because of women low educational attainments in the past. The portion of the gender wage gap due to discrimination aligns with the earlier accounts of Stiglitz (1973) whose theory on the economics of discrimination regards wage discrimination as the economic event whereby individuals with the same economic characteristics receive different wages and the difference in wages correlates with the observable non economic individual characteristics.

To deal with the problem of self selection on the gender wage gap, Blau and Beller (1988) examined the trends of the US gender wage gap using a Heckman two step procedure finding that estimates on the gender wage gap based on wage offers were larger than the estimates based on observed wages. By contrast, Blau and Kahn (2006) correct for selection by introducing part-time workers to full-time workers progressively into the analysis and then use the longitudinal nature of the dataset to recover the effect on real wage by accounting for individual with at least eight years of work experience. They find a positive selection bias in accounting for the gender wage gap with women married to high paid men having large employment gains than single women. Mulligan and Rubinstein (2008) add to the Heckman two step estimation an

[3]For a review of the literature on the gender wage gap see Blau and Kahn (2000, 2017).

identification at infinity method. The procedure estimates some of the parameters of the wage equation based on a sample of observed individual characteristics. They find that accounting for selection does not close the gender wage gap, with a negative selection of women in full-time employment in the 1970s that in the 1990s changed to positive selection.

Work experience has also been found significant in having an effect on the gender wage gap since women tend to choose occupation with low human capital and with minimal skill depreciation after a work interruption (Polachek, 1981). Model of statistical discrimination have taken into account the practice of firms who, on the basis of uncertainty on the workers' true productivity, discriminate against groups of individuals with perceived average differences (Phelps, 1972; Aigner and Cain, 1977). Goldin (2014) stresses the impact of female workforce interruptions in decreasing female wages documenting high wage penalties and costs in providing flexibility. The decreasing female wage due to work interruptions is consistent with early findings by Mincer and Polachek (1974) and Blau and Kahn (2013). Given the concentration of women in part-time jobs earning a lower wage, this concetration increases the estimates on the gender wage gap where observed individual and job characteristics appear to be the main drivers in part-time wage penalty and flexible working arrangement wage differentials (Hirsch, 2005; Bertrand et al., 2010; Mas and Pallais, 2017; Cubas et al., 2023; Li and He, 2024).

The literature on motherhood wage penalty has found a negative relationship between the decision of having children and female wages, since among other factors motherhood may decrease women productivity (Becker, 1985; Albanesi and Olivetti, 2009). By undertaking a field experiment, Correll et al. (2007) find evidence of discrimination against mothers by employers due to employers' perceptions on average differences in mothers' productivity relative to non mothers productivity. Gender differences in college majors between female and male also contributes to the gender wage gap, though to a lower extent since women have obtained gains in educational attainments relative to the past (England and Li, 2006; Bronson, 2014; Blau et al., 2000).

Recent studies on the literature on occupational segregation finds sizable differences in wages for the same occupation despite the same skills (Levanon et al., 2009). Card et al. (2016) focus on the employer-employee relationship giving emphasis on sorting across firms for women and within firm bargaining, that are the probability of a women working in a low paid job and the bonus female receive for working in high paid firms relative to men, respectively, and finding that both factors corroborate the rise of the gender wage gap. Studying wage of female workers in the five highest executive positions as ranked by the S&P 1500 firms, Bertrand and Hallock (2001) find that women earned 45% less than male workers, in part because in their study female executive were young. Likewise, sorting into occupations is often dictated by different time inputs thereby affecting the gender wage gap (Erosa et al., 2022).

The theoretical side of the relationship between occupational segregation and wage differential dates back to the work of Becker (2010) who emphasises the relevance of labour market discrimination as factor explaining gender wage differences. He identified three sources of discrimination coming from employers, coworkers and clients which all can create differences in wages between female and male. Competitive forces can drive out employer discrimination in the long run, unless discrimination is present in uncompetitive sectors of the economy (Arrow, 1973; Becker 2010). Monopsony power on the side of the employer can exacerbate gender disparities between female and male workers (Black, 1995). Black (1995) develops a search model with search costs finding that in the presence of monopsony power and employer discrimination, female workers bear higher search costs.

Lindenlaub and Prummer (2021) explores the network structure of workers to explain wage disparities. They find that jobs characterized by high uncertainty are outperformed by men because they establish looser connections over time. Since female workers have less connections, they tend to choose stable working environments with lower wages. Calvo et al. (2024) develop a marriage model to explain the gender wage gap focussing on home production complementarities. They find that marriage sorting reduces the gender wage gap when spouses share hours on home production tasks and supply a similar amount of work hours in the labour market, mainly because of technological change in the home production.

This paper differs from the aforementioned studies since it is the first to the best of my knowledge to provide causal estimates on the gender wage gap in the UK following the implementation of the Gender Wage Gap Reporting Policy enacted in the Equality Act 2010 (Specific Duties and Public Authorities) Regulations 2017, by drawing on the geographical differences of the gender wage gap across individual British regions and undertaking a synthetic control method estimation. On the methodological side of the paper, I follow Abadie and Gardeazabal (2003) and Abadie et al. (2010) in choosing a combination of British regions representative of the synthetic control group. The choice of the method is in that it allows a transparent analysis of the policy intervention on aggregate and large number of individual units for comparative case studies (Abadie, 2021).

Recent developments on the synthetic control method estimator have accounted for the presence of disaggregated data units by developing variants of the method that attribute penalisations to the discrepancies between the treated individual characteristics and the the characteristics of the synthetic control group with pairwise matching trade-off between the two groups (Abadie and L'Hour, 2021), that deal with multiple treated units (Kreif et al., 2016). Since this method has been defined as the most important innovation in policy evaluations (Athey and Imbens, 2017), its applicability spans interventions from the financial sector (Acemoglu et al., 2016), to natural disasters (Cavallo et al., 2013), to the political context (Abadie et al., 2015).

I contribute to the literature of the labour market first by estimating wage inequality in the UK through the lenses of the Blinder-Oaxaca decomposition across regions, second by providing evidence on the geography of the gender wage gap over an extended period, and third, by estimating the causal impact of a recent labour market intervention focussing on different industrial structures in the pre-intervention period across British regions in a span of time that allows me to investigate the effect of the policy in narrowing the gender wage gap.

3 Descriptive Evidence

In this Section I describe the data and present descriptive evidence that motivates the premises of the paper in tackling the geography of the gender wage gap.

3.1 Definitions and Data

I use data from the UK Quarterly Labour Force Survey (QLFS) over the period 2003q3 to 2024q4. The survey is a representative survey of individual households in the UK with comprehensive information on labour market variables characterising work related features. The responsibility of conducting the survey is in the hands of the Office for National Statistics (ONS) within the Division of Social Survey.

Since 1992 the survey was conducted on a quarterly seasonal basis with approximately $60,000$ households interviewed in each quarter. Only in 2006 the survey was switched to a quarterly calendar year to comply with the EU requirement in the Council Regulation (EC) No. 577/98. Since March 2024 the survey contains approximately $23,000$ respondent households in Great Britain and $2,500$ respondent households in Northern Ireland representing 0.3% of the Northern Ireland population.

Individuals are interviewed for 5 consecutive quarters and new individuals are recruited in each quarter. Interviews are conducted with a gap of 13 weeks to ensure that the fifth wave is conducted one year after the first wave. Wave 1 refers to the quarter an address is selected for interview and not to the specific household living at the selected address. Since 1997 survey questions pertaining earnings were asked in the first and fifth waves, thus to avoid overlapping observations I only keep respondents in the first and fifth waves.

The sample comprises more than 4 million observations in the selected sample period and it is further adjusted to reflect working people in the age group 25-64. Moreover, I drop outlier observations who reported that are working but do not have hours and wage information, and individuals who reported that they are not working but provide a wage information. To account for the age an individual obtained their highest qualification I created a new variable that subtracts to the current age how many years ago respondents obtained their highest qualification. Moreover, I create a dummy variable for female taking value 1 if the sex of the respondent is female and zero otherwise.

The final sample contains $1,031,017$ observations of which $574,429$ are female respondents and $456,588$ are male respondents. Appendix A in Table A.1 and A.2 describes the variables used in the analysis whereas Table A.3 provides summary statistics based on gender for female and male, respectively. I create dummy variables for the country of birth and the marital status of respondents. Table A.3 points that the average wage for female in the sample is £12.7 that is 25.61% lower than the wage of male in the selected sample period. While male workers report an average number of 27.39 hours, female workers rest on an average number of 17.021 hours. The average experience of male workers is approximately of 24 years close to the 23 years of experience of female workers. The vast majority of female workers are married with 22.1% of female reporting that they are single and 58.9% are married living with spouse. Likewise, 27.7% of male workers reported of being single and 59.3% are married.

While 65.16% of male workers are in full-time positions, only 33.57% of female reported of being in a full-time job. The sector at high female affluence is public administration, education and health with 27.81% of female respondents, followed by the distribution and banking, finance and insurance sectors accounting for 9.86% and 8.84% female affluence, respectively.

By contrast, 13.97% of male workers are in the public administration, education and health sectors, followed by the manufacturing and banking, finance and insurance sectors that accounts for 13.10% and 11.76% of male workers, respectively.

I create dummy variables for the country of birth and the sample contains 68.6% of female workers and 70.5% of male workers both born in England. In the analysis that follows, I focus on workers born in England.

The sample contains 13.66% and 10.98% of female and male workers with at least one child aged between 10 and 15 years old. Similarly, 12.97% and 10.50% of female and male respondents have at least one child aged between 5 and 9 years old. A similar percentage is recorded for female and male respondents that have at least one child aged between 2 and 4 years old. In terms of occupation female workers account for 20.84% and 19.47% of the administrative and secretarial and, professional occupations, respectively, which are the occupations at highest female presence. By contrast, male workers accounts for 19.81% and 17.67% of professional occupations and, managers and senior officials occupations.

Table 1 provides descriptive statistics on some of the main variables by regions in England. I group regions in three categories: North, London Midlands and South. The category North contains the North East, North West including Merseyside, Yorkshire and Humberside; category London Midlands contains East Midlands, West Midlands, Eastern and London regions; whereas category South includes the South East and South West regions of England.

The South of England reports a higher wage than the North and Midlands irrespective of gender. Nonetheless, in the South of England male wage is 25.40% higher than the female wage. While the average wage of female workers in the North is £11.68 per hour, for male workers their average wage is £14.391 per hour. In London and Midlands regions male wage exceeds the hourly wage of female workers by 23.36%.

The high wage found in the South of England is accompanied by higher worked hours than the North and Midlands hours, irrespective of gender. The gap in hours between female and male in the South registers a 66.25% higher worked hours for male than female. To reflect the higher number of hours, the distribution of male hours has a negative skewness indicating that it is skewed to the left, in contrast to the distribution of female workers whose skewness is positive across geographical regions supporting the hypothesis of a right skewed distribution.

TABLE 1.—
Labour market by regions in England

	Female			Male		
	North	London, Midlands	South	North	London, Midlands	South
Wage						
Mean	11.684	11.758	14.805	14.391	14.505	18.566
Std	6.963	7.240	9.714	8.991	9.129	12.267
Skewness	2.592	2.662	2.202	2.338	2.308	1.762
No. workers	48,301	77,773	56,903	46,553	77,758	57,178
Hours worked						
Mean	16.759	16.843	17.126	25.656	27.367	28.473
Std	18.031	18.047	18.739	21.379	21.377	21.393
Skewness	0.527	0.538	0.546	-0.045	-0.161	-0.213
No. workers	90,773	144,066	108,449	73,427	116,579	83,111
Experience						
Mean	23.087	23.095	22.138	24.472	24.294	23.035
Std	13.009	12.931	12.938	12.684	12.634	12.704
Skewness	0.164	0.160	0.249	0.008	0.019	0.137
No. workers	56,085	89,003	70,528	51,116	81,696	59,993
full-time						
Mean	0.598	0.565	0.624	0.925	0.925	0.924
Std	0.490	0.496	0.484	0.263	0.263	0.265
Skewness	-0.402	-0.262	-0.514	-3.237	-3.227	-3.190
No. workers	51,109	82,530	61,329	48,888	82,129	60,819
Occupation						
Mean	0.087	0.091	0.117	0.154	0.166	0.199
Std	0.282	0.288	0.322	0.361	0.372	0.399
Skewness	2.921	2.833	2.378	1.913	1.790	1.504
No. workers	51,101	82,525	61,310	48,861	82,088	60,801
Flexible time						
Mean	1.838	1.872	1.882	1.882	1.899	1.897
Std	0.369	0.334	0.322	0.323	0.301	0.304
Skewness	-1.832	-2.230	-2.375	-2.363	-2.654	-2.614
No. workers	29,691	48,362	35,923	28,322	47,265	35,266

NOTE. This Table presents mean, standard deviation and skewness of workers' characteristics in the UK labour market. Variables are reported by grouped regions and gender. North contains North East, North West including Merseyside, Yorkshire and Humberside of England. London, Midlands contains East Midlands, West Midlands, Eastern and London. South contains the South East and the South West of England. The variable Occupation reports the value for the managers and senior officials occupation. Data source is the British Quarterly Labour Force Survey.

Female workers working in London and Midlands of England report an average experience that is 346.51% and 4.32% larger than the North and South of England female workers, whereas

FIG. 1.—Gender wage gap over time

NOTE. The x-axis reports the period in years from 2003 to 2024, the y-axis reports level of the gender wage gap. Data source is the British Quarterly Labour Force Survey.

the average experience of male workers in the North of England is 0.73% and 6.24% higher than the average experience in the South and, London and Midlands of male workers, respectively. The proportion of female workers in a full-time positions is larger in the South than the North and Midlands of England. However, these proportions are still far below the proportions of men in full-time positions that are 54.68%, 63.72% and 48.08% larger than female in full-time in the North, Midlands and South of England, respectively. Both distributions for female and male in full-time jobs are skewed to the left.

A gap is also reported for female and male in managers and senior official occupations whereby 20% of male workers are in this occupation in the South of England compared to the 11.7% of female respondents in the South of England in this occupation. The North and the Midlands account for 16.6% and 15.4% of male workers in managerial and seniors occupations, and only 8.7% and 9.1% of female respondents in this occupation, respectively.

Finally, the flexible working pattern stays on an average of 1.8 irrespective of regions and gender, with distributions for female and male under this working pattern in the North, London and Midlands, and the South of England that are skewed to the left.

Figure 1 shows the gender wage gap in aggregate terms over time from 2003 to 2024. The gender wage gap in this paper is defined as the difference in average wage between male and female as a proportion of male workers' wage, across all jobs and not within occupations or industry sectors.[4] The gender wage gap has been declining over time, and while reaching its highest peak in 2004 accounting for 25%, by 2024 it reached 17%. On average women still earn 83p for every £1 earned by men. The 8% fall in the gender wage gap and its current figure at 17% highlights the need of further policies necessary to close this gap stemming from persistent structural inequality.

The interest of this paper is to investigate the gender wage gap spatially across regions,

[4]This definition is consistent with the ONS gender wage gap measure at this link: ONS Gender wage gap measure, although other measures have been used in the literature using the median instead of the mean. More details are available at this link: ONS gender pay gap.

Table 2.—
Horizontal segregation by regions

	Female					
	North England		London, Midlands		South England	
	Mean	Obs	Mean	Obs	Mean	Obs
Agriculture and fishing	8.391	124	8.956	317	10.229	172
Energy and water	14.169	386	14.961	627	17.354	295
Manufacturing	11.904	3,225	11.309	6,370	14.636	3,056
Construction	13.019	855	13.367	1,463	15.178	1,231
Distribution	8.249	8,777	8.536	14,341	9.968	8,679
Transport, communication	12.067	1,844	12.740	3,226	18.182	3,368
Banking, finance, insurance	12.844	6,623	13.164	10,427	18.598	11,346
Public admin, education	12.626	24,410	12.634	37,762	14.447	25,748
Other services	9.895	2,039	10.118	3,212	13.757	2,964
Total		48,283		77,745		56,860
	Male					
	North England		London, Midlands		South England	
	Mean	Obs	Mean	Obs	Mean	Obs
Agriculture and fishing	9.209	258	10.133	725	10.631	422
Energy and water	17.225	1,417	15.869	2,100	19.027	1,062
Manufacturing	14.362	10,077	13.737	19,127	16.447	7,201
Construction	14.576	4,234	14.872	6,580	17.070	4,184
Distribution	11.024	7,363	11.362	12,160	12.592	8,576
Transport, communication	14.015	5,423	14.295	9,569	19.265	8,555
Banking, finance, insurance	16.599	6,474	17.481	10,247	24.217	13,529
Public admin, education	15.710	9,620	16.341	14,495	18.428	10,986
Other services	12.437	1,668	12.913	2,705	16.574	2,608
Total		46,535		77,712		57,126

Note. This Table presents mean and observations of wage across industry sector by regions and gender over the sample period 2003-2024. Data source is the British Quarterly Labour Force Survey.

industry structures and educational level and then quantify the impact of a gender wage policy that addresses the gender wage gap at all levels. Therefore, the following Subsections provide descriptive evidence along these lines of study before delving into the estimation of the effect of the gender wage gap policy.

3.2 Spatial Vertical and Horizontal Segregation

In this Section I provide descriptive motivating evidence on the spatial vertical and horizontal segregation across British regions. Vertical segregation refers to the distribution and concentration of female and male across and within jobs that are unevenly distributed at different positions of the job distribution. While male workers tend to hold the most senior jobs earning a higher wage, female workers are often found at low level jobs than seniority thereby earning a lower wage. Horizontal segregation refers to the situations in which a specific sector is dominated

Table 3.—
Vertical segregation by regions

	Female					
	North England		London, Midlands		South England	
	Mean	Obs	Mean	Obs	Mean	Obs
Managers and senior officials	16.003	4,195	16.506	7,043	21.106	6,705
Professional occupation	18.212	8,579	18.272	14,144	20.757	12,239
Associate professional	13.573	6,625	13.513	10,399	16.835	8,857
Administrative	10.029	10,271	10.144	15,756	12.488	11,964
Skilled trades	8.191	728	8.279	1,485	9.963	821
Personal service occupations	8.591	6,459	8.451	10,153	9.139	6,661
Sales and customer service	7.975	5,349	7.930	7,986	8.718	4,317
Process, plant and machine	8.031	960	7.906	2,055	8.846	777
Elementary occupations	7.044	5,128	7.051	8,739	7.598	4,542
Total		48,294		77,760		56,883
	Male					
	North England		London, Midlands		South England	
	Mean	Obs	Mean	Obs	Mean	Obs
Managers and senior officials	19.588	7,230	19.758	13,009	24.172	11,553
Professional occupation	20.747	8,320	20.781	13,771	24.761	13,307
Associate professional	15.788	6,608	16.132	10,622	20.261	9,347
Administrative	11.633	2,592	12.020	3,698	14.945	3,041
Skilled trades	11.654	6,814	11.521	11,632	12.596	6,109
Personal service occupations	9.368	1,477	9.075	1,988	10.447	1,495
Sales and customer service	9.681	2,002	10.183	2,748	11.094	2,090
Process, plant and machine	10.241	6,511	9.991	11,618	10.948	5,008
Elementary occupations	8.372	4,986	8.372	8,648	9.038	5,201
Total		46,540		77,734		57,151

Note. This Table presents mean and observations of wage across major occupations by regions and gender over the sample period 2003-2024. Data source is the British Quarterly Labour Force Survey.

by the presence of one gender. I use the major occupation classification in the QLFS as proxy for jobs to disentangle vertical segregation and the industry sector in the QLFS to examine horizontal segregation.

Table 2 shows the wage of female and male respondents by industry sector across British regions. The Table documents two important features. First, wages tend to be higher in the South of England regardless of gender and industry sector and second, a widely affirmed finding in the literature, that is also possible to deduce from the current evidence is that the wage of male exceeds the wage of female irrespective of the industry sector.

For female in the North of England, the public administration, education and health sector is the sector with the highest turnout of female workers whose associated average wage is £12.63 per hour. The highest wage in the North is in the energy and water sector yielding £14.17 per hour, but with only 386 of female respondents working in this sector. In London and Midlands and the South the public administration sector, education and health sector maintains the highest turnout, but in London and Midlands the energy and water sector records the highest wage (£14.96) with only 627 of female in this sector, whereas in the South the banking, finance and insurance sector yields the highest wage (£18.598) with 11,346 turnout of female workers.

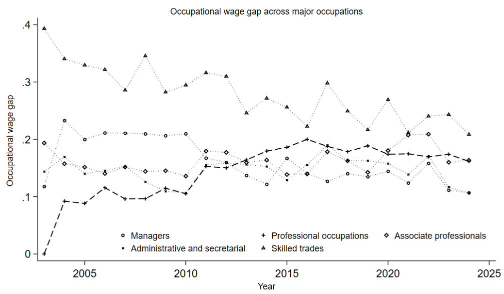
For male workers in the North of England, the manufacturing sector is the sector with the highest turnout of workers but with an average wage of £14.362 that is 19.93% lower than the wage in the energy and water sector that records the largest wage with limited turnout of male workers. London and Midlands and the South regions maintain the same wage pattern of the North with the main difference that the largest wage is recorded in the banking, finance and insurance sector that is 27.25% larger than the manufacturing sector in London and Midlands regions and 47.24% in the South of England. However, while London and Midlands record the highest turnout of male workers in the manufacturing sector, the South of England registers the banking, finance and insurance sector as sector of higher wage and higher turnout of male workers.

Furthermore, while 13,529 of male respondents are in the banking, finance and insurance sector, only 11,346 of female workers are found in this sector in the South of England with a wage between female and male that is 30.21% larger for male workers. As the vast majority of female workers are in the public administration, education and health sector that register a low wage their possibilities to obtain a higher wage remain limited.

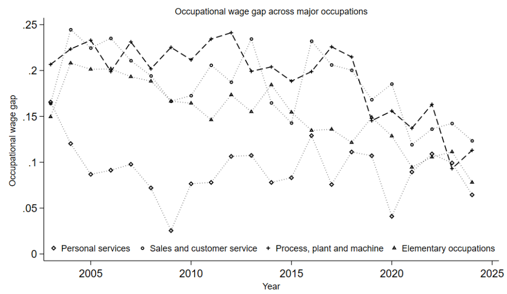
Table 3 documents wage differences across British regions by gender and major occupations. In this regard, wage in the South of England are larger than the wage in occupations in the North, London and Midlands regions regardless of gender and the wage of male workers exceeds the wage of female workers across all occupations. The vast majority of female workers in the North of England is in the administrative occupations (21.27%) earning an average wage of £10.03 per hour. The highest wage in the North of England for female is in the professional occupations (£18.21), however only 17.76% of females work in this occupation. In the London and Midlands regions 20.26% and 18.19% of female works in administrative occupations and professional occupations, earning an average hourly wage of £10.14 and £18.27, respectively. In the South of England 21.52% of female works in professional occupations and only 11.79% of female are in managers and senior officials occupations.

For male workers in the South of England 20.21% are in managers and senior officials occupations, that is almost double the percent of female workers in this sector, for a wage that is 14.53% larger than the hourly wage of female respondents. The largest presence of male workers is in the professional occupations (23.28%) with a hourly wage that is 19.29% larger than the wage of female workers in the same occupation.

London and Midlands regions show 16.73% of male workers in managers and senior officials occupations, that is double the percent of female workers in this occupation. In the North of England, male workers in the highest paid occupations occupy 15.53% and 17.88% of managers



(A) Gender wage gap occupations 1



(B) Gender wage gap occupations 2

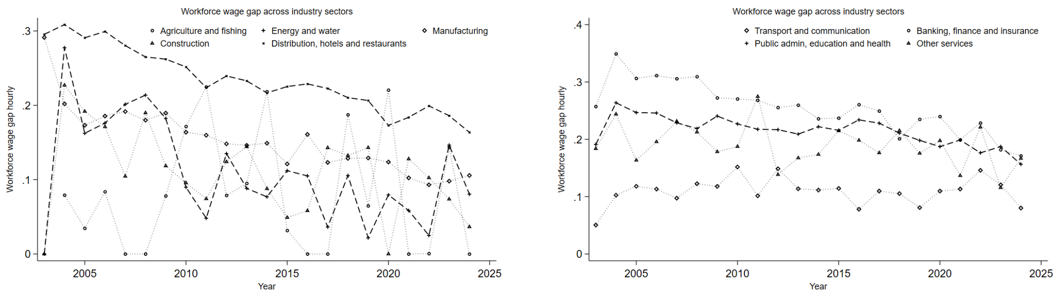
FIG. 2.— The figure shows the gender wage gap by major occupations over time. The vertical axis depicts the gender wage gap in level. The horizontal axis depicts the period in years from 2003 to 2024. The occupational wage gap is intended as the wage gap between female and male wages across major occupations. Data source is the British Quarterly Labour Force Survey.

and senior officials occupation and professional occupations, that is double the percent of female workers for what regards managers and senior officials occupations. The hourly wage of male workers rests 13.92% and 22.40% larger than the hourly wage of female workers in professional occupations and managers and senior officials occupations, respectively.

Figures A.1 and A.2 in Appendix A plot the wage of female and male across major occupations over time, respectively. It shows an increasing pattern of wages amongsts the two groups since 2003 with managers occupation reaching the largest hourly wage of approximately £29 by 2024. By contrast, by 2024 female managers obtain only £24 hourly wage despite the same occupation. The occupation of process, plants and machine registers one of the largest rise in wage of 114.28% since 2003 to recently, irrespective of the gender group.

Figure 2 shows the gender wage gap across major occupations analysed above. The wage gap is still intended as the wage gap between female and male wages and not between the highest paid and lowest paid occupations. The figure shows the occupation of skilled trades with the largest gender wage gap, which although decreasing since 2003, in 2024 it remains high at 24%. A consistent decay in the gender wage gap of manager is evident, which reaches 12% in 2024. The gender wage gap in professional occupations has actually increased over time, stabilizing to 17% in 2024, similarly to associate professional occupations.

The gender wage gap in administrative and secretarial occupations has been moving more steadily over time with a gender wage gap of 11% by 2024. Likewise, the gender wage gap in personal services occupations has experienced a less remarkable decay over time, however, personal services remains the occupation with the lowest gender wage gap in 2024 at approximately 8%. This occupation is followed by the occupation of elementary occupations with the second lowest gender wage gap at approximately 9% in 2024, while the gender wage gap in the occupation of sales and customer services reduced significantly over time and, in 2024 reached a value of approximately 14%. Process, plants and machine occupation experienced a reduction in the gender wage gap of about 50% since 2003.



(A) Gender wage gap industry 1 (B) Gender wage gap industry 2

Fig. 3.— The figure shows the gender wage gap by industry over time. The vertical axis depicts the gender wage gap in level. The horizontal axis depicts the period in years from 2003 to 2024. Data source is the British Quarterly Labour Force Survey.

In terms of horizontal segregation, Figure 3 shows the workforce wage gap across different industries over time in England. The figure shows that two industry sectors of distribution, hotels and restaurants, and banking, finance and insurance, had the largest gender wage gap until 2015, when the sector of public administration, education and health recorded a gender wage gap of 20%, and only reaching 19% until recently in 2024. However, while for the former two sectors it is apparent a steady decay over time, the latter sector has been constantly around an average gender wage gap of 20% over time reflecting the feature that wages in this sector have been changing less frequently over time and therefore, less progresses have been made to close the gender wage gap in this sector. Finally, the manufacturing sector and energy and water sector−while decreasing less pronouncedly over time−maintain a gender wage gap of about 12% and 10%, respectively.

These evidence together documents barriers for women to narrow the gender wage gap within and across regions with horizontal and vertical segregation being the major causes of the presence of the gender wage gap which continues to persist. Industrial and jobs structures underpinning each region may determine the extent to which the policy affects each region. In the estimation analysis I tackle the gender wage gap by regions by evaluating and estimating the impact of a recent policy that has been put forward in the UK to close the gender wage gap.

3.3 Educational Gender Wage Gap

This Section documents evidence on the gender wage gap by education proxied with the highest qualification. Table 4 presents differences between female and male workers in wage across geographical British regions by education qualification.

The Table shows that having a degree yields the largest wage on average for both female and male. Additionally, a degree or equivalent education in the South of England yields a wage that is 19.21% larger than the wage in the North of England. However, while wages in the South remain high for both female and male workers, the discrepancy between the two wages within the same region is 23.57%, *i.e.*, male respondents earn a wage that is 23.57% larger than the

Table 4.—
Educational gender wage gap by regions

	Female					
	North England		London, Midlands		South England	
	Mean	Obs	Mean	Obs	Mean	Obs
Degree or equivalent	17.024	12, 386	17.154	20, 087	20.294	20, 284
Higher education	12.931	4, 630	13.091	7, 399	14.496	4, 752
GCE A level	10.516	8, 300	10.692	13, 038	12.814	7, 907
GCSE grades A-C	9.586	11, 645	9.554	17, 743	11.323	10, 741
Other qualification	8.107	3, 180	8.344	6, 183	10.460	4, 881
No qualification	7.318	2, 984	7.428	5, 027	8.536	2, 674
Not known	10.593	421	10.426	578	11.694	218
Total		43, 546		70, 055		51, 457
	Male					
	North England		London, Midlands		South England	
	Mean	Obs	Mean	Obs	Mean	Obs
Degree or equivalent	20.506	11, 399	20.877	18, 648	25.077	20, 593
Higher education	16.478	3, 938	16.610	6, 260	18.307	3, 809
GCE A level	13.272	11, 230	13.764	17, 956	16.318	10, 344
GCSE grades A-C	12.037	8, 149	12.311	13, 097	14.840	8, 033
Other qualification	10.031	3, 940	10.029	8, 012	12.378	5, 696
No qualification	9.365	2, 754	9.028	4, 935	10.349	2, 760
Not known	12.119	542	11.597	659	14.803	275
Total		41, 952		69, 567		51, 510

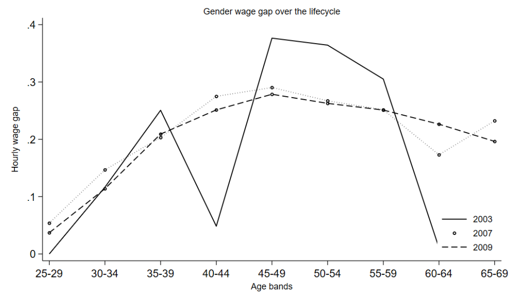
Note. This Table presents mean and observations of wage by regions and gender across the highest qualification level over the sample period 2003-2024. Data source is the British Quarterly Labour Force Survey.

wage of female workers.

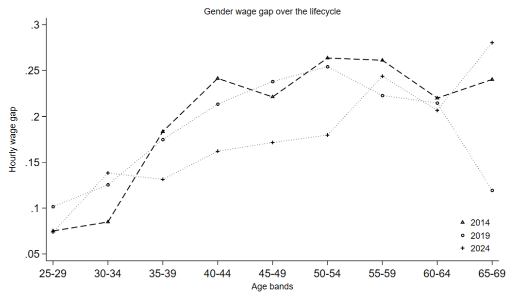
Within each region, degree or equivalent education and GCSE grades A-C are the education levels with largest female prevalence. By contrast, for male workers degree or equivalent education and GCE A levels obtain the their highest turnout. Differences in wage between female and male account for 21.70% in London and Midlands and 20.45% in the North of England in favor of male workers.

Table A.4 in Appendix A documents differences in wage between female and male by regions, however by focussing on the highest degree already held by respondents. In this regard, the overall sample shrinks as many non respondents appear. Nonetheless, the evidence on having a master reinforces the evidence of Table 4 whereby the South of England yields a larger wage than the North and London and Midlands, irrespective of wage. The gap between female and male wage within a given region for having a master accounts for 18.70%, 19.55% and 16.93% larger wage for male workers than for female, in the South, London and Midlands, and the North of England, respectively.

In terms of respondents who reported having a doctorate, significant divergences remain for



(A) Gender wage gap 2003-2009



(B) Gender wage gap 2014-2024

FIG. 4.—The figure shows the gender wage gap by age bands over time. The vertical axis depicts the gender wage gap in level. The horizontal axis depicts the age bands. Data source is the British Quarterly Labour Force Survey.

the wage of female workers, however, with the difference that between regions the South and the North of England yield the largest wage. Despite the doctorate yields the largest wage between degree levels, only 767 of female respondents undertake a doctorate in the South, that is almost half the participation of men in the same degree qualification. This frequency for female with a doctorate is even lower in the North and London and Midlands compared to men.

Furthermore, an important point to highlight is that while the second largest education level that obtains the largest turnout for female respondents is PCGE after Masters level regardless of regions, the second largest dominant education level for male workers is Doctorate, that is second after the Masters level. This feature indicates that while for males is more likely to enter higher job positions and move up the ladder of wages, for female it is less straightforward to advance in their career because of intrinsic ex-ante educational characteristics such as the type of education level already held, and especially in the presence of childcare responsibilities of which female workers face the highest burden.

Figure 4 shows the gender wage gap over the lifecycle. In panel A the years 2003, 2007 and 2009 are considered, in panel B the years 2014, 2019 and 2024 are considered. I create nine age bands given the data which are: 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64 and 65-69. Focussing on the working age until the age band 60-64, the figure shows an increasing hump-shaped pattern of the gender wage gap over the lifecycle that has been declining over time. The age band 45-49 records the highest gender wage gap in 2003 to 38% and in 2009 to 29%. By 2024, the gender wage gap for this age band stays on approximately 17.15%. In 2024, the gender wage gap remains high for the age band 55-59 at approximately 24.37%.

Figure A.3 in Appendix A shows the wage age profile for female (Panel A) and male (Panel B). The figure shows that female wage has been steadily increasing over time and the rise is more remarkable at high age bands until 55-59 when workers can enjoy the advancement in their career with a rise in wage. The same pattern is present for male workers, however, while for female their average hourly wage is less than £20 over the course of the lifecycle, for male workers the average hourly wage is less than £25 which is not a non negligible difference.

TABLE 5.—
Gender wage gap in space

	Mean	Std	Skewness	Kurtosis
North East England	0.194	0.049	2.546	10.707
North West England	0.191	0.026	0.107	2.896
Yorkshire and Humberside	0.178	0.036	-1.777	7.092
East Midlands	0.198	0.033	-2.456	9.829
West Midlands	0.190	0.021	0.352	3.037
Easter	0.248	0.039	2.091	8.578
London	0.176	0.018	0.051	2.075
South East England	0.254	0.033	-1.191	4.777
South West England	0.235	0.021	0.382	2.916
Wales	0.165	0.047	0.601	3.134
Scotland	0.182	0.031	-0.108	2.690
Northern Ireland	0.112	0.035	-1.187	5.859
Total	0.194	0.049	-0.018	4.705

NOTE. This Table presents descriptive evidence on the gender wage gap across geographical regions in the UK, over the years 2003-2024. The measure for the gender wage gap is the difference in average hourly wage between male and female as a proportion of the average male hourly wage. Data source is the British Quarterly Labour Force Survey.

3.4 Gender Wage Gap in Space

Along the lines of Section 3.2 in this Section I provide direct evidence on the gender wage gap by geographical office region and over time in England. A widely used measure in the literature for the gender wage gap is the difference in average hourly wage between male and female as a proportion of the average male hourly wage. This measure is consistent with the definition of the Office for National Statistics (ONS) measure on the gender wage gap, that also defines the gender wage gap as the difference in median hourly wage pay between male and female workers, using the median in place of the mean.[5]

Table 5 documents descriptive evidence on the gender wage gap in the UK. It shows that the South East has the highest gender wage gap (25.4%), followed by Eastern (24.8%) and South West (23.5%). The lowest gender wage gap is present in the region of Northern Ireland (11.2%) indicating that female and male hourly wages are almost of the same magnitude. Despite the low gender wage gap, the mean masks inequality effects on wage and indeed Northern Ireland is among the five regions with negative skewness.

The largest negative skewness is recorded for East Midlands (-2.456), followed by Yorkshire and Humberside (-1.777), South East (-1.191), Northern Ireland (-1.187) and Scotland (-0.108). The presence of this negative skewness suggests that female workers earn lower wage compared to men where in these regions they receive higher wages than female. Therefore, a notable group of female workers earn below the average wage. By contrast, the North East records a 2.546

[5]A description on understanding the gender pay gap is available at the ONS website at this link: ONS Understanding the Gender Pay Gap.

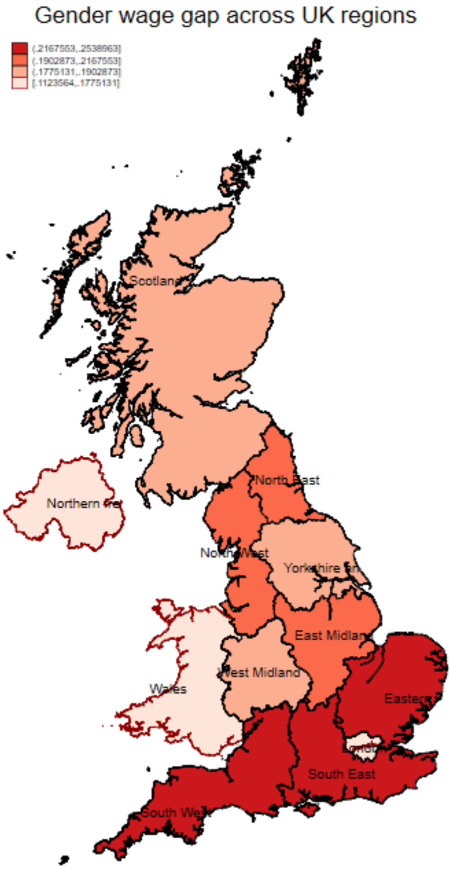


FIG. 5.—Gender wage gap across regions

NOTE. This figure presents the gender wage gap in the UK across each geographical region. Data source is the British Quarterly Labour Force Survey.

value for skewness indicating that not only the distribution is skewed to the right, but most importantly in terms of inequality there is a notable gap between the average wage and the wage of top earners, predominantly men, with a large group of female workers earning below the average wage of these two groups.

With regard to the gender wage gap kurtosis, the North East England has a very high kurtosis of 10.707 that combined with the low variation of 0.049 indicates the presence of frequent and extreme outliers in male wage earning significantly above the average wage than female workers. This metric points to a very unequal gender wage gap distribution. The economic inequality and wage distribution unfairness are also highlighted in the kurtosis of East Midlands (9.829), Easter (8.578), Yorkshire and Humberside (7.092), Northern Ireland (5.859) and South East (4.777). The regions with lower gender wage disparities can be regarded as those having a kurtosis less than 3 which suggests a more Normal distribution with less extreme values. These regions are London, Scotland, North West, South West, West Midlands, which present a more egalitarian distribution of the gender wage gap between female and male wages.

Figure A.4 in Appendix A presents the wage of female (Panel A) and male workers (Panel B)

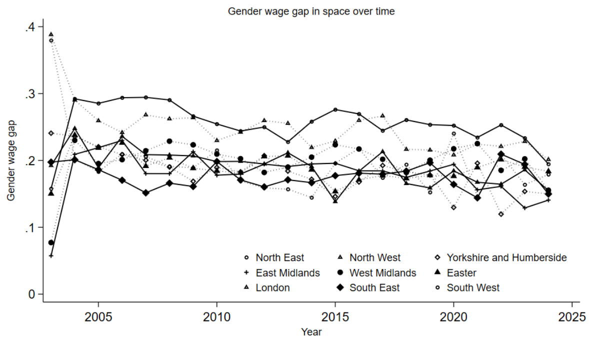


Fig. 6.—Gender wage gap in space over time

Note. The horizontal axis reports the period in years from 2003 to 2024, the vertical axis reports level of the gender wage gap across geographical regions in the UK. Data source is the British Quarterly Labour Force Survey.

over time by geographical regions in the UK. Both wages have been experiencing an increasing trend since 2003 and the South East records the largest wage for both groups over the nine regions considered. However, while the largest hourly wage for female in the South West is classified at slightly less the £25, for male workers in this region the wage is slightly less than £30 per hour. The second and third regions with the highest wage are the South West and London with an average hourly wage less than £20 for female and less than £25 for male workers.

Figure 5 shows the gender wage gap map over geographical regions and indicates Eastern, the South East and South West of England as the regions with the highest gender wage gap at an average of 24.57%. While Northern Ireland and Wales are amongst the regions with the lowest gender wage gap possibly caused by low wages and industrial labour market structures. London also presents a relatively low gender wage gap at 17.6% and as a region with high wages the low gender wage gap can be evidence of increased female wages driven by rises over the last years.

Figure 6 presents the gender wage gap over time for the nine geographical regions considered in England. The figure shows a consistent declining trend of the gender wage gap across all geographical regions since 2003 until the end of 2024. The North East of England has experienced a decay of the gender wage gap from 38% in 2003 to approximately 18% in 2024. The largest gender wage gap in 2003 is present in London (38.81%) that by 2024 reached 20.13%. The lowest gender wage gap in England in 2024 is recorded in the Yorkshire and Humberside at approximately 12.36% and East Midlands at 14.06%. London is followed by the South West with the highest percent of the gender wage gap reaching 19.45% in 2024 and has actually increased from 15.77% since 2003.

Figure A.5 in Appendix A gives a different perspective of the gender wage gap across geographical regions for some of the years considered in the analysis. The figure adds Wales, Scotland and Northern Ireland in the graph. The figure also highlights London and the North East with the highest gender wage gap in 2003 and the lowest value in 2024 obtained by Scotland

TABLE 6.—
Jobs and labour market transformations

	Female					
	North England		London, Midlands		South England	
	Mean	Obs	Mean	Obs	Mean	Obs
Full-time	12.718	29,261	12.832	44,615	16.304	36,275
Part-time	10.033	19,033	10.313	33,147	12.170	20,620
Total		48,294		77,762		56,895
Permanent	11.691	46,521	11.771	74,726	14.836	54,245
Non permanent	11.520	1,772	11.459	3,025	14.188	2,641
Total		48,293		77,751		56,886
Flexible	14.038	4,659	13.960	5,967	17.051	4,028
Not flexible	11.986	23,695	12.275	39,986	15.477	29,731
Total		28,354		45,953		33,759
	Male					
	North England		London, Midlands		South England	
	Mean	Obs	Mean	Obs	Mean	Obs
Full-time	14.618	43,416	14.711	72,585	18.943	53,473
Part-time	11.251	3,129	11.611	5,161	13.121	3,698
Total		46,545		77,746		57,171
Permanent	14.464	44,987	14.567	75,246	18.648	55,296
Non permanent	12.337	1,547	12.681	2,493	16.199	1,872
Total		46,534		77,739		57,168
Flexible	17.450	3,253	17.844	4,601	21.495	3,485
Not flexible	14.749	23,935	15.022	40,541	19.338	30,036
Total		27,188		45,142		33,521

NOTE. This Table presents mean and observations of wage by regions and gender for different classifications of job related characteristics over the sample period 2003-2024. Data source is the British Quarterly Labour Force Survey.

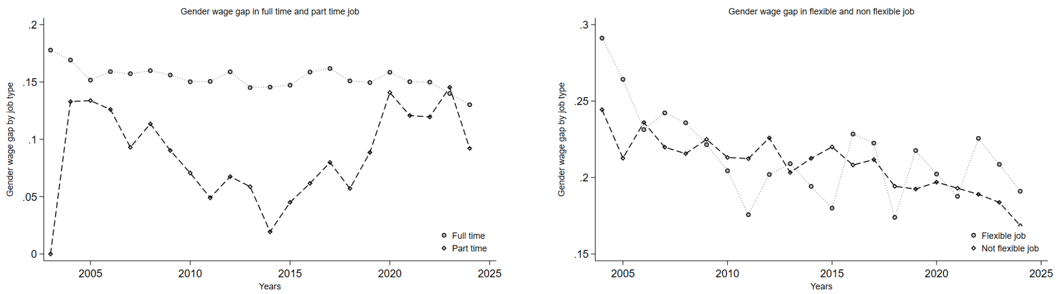
and Yorkshire and Humberside.

These figures—while important in terms of the present reduction of the gender wage gap—call for further evaluation and design of policies that ensure that the gender wage gap is closed at all levels across regions in England.

3.5 Labour Market Transformations

In this Section I analyse the gender wage gap over the transformations of jobs that have taken place over the course of 2004 to 2024. In particular, I focus on the specificity of full-time versus part-time jobs, permanent and not permanent, and flexible and not flexible working arrangements in jobs transformation.

Table 6 highlights that the vast majority of female workers are employed with a full-time job. Between regions, the South of England consistently maintains the highest wage regardless of gender. However, while only 63.75%, 57.37% and 60.59% of female are in a full-time job in



(A) Gender wage gap full-time versus part-time (B) Gender wage gap flexible and not flexible job

FIG. 7.— The figure shows the gender wage gap by job type: full-time versus part-time (Panel A), and flexible versus not flexible job working arrangement (Panel B). The vertical axis depicts the gender wage gap in level. The horizontal axis depicts the period in years 2003-2024. Data source is the British Quarterly Labour Force Survey.

the South, London and Midlands, and the North, respectively, figures are significantly different for men who constitute 93.53%, 93.36% and 93.28% of full-time workers in the South, London and Midlands, and the North, respectively. Since a full-time job brings the highest wage, this divergence can prevent female workers from obtaining job progressions over the course of their employment.

In terms of type of job, female workers in a permanent role in the South earn a wage that is 26.90% larger than the wage of female in the North of England. Male workers in the South obtain a wage that is 25.69% higher than the wage of female in the same region, while the North region yields a wage to men that is 23.72% larger than female wage in this region.

A flexible working arrangement carries the largest wage regardless of the region, however the vast majority of female and male respondents have a job with a non flexible working arrangement. A non flexible working arrangement brings to male workers a 24.95%, 22.38% and 23.05% higher wage than female wage in the South, London and Midlands, and the North, respectively, which is a non negligible difference in female wage.

Figure 7 presents the gender wage gap according to two job type patterns: full-time versus part-time (Panel A) and flexible and not flexible working arrangement (Panel B). Two notable results appear. First, the gender wage gap in full-time jobs is significantly larger than part-time jobs, also in line with the observation that full-time jobs carry a higher wage. In 2024 the gender wage gap in full-time jobs is approximately 14% yielding a decrease of 28.57% since 2003. While the gender wage gap in full-time jobs has been slightly declining over time, the gender wage gap in part-time jobs experienced a remarkable decay until 2015, at which point reverted back at increasing and reaching 9% in 2024.

Regarding jobs with flexible and not flexible working arrangements, Panel B shows that the two job types have experienced a similar declining job pattern over time, but of a slightly different magnitude. Starting with 29% and 24% gender wage gap in 2003 for flexible and not flexible jobs, respectively, the two job types experience a declining trend that in 2024 reduces

Table 7.—
Structural wage inequality

	2003		2014		2024		All sample	
	Female	Male	Female	Male	Female	Male	Female	Male
Within inequality		0.145		0.154		0.139		0.158
Between inequality		0.061		0.056		0.047		0.057
Gini coefficient	0.277	0.291	0.297	0.317	0.266	0.293	0.308	0.324

Note. This Table measures of inequality to compute the amount of structural inequality in wage between and within female and male in the UK. All sample refers to all sample period 2003-2024. Data source is the British Quarterly Labour Force Survey.

to 21% and 17%, which is a decline since 2003 of 38.10% and 41.18%, respectively.

Figures A.6 and A.7 in Appendix A graph female and male wages as a function of the firm size for full-time and part-time employment. I use as a metric for firm size the number of employees that respondents have reported in the survey. In addition, I distinguish between female and male in full-time and part-time employment on the x-axis, instead of considering the aggregate number of employees. The figure shows that for full-time employment the larger the firm size the higher the wage for both female and male. The difference remains in the magnitude of the wage which is lower for female workers, and at the same time, fewer female than male workers are employed in a given firm. In 2024 the average female hourly wage is £19 corresponding to a large firm size, while for male the hourly wage in correspondence of large firm size is £23.

The majority of the evidence presented in this Section point towards a decline in the gender wage gap by 2024. Therefore, in the following Sections I study how much of these declines over several factors can be attributed to the introduction of the Gender Wage Gap Reporting Policy by examining the extent to which these factors influence the gender wage gap in each region.

3.6 Inequality in the Gender Wage Gap in Space

To investigate differences in individual characteristics between female and male affecting the gender wage gap across geographical regions, in this Section I perform measures of inequality. First, I compute the Gini coefficient and how much of the gender wage gap accounts within and between female and male across British regions, second I perform a Blinder-Oaxaca decomposition amongsts female and male workers to investigate the unexplained part of inequality.

Table 7 presents measure of wage inequality between female and male separately for three years 2003, 2014, 2024 and all sample. The majority of wage inequality between female and male is within each group which accounts of 14.5% in 2003, 15.4% in 2014 and 13.9% in 2024, resulting in 15.8% of within wage inequality in all sample. While the Gini coefficient for female and male is first increasing since 2003 to 2014, a decay of 11.54% (female) and 8.19% (male) is recorded by 2024 since 2014. While an apparent proportion of structural wage inequality

Table 8.—

Structural wage inequality in space

	2003		2014		2024		All sample	
	Female	Male	Female	Male	Female	Male	Female	Male
North East	0.194	0.201	0.266	0.257	0.220	0.251	0.281	0.293
North West	0.220	0.307	0.258	0.296	0.256	0.283	0.297	0.306
Yorkshire and Humberside	0.233	0.232	0.280	0.286	0.237	0.267	0.296	0.282
East Midlands	0.268	0.200	0.290	0.302	0.250	0.279	0.300	0.310
West Midlands	0.301	0.200	0.284	0.312	0.259	0.274	0.293	0.312
Eastern	0.293	0.284	0.309	0.321	0.269	0.300	0.315	0.329
London	0.215	0.307	0.311	0.343	0.284	0.301	0.320	0.340
South East	0.259	0.310	0.309	0.322	0.289	0.308	0.321	0.331
South West	0.350	0.312	0.277	0.301	0.244	0.285	0.271	0.314
Wales	0.285	0.309	0.284	0.259	0.236	0.259	0.290	0.298
Scotland	0.280	0.307	0.282	0.304	0.253	0.288	0.296	0.309
Northern Ireland	0.120	0.294	0.281	0.306	0.269	0.276	0.299	0.308

Note. This Table presents the Gini coefficient across British regions over time. All sample refers to all sample period 2003-2024. Data source is the British Quarterly Labour Force Survey.

exists between the two groups, this inequality tends to be moderate. However, the fall in the inequality in wage by 2024 after the Gender Wage Gap Reporting Policy was introduced in 2017 is indicative of the presence of causal effects of the policy on wages and therefore, on the gender wage gap which I explore in Section 4.

Table 8 shows the Gini coefficient for each geographical British region over the years 2003 to 2024 between female and male. Two notable features appear. First, the inequality in female wage tends to be lower than the wage inequality for male workers. Amongsts female, the North East (19.4%) and Northern Ireland (12%) are the regions with the lowest wage inequality in 2003, North West (25.8%) in 2014, North East (22%), Wales (23.6%) and Yorkshire and Humberside (23.7%) in 2024. The region at high rate of Gini coefficient in 2024 is the South East. Keeping constant a given region, female wage inequality shows a steady increasing pattern until 2014 before reverting back to decrease. Averaging over the all sample, the South West records the lowest Gini coefficient (27.1%) whereas the highest wage inequality for female is present in the South East of England (32.1%).

A slightly different picture is highlighted for male wage inequality. In this regard, the South East maintains the highest wage inequality (30.8%) in 2024 which, however, has decreased since 2003 by 0.65%. By contrast, the region with the lowest wage inequality as measured by the Gini coefficient is the North East (25.10%) which has instead increased by 19.92% since 2003. Averaging over the all sample Yorkshire and Humberside have the lowest male wage inequality (28.2%) while London features the largest male wage inequality (34%).

I now investigate the wage inequality due to job and industrial structures between female and male within a given region. To do it I compute the Blinder-Oaxaca decomposition on wage between the groups of female and male workers in a given region. Therefore, I compute it to disentangle wage differences between these two groups across spatial regions, and not within wage inequality across geographical regions.

The Blinder-Oaxaca decomposition was introduced by Blinder (1973) and Oaxaca (1973) to provide a measure to disentangle inequality amongsts any two given groups. In particular, it allows to analyse the extent to which differences in means of predicted outcomes are due to observable characteristics and therefore, all inequality that is left over is due to unobservable characteristics. While the literature has previously studied the inequality in the gender wage gap or differences in wages based on gender through the Blinder-Oaxaca decomposition (Stanley and Jarrell, 1998; Weichselbaumer and Winter-Ebmer, 2005), I differ from them because I focus on the inequality between female and male wages across spatial regions in the UK, in addition to considering an extended sample of individuals over time and across space.

The theoretical framework that I investigate for the Blinder-Oaxaca decomposition is the following:

$$\mathrm{wage}^n_{i,t} = \beta^n_0 + \sum_{j=1}^{l} \beta^n_j x^n_{i,t} + \epsilon^n_{i,t}, \tag{1}$$

where in equation (1) the subscript j identifies each regressor used for individual i at time t, the superscript n is an indicator for female or male, the term β^n_0 is the intercept, the term β_j is the coefficient on each regressor whose vector of covariates includes dummy variables, $x_{i,t}$, and $\epsilon_{i,t}$ identifies the error term. This specification is computed for female and male wage separately, in such a way to lead to the following Blinder-Oaxaca decomposition:

$$\overline{\mathrm{wage}}^n = \beta^n_0 + \sum_{j=1}^{l} \beta^n_j \overline{x}^n_j, \tag{2}$$

where in equation (2) $\overline{\mathrm{wage}}$ is the average wage computed in the two groups $n = \{\text{female,male}\}$ and $\overline{x}^n_j$ is the mean value of each regressor in each group. The mean difference equation is then given by the following specification:

$$(\overline{\mathrm{wage}}^m - \overline{\mathrm{wage}}^f) = (\beta^m - \beta^f) + \sum_{j=1}^{l} (\beta^m_j \overline{x}^m_j - \beta^f_j \overline{x}^f_j), \tag{3}$$

where the average regressor $\overline{x}^n_j$ considers the average difference of each considered variable in level and the coefficients β^n_j measures the impact difference of each regressor in the two groups. Equation 3 can be characterised in terms of the Blinder-Oaxaca decomposition as:

$$(\overline{\mathrm{wage}}^m - \overline{\mathrm{wage}}^f) = (\beta^m - \beta^f) + \sum_{j=1}^{l} \beta^f_j (\overline{x}^m_j - \overline{x}^f_j) + \sum_{j=1}^{l} \overline{x}^f_j (\beta^m_j - \beta^f_j) + \sum_{j=1}^{l} (\beta^m_j - \beta^f_j)(\overline{x}^m_j - \overline{x}^f_j), \tag{4}$$

where in equation (4) the first difference term on the right hand side accounts for all inequality in wage that is explained by the model, the second difference term is the endowment effect that is the change in the mean predicted wage of female due to observable characteristics included in the model, the third difference term is the coefficients effect that is the change in the mean predicted wage of female when approaching the wage of male, and the last difference term is the interaction term which considers contemporaneous effects of observable characteristics and coefficients on wage inequality.

Table 9.—
Structural workforce wage inequality in space with Blinder-Oaxaca decomposition

	2024			All sample		
	North	London, Midlands	South	North	London, Midlands	South
Inequality						
Male	22.051***	22.257***	27.097***	15.966***	16.383***	20.735***
Female	18.272***	18.503***	21.963***	13.164***	13.371***	16.645***
Difference	3.776***	3.754***	5.134***	2.803***	3.013***	4.090***
Endowments	0.734**	1.010***	2.175***	1.071***	1.131***	2.162***
Coefficients	2.197***	1.891***	2.705***	1.324***	1.622***	2.327***
Interaction	0.844	0.854*	0.253	0.407***	0.261***	-0.398***
Observables						
Highest qual	-0.181**	-0.311***	0.002	-0.012	-0.079***	0.042*
Experience	-0.023	0.240***	0.100	0.115***	0.129***	0.053***
Age qual	-0.025	-0.046	-0.022	-0.015***	-0.008**	0.005
Hours	0.124	0.266*	0.563**	0.301***	0.297***	0.520***
Flexible job	-0.020	0.005	-0.005	-0.042***	-0.006**	-0.001
Part-time	0.192	0.074	0.492**	0.156***	0.207***	0.456***
Sector	0.391**	0.356***	0.531***	0.270***	0.268***	0.248***
Occupation 2	0.026	0.040	-0.025	-0.002	-0.001	-0.026***
Occupation 3	-0.038	-0.015	-0.033	-0.031***	-0.011	-0.049***
Occupation 4	1.105***	1.101***	1.273***	0.952***	0.993***	1.168***
Occupation 5	-0.973***	-1.108***	-1.016***	-0.864***	-0.945***	-0.834***
Occupation 6	0.921***	0.823***	0.757***	0.583***	0.620***	0.738***
Occupation 7	0.335***	0.400***	0.090	0.421***	0.434***	0.328***
Occupation 8	-0.906***	-0.803***	-0.595***	-0.691***	-0.749***	-0.561***
Occupation 9	-0.163*	-0.005	0.007	-0.061***	-0.045***	-0.089***
Kids < 2	-0.021	0.014	0.071	0.025***	0.039	0.122***
Kids 2-4	-0.002	-0.016	0.004	0.004	0.016***	0.053***
Kids 5-9	-0.005	-0.007	-0.009	-0.020***	-0.015***	-0.004
Kids 10-15	-0.002	-0.009	-0.011	-0.018***	-0.012***	-0.009*
No. obs	2,474	4,181	2,749	39,182	63,873	47,440
No. male	1,199	2,064	1,345	19,781	32,656	24,251
No. female	1,275	2,117	1,404	19,401	31,217	23,189

Note. This Table presents of the Blinder-Oaxaca decomposition between female and male wage across different spatial regions in 2024 and all sample period. Observables refer to individual observable characteristics. Significance is ***p< 0.01, **p< 0.05 and *p< 0.10 critical values. Data source is the British Quarterly Labour Force Survey.

In performing the Blinder-Oaxaca decomposition I use three spatial bands, consisting of North of England, London and Midlands, and the South of England. The North of England band contains the North East, the North West and Yorkshire and Humberside; the London and Midlands band contains East Midlands, West Midlands, Eastern and London; the South band contains the South East and the South West of England. These three spatial bands are used to investigate between wage inequality within each geographical region. I specify indicator dummies for the variable occupation excluding the dummy for the occupation of managers as this category is kept as the reference, and I investigate a threefold decomposition.[6]

Table 9 presents the results of the Blinder-Oaxaca decomposition, and the complementary part to the analysis is presented in Table A.5 in Appendix A. The reference group in this analysis are female workers. The results are presented for the year 2024 and for all sample period, for the North, London and Midlands, and the South of England. In 2024 the mean predicted wage of male is £22.051 while for female is £18.272 with a difference of £3.776. Averaging over the all sample period reduces the estimates considerably with a mean predicted wage for male of £15.966 and for female of £13.164 resulting in a difference of £2.803. As these estimates are statistically significant at 1% critical value, they suggest that 19.44% of the wage inequality between female and male in 2024 was due to observable characteristics of which the occupation of administrative and secretarial contributed the most in wage disparities with 29.26% of the inequality, followed by personal services occupation with 24.39% of the wage disparities between female and male.

These results indicate that closing the difference between female and male wages in these two occupations would lead to 29.26% and 24.39% reduction in wage inequality in the North of England. Over the whole sample period, these figures are even more impactful in the sense that differences in observable characteristics contributing to wage inequality account for 38.21% of the disparities of which occupation of administrative and secretarial and personal services keep the largest impact. In particular, closing the gender wage gap in these occupations would lead to a reduction of 33.96% and 20.81% in the two respective occupations. Occupations of skilled trades and process, plants and machine have a statistically significant negative impact on wage inequality in the North which means that removing any difference between female and male would lead to an increase in wage inequality of about 25.77% and 23.99% in these occupations in 2024, and of about 30.82% and 24.65% rise in wage inequality when considering the entire sample period.

The differential effect on coefficients explains 58.18% of wage inequality between female and male of which experience had the largest contribution, with an impact that can lead to a 70.10% reduction in wage inequality between female and male. Over the all sample instead,

[6]The dummies for occupations included in the analysis are: occupation 2 for professional occupations, occupation 3 for associate professional, occupation 4 for administrative and secretarial, occupation 5 for skilled trades, occupation 6 personal services, occupation 7 for sales and customer services occupation, occupation 8 for process, plants and machine occupations, and occupation 9 for elementary occupations.

having a flexible working pattern in the North contributes to 45.31% of the wage inequality, and therefore considering flexible working patterns in policies aimed at closing the gender wage gap would lead to a 45.31% reduction in wage inequality in the North of England. The differential effect in coefficients is also influenced by the intensive margin of hours, however in this case, removing any difference between female and male would raise wage inequality by 44.59%.

The estimates for London and Midlands point towards a mean difference effect of £22.257 and £18.503 for female and male in 2024, with a difference of £3.754. This means that 33.31% of wage inequality is due to observable characteristics of which the occupation of administrative and secretarial contributed the most with 39.22% of the difference. Likewise, addressing differences in female and male wage in personal services occupation and the industry sector can lead to reduction in wage inequality of 21.92% and 9.48%, respectively. By contrast, removing female and male categories in skilled trades occupation would lead to an increase in wage inequality of 29.51%.

Over the whole sample period the coefficients effect accounts for 53.83% of wage inequality between female and male and the greatest contribution is brought by the industry sector accounting for 38.31 of wage disparities. The age obtained the highest qualification and having a part-time job deliver a strongly statistically significant negative impact on wage inequality, which means, removing female and male indicator for these type of regressors leads to an increase in wage inequality of 29.07% and 9.66%, respectively. The simultaneous effects between regressors and coefficients bring a total difference of 8.66% of which removing differences in wages between female and male in having a part-time job would lead to a 8.23% reduction in wage inequality.

Finally, analysing the results for the South of England they indicate a mean predicted wage for male of £27.097 and for female of £21.963 with a difference of £5.134 in 2024. The three values are the largest recorded amongsts the three geographical regions, suggesting that not only wages are higher in the South but also that there may be more inequality associated with female and male occupational characteristics. Observable characteristics account for 42.36% of wage inequality with the occupation of administrative and secretarial, personal services, hours and industry sector yielding the largest contribution of 24.79%, 14.74%, 10.97% and 10.34% in wage inequality. The coefficient effects is 52.69% of wage disparities with having a kid aged between 10-15 bringing 12.37% of wage inequality, followed by the constant term which however accounts for unobservable features, which yields 277.31% of wage inequality for characteristics not included into the model.

The same pattern in the South of England remains valid for the all sample period, in which case the total effect in observable characteristics of endowment results in 52.86% of wage disparities between female and male. The occupations of administrative and secretarial and personal services occupations keep the largest impact on wage inequality of 28.56% and 18.04%, followed by part-time job, industry sector and having a kid aged less than 2 years old, which result in 11.15%, 6.06% and 2.98% of wage inequality. The differential coefficient effect has

56.89% impact on wage inequality between female and male, where the industry sector is the main contributor of wage disparities between female and male and closing these differences in the industry sector would lead to 73.06% reduction in wage inequality.

Occupations of administrative and secretarial and personal services, while statistically significant, they have now a negative sign which indicates that removing female and male groups when controlling for these occupations can lead to an increase in wage inequality of 4.69% and 4.23%, respectively. The negative sign is then transmitted into the simultaneous effects coefficient with a total impact on wage inequality of 9.73%. However, their individual impact effect is now positive yielding 3.49% and 3.28% of wage inequality. Having a kid aged less than 2, between 2-4 and between 10-15, they all have a negative impact on wage inequality whereby each of them is estimated to lead to a 2.15%, 0.41% and 1.05% rise in wage inequality. Similarly, removing female and male groups when controlling for the industry sector and hours can lead to a 8.82% and 7.24% rise in wage inequality.

The Blinder-Oaxaca decomposition analysed in this Section carries some limitations as it focusses on means of the outcome variable between two groups to infer inequality in the outcome variable, without having a distributional approach. Unobservable characteristics that usually account for the discrimination effect can clearly lead to selection bias since in these regards the two groups may not be comparable thereby biasing the results. Furthermore, measurement errors may still persist between the two groups of coefficients since they are average impact coefficients and the order of the regressors can change the contribution into the explained, unexplained and interaction effects of the decomposition.

For these reasons in Section 4 I investigate more in depth wage inequality between female and male with quasi-experimental methods over industrial structures, focussing in particular, to evaluating the impact of a recent policy−the Gender Wage Gap Reporting Policy as part of the Public Sector Equality Duty−applied in the UK aimed at closing the gender wage gap.

4 Empirical Evidence

In this Section I evaluate the impact of the Gender Wage Gap Reporting Policy enacted into the The Equality Act 2010(Specific Duties and Public Authorities) Regulations 2017 as Gender Pay Gap regulations, specifically tailored for employees in balancing career progression between female and male and increase transparency in pay.

The Gender Wage Gap Reporting established the rule of reporting disparities between female and male wages for firms with a number of employees equal or larger than 250, as a means to promote transparency and close the gender wage gap. Since the Gender Wage Gap Reporting is part of the The Equality Act 2010 (Specific Duties and Public Authorities) Regulations 2017, it is a legal requirement when firms have equal or more than 250 employees. According to this requirement, firms need to report the mean and median of the gender wage gap and the distribution of female and male along the wage distribution amongsts other requirements.[7]

To investigate the impact of these policies across spatial regions I employ a quasi-experimental method to study the causal variation of this policy on the gender wage gap, its relation with industrial structures and structural inequality across regions. In particular, I evaluate the aforementioned impact with a synthetic control method. Section 4.1 describes the theoretical method and Section 4.2 presents the estimated results.

4.1 Synthetic Control Method Theory

The synthetic control method estimator allows for comparative case studies to estimate and evaluate the impact of an intervention affecting one specific unit. Given the motivating evidence in Section 3 in which the South West of England is one of the regions that has the largest gender wage gap, I assume that this geographical region is the only one affected more than the others by the intervention. The intervention is the enactment of the Gender Wage Gap Reporting of the Equality Act 2010 as a means to raise transparency, thereby reducing the gender wage gap.

The model relies on a panel data structure with treated and control units of observations over time. The comparative case studies for the synthetic control is referred to the characteristics of comparing the outcome of the intervention on the policy of interest of the treated units with the outcome of the control units that were not exposed to the intervention, however they are similar to the treated units and comparable over several characteristics with common factors. The synthetic control method chooses the appropriate comparison group given a set of individual observations in a small number of aggregate units that are the geographical regions.

To formalise the argument, suppose the model contains $j = 1, 2, ..., J + 1$ observations of which some are treated units, $i.e$, unit 1 for simplicity and, the rest of observations $j = 2, .., J+1$ are untreated units not exposed to the intervention. The data are observed over $t = 1, 2, ..., T$ periods, with T_0 being the time at which the intervention occurs. The outcome of interest is $Y_{j,t}$ for each unit j at time t, and the k regressors for the outcomes for each unit j are denoted as $X_{1j}, ..., X_{kj}$ which are collected in a vector of dimension $(k \times 1)$. A matrix for the regressors of untreated units of dimension $(k \times J)$ is also stored. The outcome of each unit j not exposed to the treatment is denoted as Y^0_{jt} whereas the outcome of the treated units is denoted as Y^1_{1t}, which are the potential outcomes for both types of units. Both outcomes are the outcomes of the potential outcome framework for causal inference developed by Rubin (1974). The impact of the policy intervention with the impact changing over time can be written as:

$$\eta_{1t} = Y^1_{1t} - Y^0_{1t}, \tag{5}$$

since only unit 1 is treated. The problem is that for the treated unit only the outcome under the treatment post-intervention is observed, and since the outcome of how the treated unit would

[7] I provide more details on the Gender Wage Gap Reporting Policy in Appendix B.

have behaved in the absence of treatment is not observed, Y^0_{1t}, it needs to be estimated.

As highlighted in Abadie (2021), the goal of the comparative case studies is to provide an estimate for the unobserved outcome Y^0_{1t} using one or few observations of untreated units that have similar characteristics at the time of the intervention. The procedure allows to recover the counterfactual outcome of what the outcome would have been, had the policy not been introduced.[8] The synthetic control method selects a combination of few observations in the set of untreated units that best represents the characteristics of the treated units at the time of the intervention instead of relying on only one untreated unit to estimate the unobserved outcome. The synthetic control method gives a weight to each untreated unit to use, and its associated vector of weights of dimension $J \times 1$ is denoted as $W = (w_2, ..., w_{J+1})'$. Therefore, the synthetic control method estimator can now be denoted as a weighted average of the untreated units as follows:

$$\hat{Y}^0_{1t} = \sum_{2}^{J+1} w_j Y_{jt}, \quad \forall t \geq T_0, \tag{6}$$

such that $w_j \geq 0$ and $\sum_2^{J+1} w_j = 1$, with the average treatment effect on treated given by $\hat{\eta}_{1t} = Y^1_{1t} - \hat{Y}^0_{1t}$, contemporaneously the vector of weights solves the following minimisation problem $\min_W ||X - X_0 W||$, where X is the matrix of regressors for treated units, X_0 is the matrix of regressors for untreated units and $|| \cdot ||$ is the distance norm. The choice of the distance metric varies from nearest neighbor, to kernel matching, caliper matching and one to many nearest neighbor. Since extrapolation with weights summing to unity is not allowed, the conterfactual estimate is made of only a small number of untreated units. When the choice of the weight matrix equals $w_j = \frac{1}{J}$, $\forall j$, the estimation can be conceived as a difference in differences estimation.

In practice the choice of the weights is based on the observation that the conterfactual estimate needs to resemble the value of the treated units before the intervention (Abadie, 2021). Abadie and Gardeazabal (2003) and Abadie et al. (2010) propose the previous minimisation problem for the choice of the synthetic control estimators that can be further charactersied as:

$$||X - X_0 W|| = \left(\sum_{m=1}^{k} p_m \left(X_{m1} - w_2 X_{m2} - ... - w_{J+1} X_{mJ+1} \right)^2 \right)^{1/2}, \quad \text{s.t} \quad \sum_{2}^{J} w_j = 1, \quad w_j \geq 0, \tag{7}$$

which delivers a synthetic control method estimator $\hat{W} = (\hat{w}_2, .., \hat{w}_{J+1})$, where p_m are positive constants that weights the importance of each regressor in determining the outcome of the treated units. The resulting synthetic control average treatment effect on treated can be written as $\hat{\eta}_{1,t} = Y_{1t} - \sum_{j=2}^{J+1} \hat{w}_j Y_{jt}$. The choice of the vector that contains the positive constants, $P = (p_1, p_2, ..., p_k)$, is often the inverse of the variance matrix of the regressors so as to obtain a unit variance for each row, or to minimise the mean squared prediction error (Abadie and

[8]A recent literature review on the synthetic control method estimator is available in Abadie (2021).

Gardeazabal, 2003; Abadie et al. 2010), or chosen with out of sample validation still to minimise the mean squared prediction error (Abadie et al., 2015).

The vector P helps to attribute importance to the regressors that contribute the most to the counterfactual outcome Y_{1t}^0, since the purpose of the synthetic control is to obtain an estimate for the path of Y_{1t} for the post-intervention period $t > T_0$ in the absence of the intervention. To accomplish this, the data for the pre-intervention period are used as a representative for Y_{1t}^0, since Y_{1t}^0 is the actual outcome observed before the intervention, $t = 1, 2..., T_0$, and which can then be used by the vector P to assign the relative importance of the regressors in the synthetic control estimator. Since this procedure makes use of the units before the intervention, in the out of sample validation synthetic control the pre-intervention period is divided in two groups: the training period and the validation period with equal units of observations each. The training period is used to compute the weights, whereas the validation period is used to minimise the mean squared prediction error and picks the best representative of positive P values. The out of sample validation method allows to obtain a more accurate estimate for the synthetic control group path before and after the intervention, thereby dealing with the parallel trend assumption (Abadie, 2021).

In my analysis the intervention is the enactment of the Gender Wage Gap Reporting Policy which was officially passed in the UK in 2017, albeit some delays of policy implementation in some regions, and the treated unit is the the South West. The non treated units are the rest of geographical regions in the UK: the North West, the North East, South East, the Easter, London, East and West Midlands, Wales, Scotland and Northern Ireland.

The essence of the synthetic control estimator is to consider in addition to the average treatment effect on treated discussed above, a linear factor model for the unobserved outcome:

$$Y_{jt}^0 = \delta_t + \theta_t Z_j + \lambda_t \mu_j + \epsilon_{jt}, \tag{8}$$

where the equation (8) includes a time trend, δ_t, the vector of coefficients for observed and unobserved units, θ_t, and λ_t, that allow for time varying factors and unit specific factors, respectively, on covariates Z_j and factor loadings μ_j, and the transitory error term, ϵ_{jt}. The terms δ_t and λ_t are common factors with the difference that the former incorporates constant loading across units, whereas the latter contains changing loadings across units. Each weight will deliver a singular synthetic control and the value of each outcome variable can be written as

$$\sum_{2}^{J+1} w_j Y_{jt} = \delta_t + \theta_t \sum_{2}^{J+1} w_j Z_j + \lambda_t \sum_{2}^{J+1} w_j \mu_j + \sum_{2}^{J+1} w_j \epsilon_{jt}, \tag{9}$$

which under the assumption of $\sum_{s=1}^{T_0 \lambda_s} / T_0 \neq 0$, then equation (9) leads to the synthetic control method estimator for η_{1t}:

$$\hat{\eta}_{1t} = Y_{1t} - \sum_{2}^{J+1} \hat{w}_j Y_{jt}, \quad \forall t = T_0 + 1, ..., T. \tag{10}$$

The bias of the estimation of $\hat{\eta}_{jt}$ relies on the ratio between the scale of the transitory error terms between treated and untreated units and the time periods before the intervention. A characterisation of the source of the bias, is present in Abadie et al. (2010) who point that when the covariates satisfy $X_1 = \hat{W} X_0$, then the synthetic control estimator equals Z_1. However, μ_1 is not observed, and therefore, the synthetic control can provide a reliable estimate only if the difference between the values of the error term for the treated and untreated units is enough to compensate for the unobserved factor loadings. For this to occur, two conditions need to be met: first, the scale of the transitory error term must be large to allow for enough variation in the unobserved shock with small variance and second, the number of the pre-intervention periods must be small enough to provide a reasonable match with the outcomes before the intervention for the treated units.

Since the size of the bias moves inversely with the size of T_0, a large T_0 may not provide an unbiased synthetic control estimate when the fit is not perfect, that is the approximation of the synthetic control over the treated units pre-intervention with the treated units outcomes is not good. In addition, this over fitting source of bias rises with the number of untreated units, J, (Abadie et al., 2010), since the bias depends positively on J, and therefore, a case in which the approximation of the loadings μ_j with μ_1 is bad, can lead to further contribution in raising the bias. In practice, a reasonable approach to reduce the source of the bias is to include in the control group only the untreated unit observations that best represent the treated units, namely those observations with few differences in the values of the observed characteristics Z_j, and small differences in the value of the unobserved outcomes, μ_j. Since the aim of the synthetic control is to estimate Y_{1t}^0, for $t > T_0$, that is the outcome of the treated units in the absence of the treatment after the intervention period, its reliability relies on the ability to simulate the pattern of the treated units before the intervention period.

Inference for synthetic control estimators is attained with permutation methods whereby the intervention is assigned separately to each unit in the control group and a placebo effect, $(Y_{jt} - \hat{Y}_{jt}^0)$, is extracted for each unit in the permutation through in time placebo and in space placebo effects. The effects for the treated and untreated units is then used to construct a permutation distribution (Abadie et al., 2010). A test for an accurate fit of the post-intervention period with the pre-intervention period is proposed in Abadie et al. (2010) and takes into account the root mean squared prediction error (RMSPE) as follows:

$$R_j(t_1, t_2) = \left(\frac{1}{t_2 - t_1 + 1} \sum_{t_1}^{t_2} \left(Y_{jt} - \hat{Y}_{jt}^0 \right)^2 \right)^{1/2}, \quad \forall 0 \leq t_1 \leq t_2 \leq T, \quad \forall j = 1, 2, ..., J + 1; \tag{11}$$

where the term $\hat{Y}_{jt}^{0}$ is effectively the synthetic control estimators of the untreated units subject to the intervention. Therefore, it is possible to obtain as measure of quality of fit the ratio between RMSPE pre and post-intervention, that is:

$$r_j = \frac{R_j(T_0+1,T)}{R_j(1,T_0)}, \quad \forall j, \tag{12}$$

and its associated permutation distribution and p-values is computed as:

$$p = \frac{1}{J+1}\sum_{j=1}^{J+1} \mathbb{1}_{+}(r_j - r_1), \tag{13}$$

where the term $\mathbb{1}_{+}$ is a indicator function on the difference between RMSPEs taking value one for nonnegative differences and zero otherwise. Confidence intervals are then constructed on the basis of inversions of constructed p-values. As discussed in Abadie (2021), one sided inference can be obtained by substituting $(Y_{jt}-\hat{Y}_{jt}^{0})$ into $R_j(T_0+1,T)$ however using its respective positive and negative values, *i.e.*, $(Y_{jt}-\hat{Y}_{jt}^{0})^{+}$ and $(Y_{jt}-\hat{Y}_{jt}^{0})^{-}$, which gives substantial gains in the quality of the fit.

There are several advantages in the use of synthetic control method estimators. Firstly, by using weights whose sum equal one the synthetic control avoid any sort of extrapolation, thereby making transparent the comparison between the treated units and the weighted average of untreated units used to track their trajectory of pre-intervention period. Second, the synthetic control weights are very sparse. In this context, an insightful interpretation on reliability of the synthetic control is provided in Abadie (2021) and is based on the convex hull interpretation. In particular, when the values of the predictors of the treated units fall outside of the convex hull of the predictors of the untreated units, it can be taken as evidence of the presence of sparsity which can be increased by raising the number of nonzero weights and, that is consequence of the curse of dimensionality. More specifically, the synthetic control in equation (7) is unique and sparse, and the distances of each treated unit predictor with the synthetic control are small, that is $(X_{11} - w_2X_{12} - ... - w_JX_{1J+1}) \approx 0$, ..., $(X_{k1} - w_2X_{k2} - ... - w_JX_{kJ+1}) \approx 0$.

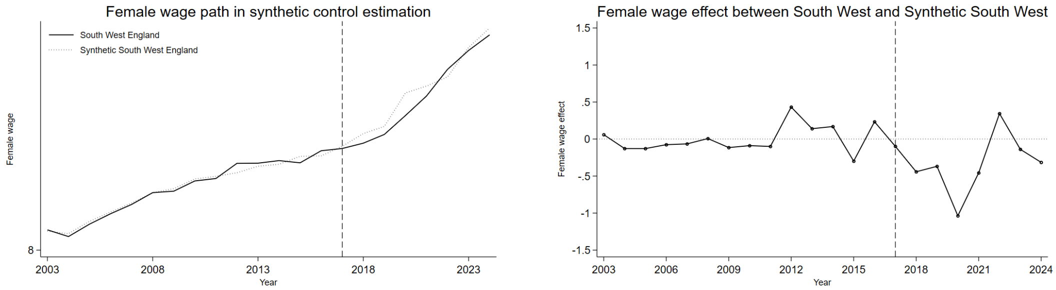
The validity of synthetic control method estimators relies on the following identifying assumptions. First, there must be no anticipation effects, that is, individuals need not to react in advance of the intervention, and components of the intervention need not be put in place before the time of formal intervention. In the opposite case, the violation of this assumption can lead to a biased synthetic control and if anticipatory effects are found, they can be overcome by backdating the intervention to estimate the full economic effect of the policy intervention. Second, the stable unit treatment value assumption requires outcome units need to be invariant to the treated units (Rubin, 1980). In practice, it requires to remove from the control group those units with outcomes affected in a second order by the intervention on the treated units. Likewise, for the control group it is suggested to use units that are subject to the same economic shocks as the treated units under intervention. Since spillover effects may arise from units close in proximity with the units in the control group, this can bias the estimates of the synthetic control, thus units affected by spillover effects would need to be removed.

The convex hull assumption discussed above requires that a convex combination of untreated units can approximate the path of the treated units in the absence of the intervention in the post-intervention period, on the basis of the close predictors that simulate the path of the treated units in the pre-intervention period. In case these differences in predictors are too large, a good proxy is to modify the level of the outcome variable in time differences, $\Delta Y_{jt} = Y_{jt} - Y_{jt-1}$, or growth rates, $\left(\frac{Y_{jt}-Y_{jt-1}}{Y_{jt-1}}\right) \times 100$. Differencing implies that the linear factor model becomes $\Delta Y^0_{jt} = \Delta\delta_t + \Delta\theta_t Z_j + \Delta\lambda_t\mu_j + \Delta\epsilon_{jt}$, and therefore the bias can be reduced only in the presence of small variations in the common factors, θ_t and λ_t. This reduction in bias because of the difference in differences approach, is counterbalanced by the large variance of the shocks $\Delta\epsilon_{jt}$ than ϵ_{jt}, in which case the bias can increase and with it, the risk of over fitting the synthetic control will also rise.

Finally, the choice of the comparison group requires that some units in the comparison group are independent from the policy intervention, namely not all control units have to be affected by the policy intervention taking place for the treated units. If these types of units exist, they need to be removed along with those units that have been affected by large shocks, that however, would have not affected the treated units in the absence of the intervention in the pre-intervention period. By contrast, the control group needs to contain units that have similar individual characteristics to the treated units. In this regard, Abadie and L'Hour (2021) suggest to include a penalisation term in the estimation of the synthetic control which takes into account the distance between the characteristics of the treated units and the individual characteristics of the synthetic control group. The authors also propose an extension of the synthetic control estimators in the presence of multiple treated units. Moreover, the larger the periods of the pre-intervention time, the lower the bias of the synthetic control estimator. Similarly, the larger the number of periods post-intervention, the most reliable the synthetic control is. Therefore, it is essential to have an extended sample period before and after the intervention of the policy to obtain a valid estimate of the synthetic control estimator.

4.2 Empirical Results on the Gender Wage Gap Inequality in Space

The results in this Section are based on investigating the effect of the Gender Wage Gap Reporting Policy on the gender wage gap outcome. The empirical evidence in Section 3 has highlighted a significant high gender wage gap in the South West of England. Therefore, the South West is considered as the treated unit of the intervention, and I let the procedure to construct a reliable comparison group. While the policy has been enacted over the whole UK territory, the analysis I undertake is a conterfactual experiment that I implement to study reductions in the gender wage gap particularly in the South West of England.



(A) Female wage path in synthetic control estimation

(B) Female wage effect between South West and Synthetic South West

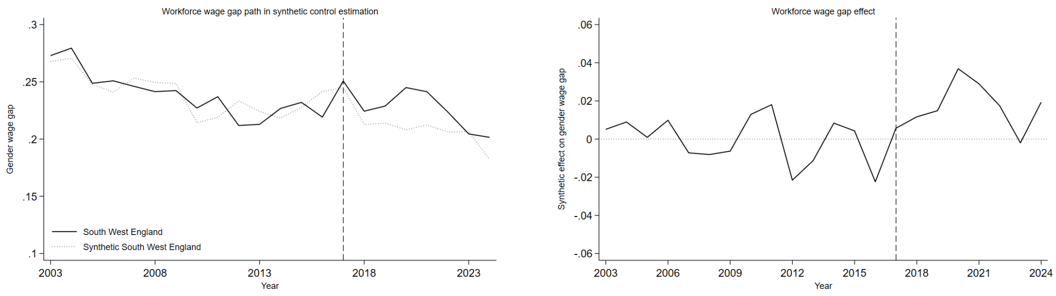
FIG. 8.—The figure shows the path of female wage between the South West and Synthetic South West (Panel A), and the female wage gap (Panel B). The vertical line in 2017 is the year when the Gender Wage Gap Reporting was introduced. The vertical axis is shown in level. The horizontal axis reports the period in years. Data source is the British Quarterly Labour Force Survey.

I first present the results on the synthetic control method estimator that uses the nested optimisation technique to compute the weights of the regressors for the treated and untreated units in the control group to obtain a convex combination of the untreated units characteristics that best approximate the characteristics of the treated units pre-intervention period. Then, I provide the results with an efficient weighting scheme optimisation technique as proposed by Abadie and Gardeazabal (2003).

The Gender Wage Gap Reporting Policy was enacted in 2017 which leaves me with 14 years of data in the pre-intervention period. The outcome variable of interest is the gender wage gap measured as the difference in mean earnings between male and female relative to male workers' earnings across all jobs. I construct the control group (donor pool) as a weighted average of the regions in the United Kingdom that mostly resembled the values of the regressors for the gender wage gap in the South West prior to the Gender Wage Gap Reporting Policy. The choice is central to evaluate how the gender wage gap would have evolved after 2017 in the absence of the Gender Wage Reporting Policy, which provides the counterfactual estimated by the synthetic control.

The choice of the comparison group is more challenging since the Gender Wage Gap Reporting is a state wide policy applied to whole regions in the UK. To deal with the choice of a reliable control group, I first use pre-intervention patterns using data before the intervention. Then, I consider the regions that had a delayed implementation of the policy into the donor pool such as Northern Ireland whose policy was officially introduced in November 2024 and is expected to be enforced in 2027 with Gender Wage Gap Reporting starting in 2028.

Regressors include experience, squared experience, age obtained highest qualification, the intensive margin of hours, the average of hours in period 2013-2017, the highest qualification held, dummy variables for the industry sector, dummy variables for occupation, a dummy variable for full-time and part-time jobs, variables for the number of kids aged less than 2, between 2-4, between 5-9 and between 10-15, dummy variables for the marital status, and I add years for



(A) Path wage gap in synthetic estimation

(B) Effect workforce wage gap

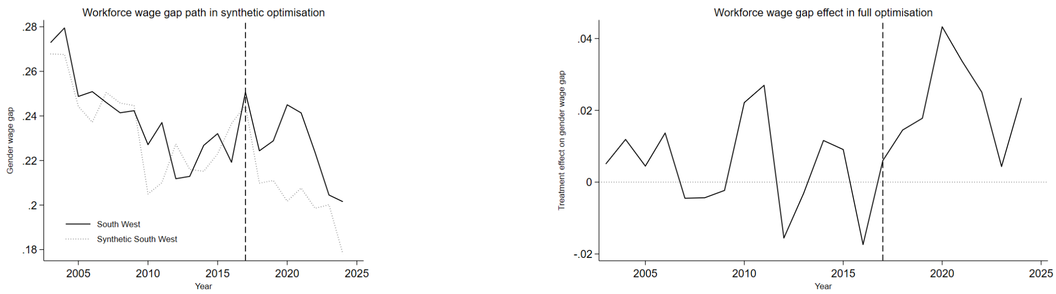
FIG. 9.—The figure shows the path of the wage gap between the South West and Synthetic South West (Panel A), and the effect of the wage gap (Panel B). The vertical line in 2017 is the year when the Gender Wage Gap Reporting was introduced. The vertical axis is shown in level. The horizontal axis reports the period in years. Data source is the British Quarterly Labour Force Survey.

lagged female wage in the years 2004, 2007 and 2017. The estimated effect is then the difference in the gender wage gap between the South West and the Synthetic South West.

First, I assess the reliability of the synthetic control and in particular, the choice of the comparison group by analysing the effect of the policy on the wage of female workers. Figure 8 Panel A presents the path of female wage before and after the implementation of the Gender Wage Gap Reporting Policy for the South West and the Synthetic South West for the period 2003-2024. The synthetic control group reproduces the path of female wage of the treatment group in the pre-intervention period 2003-2017 extremely well. This implies that the synthetic control group provides a good approximation of female wage in the South West of England for the period 2017-2024 in the absence of the intervention of Gender Wage Gap Reporting Policy. Panel B depicts the effect of the policy computed as the difference in female wages between the South West and the Synthetic South West. The figure suggests that the policy had an important effect on female wages that decreased the difference in female wages for the first three years after the policy and increased it afterwards by less than 0.5%.

The results are further corroborated in Table C.1 in Appendix C which reports the value of the regressors for the treated and the synthetic control group, as well as the weights associated with each region introduced into the donor pool. The results indicate that female wages prior to the Gender Wage Gap Reporting Policy is best represented by the regions combination of West Midlands, Wales, Eastern, Yorkshire and Humberside, East Midlands, South East, with the other regions receiving zero weight. The synthetic South West performs accurately well in reproducing the characteristics of the regressors of the South West prior to the policy providing the basis for a suitable control group for the South West for the analysis of the Gender Wage Gap Reporting Policy below. The root mean squared prediction error is 0.18 indicating a reasonably good fit of the characteristics of the synthetic control group with the South West female wage before the intervention of the policy.

I now present the results on the gender wage gap implied by the policy intervention. Figure



(A) Path wage gap in synthetic full optimisation (B) Effect workforce wage gap in full optimisation

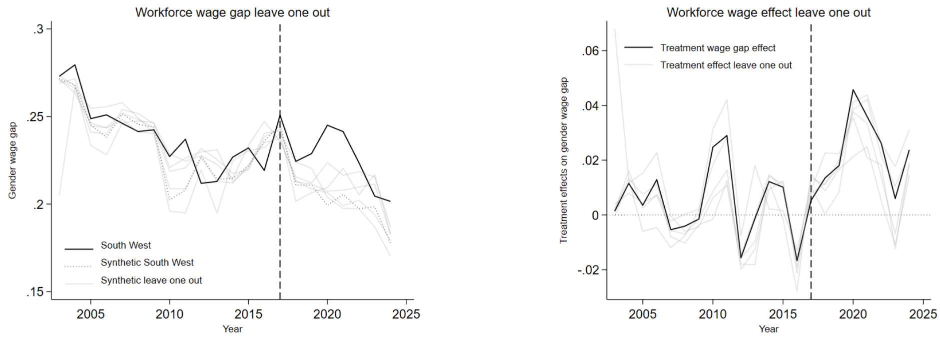
FIG. 10.— The figure shows the path of the wage gap between the South West and Synthetic South West (Panel A), and the effect of the wage gap (Panel B). The vertical line in 2017 is the year when the Gender Wage Gap Reporting was introduced. The vertical axis is shown in level. The horizontal axis reports the period in years. Data source is the British Quarterly Labour Force Survey.

9 shows the path of the gender wage gap before and after the policy intervention (Panel A) and its effect computed as the difference between the gender wage gaps in the South West and the Synthetic South West (Panel B). The synthetic control South West reproduces reasonably the path of the gender wage gap prior to the passage of the Gender Wage Gap Reporting and therefore it provides a good approximation for the path of the gender wage gap in the South West prior to the intervention.

The results are further highlighted in Tables C.2 and C.3 in Appendix C which report the mean values of the regressor characteristics of the South West in comparison with the Synthetic South West. The regressors all reproduce well the prevalence of the gender wage gap before the intervention 2003-2017, maintaining close similarities across the two groups thereby suggesting that the synthetic control group provides a reasonable description for the path of the gender wage gap in the South West before the introduction of the policy.

The Tables also report the weights associated with each region. It shows that the synthetic control group is made of Eastern, South East, East Midlands, Yorkshire and Humberside, and Wales regions. Panel B of Figure 9 depicts the effect of the policy computed as the difference in the gender wage gap between the South West and the Synthetic South West. The root mean squared prediction error is also very small 0.012 indicating that the predictors in the pre-intervention period approximate well regressor characteristics of the South West without the intervention. The impact of the policy appears limited, since structural inequalities still persist and the gender wage gap effect increases after the policy intervention 2017-2021 for then to decrease. The structure of labour markets in each region can hinder the effect of the policy on the gender wage gap, preventing it to achieve its intended effects of reducing the gender wage gap in the South West of England.

The effect on the gender wage gap is also masked by the fact that some regions such as Norther Ireland implemented the Gender Wage Gap Reporting Policy with delays. To account for this fact and improve the performance of the model, I implement a nested full simultaneous



(A) Path wage gap in synthetic leave one out (B) Effect workforce wage gap leave one out

FIG. 11.— The figure shows the path of the wage gap between the South West and Synthetic South West (Panel A), and the effect of the wage gap (Panel B). The vertical line in 2017 is the year when the Gender Wage Gap Reporting was introduced. The vertical axis is shown in level. The horizontal axis reports the period in years. Data source is the British Quarterly Labour Force Survey.

optimisation which finds the best combination between regressors and control group weights simultaneously and it is expected to provide more accurate estimates of the pre-intervention characteristics of the synthetic control group. The results are reported in Figure 10 and in Tables C.4 and C.5 in Appendix C.

The figure shows a partial improvement in fitting the pre treatment regressor characteristics of the South West and the resulting average treatment effect on the gender wage gap in the post-intervention period is 0.0232. Isolating the average treatment effect on treated suggests a positive impact effect over all years considered in the post treatment period. To note that the simultaneous weighting scheme now considers the following regions in the Synthetic South West: Easter, South East, Wales, East Midlands and Yorkshire and Humberside, however with a different weight balanced towards the South East and Wales as evidenced in Tables C.4. Additionally, Tables C.4 and C.5 point that there is a moderate resemble of the regressors of the South West in the absence of the policy with the regressor characteristics of the Synthetic South West in the pre-intervention period.

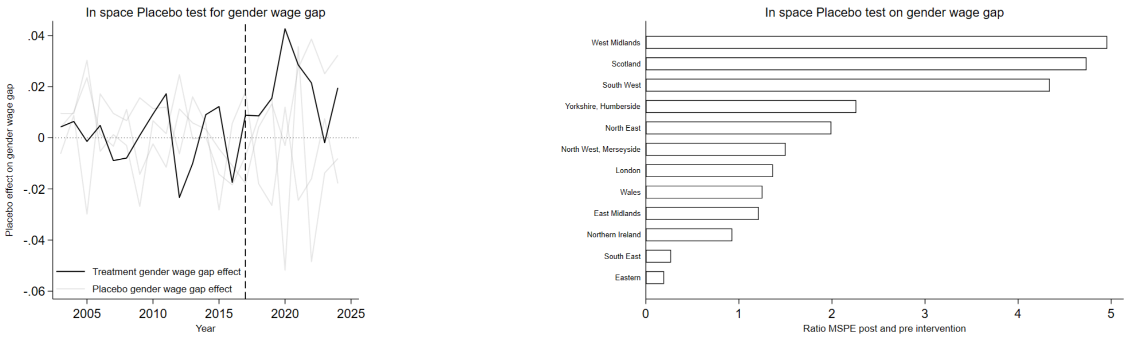
To assess the robustness of the estimates I implement a synthetic control with nested leave one out synthetic methodology whereby each unit at a time of the synthetic control group is left out from the estimation and this is performed in multiple turns. This methodology ensures stability of the results, and in particular, it helps to assess whether the synthetic control group is highly dependent on one specific region. If the nested synthetic leave one out methodology delivers estimates that differ significantly from the regressor estimates of the synthetic in full optimisation, then I interpret the analysis did not provide a reliable synthetic control group as it is very sensitive to the inclusion of a region in the synthetic control group. If, on the other hand, the nested synthetic leave one out estimation delivers estimates close to the synthetic control method in full optimisation, then I interpret that the analysis provides reliable and stable estimates for the synthetic control group.

The results are reported in Figure 11 which shows the gender wage gap in the South West, Synthetic South West group and synthetic group with leave one out experiment (Panel A) and the effect on the gender wage gap in comparison with the leave one out experiment (Panel B). The results show that the profile of the gender wage gap and its associated effect with the leave one out in place is in close proximity to the respective paths of the Synthetic South West group, thereby indicating that the synthetic control model is robust. The average treatment effect on the gender wage gap in the post-intervention period is 0.0243 that is very close to the average treatment effect obtained with full optimisation. The treated units experienced a 2.43% rise in the gender wage gap which indicates the possibility of other economy wide factors contributing to the effect of the policy on the gender wage gap.

I now implement placebo tests to study the statistical significance of the estimates following the procedure by Abadie and Gardeazabal (2003) and Bertrand et al. (2004). In particular, I implement the synthetic control method to the rest of regions by iteratively reassigning the region used as treatment in the control group. The results will lead to an indication of how frequent the observed results are, if regions that did not implement the policy like Northern Ireland are taken as the place of policy intervention. Therefore, I conduct in space placebo tests. Furthermore, I assess the significance of the treatment period by testing for time trends through in time placebo tests.

Figure 12 reports the results for the in space placebo tests. Panel A shows the path of the gender wage gap effect by using the North West region in the treatment study, where this region was in the synthetic control group. The gray lines depict the difference between the gender wage gap in each state in the synthetic control group with its respective synthetic group, whereas the black line identify the gender wage gap effect for the South West. The effect of the placebo treated unit is different from the effect of the South West analysed above, which combined with the fact that the placebo treated units effects are not significant, suggest that the results are robust. Additionally, the effect on the South West gender wage gap is large relative to the synthetic group, providing a good fit for the outcome of interest. Isolating the effects over time in the post-intervention period, I find an average treatment effect on treated of -0.19% in 2023.

Panel B shows the distribution of ratios of the mean squared prediction error (MSPE) after the intervention and before the intervention. The MSPE in the pre-intervention period measures the squared difference between the gender wage gap in the South West and its synthetic control group in the period 2003-2017. The results show a very large MSPE ratio for the actual treated region South West (4.341) which indicates that the Gender Wage Gap Reporting Policy had a strong intervention effect with a significant real impact. However, the synthetic regions West Midlands and Scotland also appear to have a high MSPE which implies that external factors may have contributed to the estimated gender wage gap effect in the synthetic regions. The probability of obtaining a MSPE ratio of post- to pre-intervention period for the gender wage gap as large as the South West is 0.25 (3.12), which occurs if the policy were to be put in place



(A) Path wage gap in space placebo test

(B) Ratio MSPE post and pre-intervention

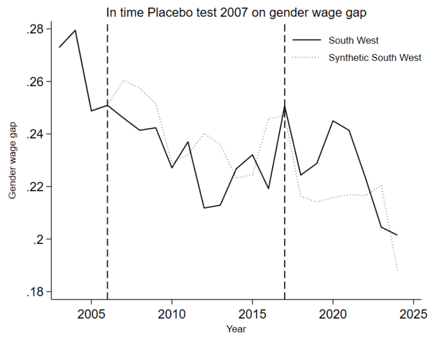
Fig. 12.— The figure shows the in space placebo path of the wage gap between the South West and Synthetic South West (Panel A), and the ratio of the MSPE post-intervention to pre-intervention (Panel B). The vertical line in 2017 is the year when the Gender Wage Gap Reporting was introduced. The vertical axis is shown in level. The horizontal axis reports the period in years. Data source is the British Quarterly Labour Force Survey.

at random in one of the region in the synthetic control group. Nonetheless, this result combined with the evidence that the MSPE in other synthetic regions such as East Midlands, Northern Ireland, South East and Eastern, is rather small corroborate the uniqueness of the estimated gender wage gap effect in the treated South West region.

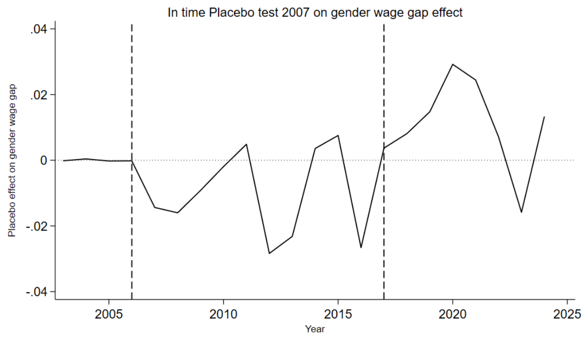
To further investigate the validity of the results I perform in time placebo tests using as date of intervention dates where the policy did not actually occur. I implement this test iteratively one at a time for each date. If the placebo test detects a significant different effect on the treated unit, then the results may be invalidated by time trends. If, on the other hand, the placebo test with different time intervention shows no significant effect then I interpret that the results provide valid estimates for the gender wage gap policy intervention. The results for the placebo test in 2007 are reported in Figure 13. Panel A shows the path of the gender wage gap with the placebo test performed in 2007 and Panel B shows the associated effect between the South West gender wage gap and the respective synthetic control group.

The path of the gender wage gap in the placebo study does not differ from the paths studied in the main analysis, evidenced in Figures 9 and 10, which suggests that the estimated treatment effect provides consistent and reliable estimates for the intervention period. As the path of the gender wage gap after the in time placebo policy intervention in 2007 decreases, the estimates on the average treatment effect on treated is -1.60% in 2008 until 2023, with however a positive impact effect of 1.33 in 2024. The path of the gender wage gap in the post-intervention period is not fully tracked, since there are only 7 years in the post-intervention period which may affect the source of the bias. In practice, the longer the period the lower the bias and the more reliable estimates are. Therefore, the effect of the policy needs time to materialise.

I report in Figure C.1 in Appendix C the in time placebo test for the year 2012 prior to the intervention of the policy. The results are remarkably close to the main estimated effect on the gender wage gap with 2017 actual year of intervention with no significant different effect.



(A) Path wage gap in time placebo test 2007



(B) Placebo wage gap effect 2007

FIG. 13.— The figure shows the in time placebo path of the wage gap between the South West and Synthetic South West (Panel A), and the effect on the gender wage gap (Panel B). The vertical lines in 2007 and 2017 are the year used for placebo test and the year when the Gender Wage Gap Reporting was introduced, respectively. The vertical axis is shown in level. The horizontal axis reports the period in years. Data source is the British Quarterly Labour Force Survey.

Isolating also in this case the average treatment effect on treated across years, suggests a negative impact effect of 1.54% in 2013 and 0.19% in 2023 and, an overall impact effect in the post treatment period of 1.92%. Therefore, the in space and in time placebo tests strengthen the validity of the analysis.

Since the placebo studies show that the estimated gap for the South West remains large related to the rest of regions, then this is evidence that the analysis provide significant evidence for the reduction in the gender wage gap three years after the introduction of the policy. Interventions like the Gender Wage Gap Reporting Policy require time for the desired effect to take place, such as reducing the gender wage gap. Indeed, the treatment effect on the gender wage gap rises after the 2017−year of intervention−for then to decrease. The rise in the three years after the policy implementations takes most of the effect on the average treatment effect on treated, which is a positive impact effect on the gender wage gap.

5 Mechanism

Since the analysis in the previous Section has pointed towards a positive impact effect on the Gender Wage Gap Reporting Policy intervention, in this Section I study the mechanism that leads to a reduction in the gender wage gap by studying the importance of each regressor characteristics on the gender wage gap. In particular, I control for factors that made the labour market more rigid, whereby workers are less willing to exchange their leisure time for a higher wage. Jobs with flexible working arrangements can have a positive impact on the gender wage gap by reducing it only if the stipulated work arrangement does not lead to a decline in female wage preventing women from further career development.

This Section is not intended to provide causal estimates on the gender wage gap which has been done in Section 4.2, rather to explain the mechanism leading to the gender wage gap

Table 10.—
Regression estimates on the gender wage gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hours	0.013***	0.015***	0.021***	0.018***	0.021***	0.016***	0.013***
	(0.004)	(0.005)	(0.004)	(0.002)	(0.003)	(0.001)	(0.001)
Fem. fulltime hours	-0.007**	-0.008**	-0.009***	-0.002	-0.006**	-0.006***	-0.006***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Experience		-0.005	-0.009***	-0.005***	-0.006**	-0.009***	-0.010***
		(0.004)	(0.005)	(0.001)	(0.003)	(0.002)	(0.003)
Age qualif			-0.044***	-0.035***	-0.021*	-0.026***	-0.021***
			(0.008)	(0.008)	(0.000)	(0.008)	(0.006)
Qualif held				0.002***	0.002***	0.002***	0.001
				(0.000)	(0.000)	(0.001)	(0.000)
Kids 10-15					-0.149	-0.318	-0.290
					(0.267)	(0.225)	(0.186)
Full-time					-0.605***	-0.675***	-0.227**
					(0.138)	(0.115)	(0.083)
Occ. process machine						-1.532***	-1.253***
						(0.362)	(0.240)
Manufacturing						0.458**	0.155
						(0.199)	(0.164)
Other sectors						-0.336	-0.474
						(0.341)	(0.164)
Married							0.468***
							(0.067)
Separated							-0.249
							(0.293)
Divorced							0.713***
							(0.215)
Widowed							0.647
							(0.477)
No. female full-time							0.009
							(0.009)
No. female flexitime							-0.002
							(0.004)
Constant	0.187***	0.296**	1.241***	0.700***	1.040***	1.474***	0.784***
	(0.061)	(0.110)	(0.197)	(0.167)	(0.318)	(0.203)	(0.298)
R^2	0.173	0.208	0.353	0.529	0.609	0.702	0.760
Number obs.	264	264	264	264	252	252	252

Note. Estimated impact on the gender wage gap with standard errors clustered by regions. Standard errors are reported in parenthesis. Significance is ***p< 0.01, **p< 0.05 and *p< 0.10 critical values. Data source is the British Quarterly Labour Force Survey.

via each regressors. Therefore, I first inspect the impact of the regressors on the gender wage gap, then I investigate the contribution of each regressor on female in full-time employment. I consider as treated outcome variable female in full-time employment since the presence of wage inequalities between female and male wages have an influence on the decision of female in taking up a full-time employment.

Table 10 presents the regression estimates on the gender wage gap outcome variable. The specification contains dummy variables for occupation process, plant and machine, dummy variables for the sectors of manufacturing and other sectors, dummy variables for marital status: married, separated, divorced and widowed, a dummy variable for full-time employment. The variable fem. full-time hours represents the intensive margin of female in full-time employment. The variables no. female full-time and no. female flexitime are the number of female employees in full-time and flexible time employment, respectively. Moreover, I compute the mean dataset along the region characteristics and years.

The results show that the intensive margin has a positive impact on the gender wage gap partly because raising hours would lead to a one to one rise in female and male wages washing out the impact on the gender wage gap. Therefore, to detect the true impact on the wage gap I include the number of hours for female in full-time employment. The results now indicate the expected effect of reducing the gender wage gap between 0.006-0.009 across all specifications with an average effect of 0.007. The length of experience the worker has gained has also the desired effect of contributing to reduce the gender wage gap. A one year increase in experience reduces the gender wage gap between 0.005 and 0.01 with the estimated impact being statistically significant at 1% critical level.

Occupational segregation is an important factor to the gender wage gap as evidenced in Section 3. Its impact on the gender wage gap is further highlighted in the regression with a consistent negative impact of 1.532 in the occupation of plant, process and machine that tend to have more standardised wages often similar between female and male thereby leading to a fall in the gender wage gap. Since the results are significant at 1% critical value, it is possible to exclude confounding factors affecting the gender wage gap. By contrast, the industry sector such as manufacturing and other sectors have a less prominent role across specifications.

Moreover, the higher the education attained, the higher the wage and therefore, the higher the gender wage gap as highlighted in the analysis. Indeed, the highest qualification attained has a statistically significant positive effect of 0.002 on the gender wage gap. This is due since the larger gender wage gap is present in higher pay occupations, as higher education brings higher wages the two characteristics can correlate thereby increasing the gender wage gap and being the second qualifier after hours in rising wage disparities between female and male, since female workers are compensated lower than male workers despite the same level of education.

The most important effect in contributing to reducing the gender wage gap is for the regressor of being in full-time employment. Being in full-time employment reduces the gender wage gap between 0.227 and 0.675 which is an important effect since the results are significant at 1% critical value and robust and invariant between regression specifications. The regressors included in the analysis explain most of the variation in the gender wage gap since the coefficient of determination rises as the more regressors are included in the analysis; with the full

TABLE 11.—
Regression estimates on female full-time employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gender wage gap	-0.528**	-0.566**	-0.549***	-0.553***	-0.687***	-0.646***	-0.173***
	(0.218)	(0.251)	(0.138)	(0.143)	(0.134)	(0.124)	(0.043)
Hours	0.008**	0.011	0.008***	0.008***	0.007***	0.007***	0.003*
	(0.004)	(0.007)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Fem. fulltime hours	-0.007**	-0.008**	-0.011**	-0.011**	-0.008***	-0.008***	-0.004*
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
Experience		-0.005	-0.009***	-0.001	-0.004	-0.003	-0.001
		(0.008)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Age qualif			-0.058***	-0.056***	0.023**	-0.021**	-0.001
			(0.016)	(0.016)	(0.009)	(0.009)	(0.009)
Qualif held			0.001	-0.001	0.001**	0.001**	0.002***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Kids 10-15				-0.093	-0.215	-0.163	-0.039
				(0.161)	(0.168)	(0.172)	(0.136)
Occ. process machine					-1.153***	-0.807**	-0.402
					(0.248)	(0.403)	(0.248)
Manufacturing						-0.200	0.017
						(0.192)	(0.119)
Other sectors						0.162	-0.174
						(0.342)	(0.141)
Married							-0.600***
							(0.107)
Separated							-0.311
							(0.381)
Divorced							-1.485***
							(0.204)
Widowed							0.321
							(0.376)
No. female full-time							0.049***
							(0.019)
No. female flexitime							-0.000
							(0.003)
Constant	0.779***	0.884***	-0.292	-0.211	0.621**	612*	0.945***
	(0.091)	(0.229)	(0.432)	(0.431)	(0.317)	(0.340)	(0.293)
R^2	0.168	0.185	0.544	0.545	0.644	0.648	0.806
Number obs.	264	264	252	252	252	252	252

NOTE. Estimated impact on probability of female full-time employment with standard errors clustered by regions. Standard errors are reported in parenthesis. Significance is ***p< 0.01, **p< 0.05 and *p< 0.10 critical values. Data source is the British Quarterly Labour Force Survey.

specification explaining 76% of variations in the gender wage gap.

The analysis has pointed out an important impact of being in full-time employment on the gender wage gap, although many female workers have to balance their working time with family and caregiving responsibilities preventing them from looking for a full-time employment.

Therefore, I reverse engineer the mechanism and investigate the other side of the spectrum and in particular, whether the gender wage gap has an effect on the probability of being in full-time employment for female workers. The results are reported in Table 11.

The Table shows a statistically negative impact of the gender wage gap on the probability of female being in full-time employment. In particular, the decline is estimated to be between 17.3% and 68.7% across all specifications. Wage disparities contribute significantly onto the decision of women in taking full-time employment. The impact of years of experience on female full-time employment is also negative. This might be counterintuitive, however with the existent gender wage gap female workers may decide to work part-time or exit the labour market since the type of job may become unattractive. Difficulties in career progressions and promotion opportunities can hinder the effect on females in full-time employment, since−albeit the experience−women may decide not to take a full-time employment.

The variable married denotes a significant negative relation with female being in full-time employment as family responsibilities prevent women from taking a full-time job. While these outcomes on female prospects are not uncommon events, this Section demonstrates that structural inequality reverberated into wage disparities between female and male limits female job progression and growth.

6 Conclusion

I provide the first empirical evidence of the impact of the Gender Wage Gap Reporting Policy in the UK and I have examined the workforce wage inequality across British regions. The Equality Act 2010 (Gender Pay Gap Information) Regulations 2017 provides legislative steps to increase transparency in pay information in order to reduce the gender wage gap. The steps which include giving annual public information on several metrics of the wage distributions between females and males are mandatory for organisations with 250 or more employees. I try to identify the effect of the policy by using geographical variations in the pre-intervention period of the regions shaped by their industrial structures for whom the implementations of the policy occurred with delays such as Northern Ireland.

The results reveal a positive causal impact effect of the policy on the gender wage gap which is economically significant. The policy appears to have increased the gender wage gap in the South West in the three years after the policy implementation before reducing it. The rise in the three years after the policy implementation takes almost all the estimated impact effect. While the analysis finds a causal impact effect of 2.32% on the gender wage gap, it is important to note two important facts. First, structural inequality due to regional industrial and jobs structures that drives wage inequality still persists as highlighted in the descriptive evidence Section 3 of this paper, and second the impact effect of the policy takes time to materialise. The regions with the largest gender wage gap takes whole of the intended impact effect that is meant to be negative. Therefore, the positive impact effect on the gender wage gap cannot be attributed in whole to the policy itself. Moreover, I find that the results are robust to several different experiments.

There are two areas of further investigation. First, digital technologies can facilitate but at the same time hinder female workers from taking full-time employment at a more seniority level. Incorporating digital obstacles in the analysis can shed further lights on the gender wage gap, which I leave for future research. Second, a model that can reconcile the empirical evidence of this paper is needed. Therefore, in a current research paper I develop a search and matching model along the lines of Becker (1973, 1974) marriage model and I introduce a gender specificity with a geographical space characteristic that explain the gender wage gap in space studied in this paper, and I quantify the effects of pay transparency policies such as the The Equality Act 2010 (Specific Duties and Public Authorities) Regulations 2017, on workers' productivity and economic growth.

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Appendix to

Workforce Wage Gap in Space, Labour Market Transformations and Structural Inequality

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A Additional Descriptive Statistics

This Appendix provides further summary statistics providing insights on the subsequent estimation analysis.

A.1 Data Details

Tables A.1 and A.2 list a description of the main variables used in the analysis of the gender wage gap.

I further create derived variables in the analysis such as experience, which I derive as the difference between current age and the age obtained the highest qualification, and therefore squared experience is the variable experience to the square. The age obtained the highest qualification is a derived variable which I compute by taking into consideration that some individuals responded in terms of age and some others in terms of years, with missing value being removed.

The variable government office regions provide the office regions of respondents for the regions of Great Britain and separately for Scotland, Wales and Northern Ireland. These are: North East, North West including Merseyside, Yorkshire and Humberside, East Midlands, West Midlands, Eastern, London, South East, South West, Wales, Scotland and Northern Ireland. The categorical variable industry sectors contains the following categories: agriculture and fishing, energy and water, manufacturing, construction, distribution hotels and restaurants, transport and communication, banking finance and insurance, public administration education and health, other services, workplace outside the UK.

The type of degree already held contains the following categories: higher degree, first degree, foundation degree, graduate member of professional institute, other. On the other hand the type of degree already held specifies the degree as: doctorate, masters, PGCE, other postgraduate degree or professional qualification and don't know categories. The categories for major occupation are: managers and senior officials, professional occupations, associate professionals and technicians, administrative and secretarial, skilled trades occupations, personal service occupations, sales and customer service occupations, process plant and machine operatives, elementary occupations.

TABLE A.1.—

Description of variables

Variable	Description
Age	Continuous variable.
Year Qual 1	When obtained highest qualification, given in age or year.
Year Qual 2	Age obtained highest qualification.
Year Qual 3	Year obtained highest qualification since 1970 to 2023.
Female	Dummy variable equals to 1 if the individual is female, generated from variable sex, and 0 otherwise.
No. of employees	Continuous variable indicating the number of employees in the workplace.
England	Dummy variable equals to 1 if the country of birth is England, and 0 otherwise.
India	Dummy variable equals to 1 if the country of birth is India, and 0 otherwise.
N Ireland	Dummy variable equals to 1 if the country of birth is Northern Ireland, and 0 otherwise.
Pakistan	Dummy variable equals to 1 if the country of birth is Pakistan, and 0 otherwise.
Poland	Dummy variable equals to 1 if the country of birth is Poland, and 0 otherwise.
Rep of Ireland	Dummy variable equals to 1 if the country of birth is the Republic of Ireland, and 0 otherwise.
Scotland	Dummy variable equals to 1 if the country of birth is Scotland, and 0 otherwise.
Wales	Dummy variable equals to 1 if the country of birth is Wales, and 0 otherwise.
UK, Britain-dnk	Dummy variable equals to 1 if the individual did not know country of birth, and 0 otherwise.
Other	Dummy variable equals to 1 if the country of birth is any other country of birth, and 0 otherwise.
Kids < 2	Continuous variable 0-3, number of dependent children in family aged under 2.
Kids btw $2-4$	Continuous variable 0-3, number of dependent children in family aged between 2 and 4.
Kids btw $5-9$	Continuous variable 0-4, number of dependent children in family aged between 5 and 9.
Kids btw $10-15$	Continuous variable 0-4, number of dependent children in family aged between 10 and 15. and 0 otherwise.
Married	Dummy variable equals to 1 if the individual is married living with spouse, and 0 otherwise.
Divorced	Dummy variable equals to 1 if the individual is divorced, and 0 otherwise.
Widowed	Dummy variable equals to 1 if the individual is widowed, and 0 otherwise.
Currently or previously in civil partners	Dummy variable equals to 1 if the individual is currently or has been previously in civil partners, and 0 otherwise.
Hours	Continuous variable for number of total hours 0-97 and over in main and second job.
Hour pay	Continuous variable in pound sterling for gross hourly pay.
Working	Dummy variable equals to 1 if the individual did paid work in reference week, and 0 otherwise.
Flexitime	Dummy variable equals to 1 if the respondent has a flexible working pattern

NOTE. This Table gives a description of the variables used in the analysis. Data source is the British Quarterly Labour Force Survey.

TABLE A.2.—
Description of variables, continuation.

Variable	Description
Industry sector	Categorical variable with industry sectors within and outside the UK.
Degree held	Categorical variable with seven categories of degrees held.
Type of degree held	Categorical variable characterising qualification already held by respondents.
Full-time part-time	Categorical variable containing full-time and part-time respondents.
Employment status	Categorical variable containing four categories.
Occupation	Categorical variable for occupation in major group.
Job type	Dummy variable equals to 1 if the job is permanent, and 0 otherwise.

NOTE. Continuation of Table A.1 which gives a description of the variables used in the analysis. Data source is the British Quarterly Labour Force Survey.

A.2 Summary Statistics

Table A.3 provides summary statistics on the main variables of the analysis based on gender.

Table A.3.—

Summary statistics for female and male

	Female			Male		
Variable	Obs	Mean	Std	Obs	Mean	Std
Labour variables						
hours	573, 624	17.021	18.190	455, 311	27.386	21.442
hourpay	309, 460	12.700	8.099	303, 661	15.952	10.430
Country of birth						
dummyEngland	574, 289	0.686	0.464	456, 446	0.705	0.456
dummyWales	574, 289	0.041	0.199	456, 446	0.043	0.203
dummyScotland	574, 289	0.085	0.279	456, 446	0.087	0.281
dummyNIreland	574, 289	0.046	0.211	456, 446	0.044	0.205
dummyUKBritainDN	574, 289	0.001	0.023	456, 446	0.001	0.026
dummyHongKong	574, 289	0.001	0.024	456, 446	0.001	0.024
dummyChina	574, 289	0.001	0.023	456, 446	0.000	0.020
dummyRepIreland	574, 289	0.001	0.075	456, 446	0.001	0.072
dummyOther	574, 289	0.114	0.318	456, 446	0.098	0.298
Individual characteristics						
agequal	368, 748	20.453	5.022	325, 681	20.816	4.825
experience	368, 748	23.372	12.934	325, 681	24.353	12.612
experience2	368, 748	713.564	648.687	325, 681	752.139	636.559
dummySingle	574, 428	0.221	0.415	456, 588	0.277	0.447
dummyMarried	574, 428	0.589	0.492	456, 588	0.593	0.491
dummySeparated	574, 428	0.039	0.193	456, 588	0.027	0.162
dummyDivorced	574, 428	0.116	0.321	456, 588	0.086	0.281
dummyWidowed	574, 428	0.033	0.179	456, 588	0.013	0.113
Family background						
kidsless2	574, 219	0.066	0.259	456, 398	0.066	0.258
kidsbtw2-4	574, 219	0.122	0.364	456, 398	0.104	0.338
kidsbtw5-9	574, 219	0.215	0.515	456, 398	0.175	0.472
kidsbtw10-15	574, 219	0.259	0.582	456, 398	0.209	0.532
Job characteristics						
dummyFulltime	330, 377	0.584	0.493	321, 410	0.926	0.262
dummyParttime	330, 377	0.416	0.493	321, 410	0.074	0.262
dummyAgriculture	329, 916	0.005	0.069	320, 939	0.009	0.097
dummyEnergy	329, 916	0.008	0.089	320, 939	0.029	0.167
dummyManufacturing	329, 916	0.065	0.247	320, 939	0.186	0.389
dummyConstruction	329, 916	0.021	0.141	320, 939	0.092	0.289
dummyDistribution	329, 916	0.172	0.378	320, 939	0.148	0.355
dummyTransport	329, 916	0.045	0.297	320, 939	0.128	0.334
dummyBanking	329, 916	0.154	0.361	320, 939	0.167	0.373
dummyPublicadmin	329, 916	0.484	0.511	320, 939	0.199	0.399
dummysectOther	329, 916	0.047	0.213	320, 939	0.040	0.197

Note. This Table presents mean and standard deviation for female and male in the considered sample period 2003-2024. Data source is the British Quarterly Labour Force Survey.

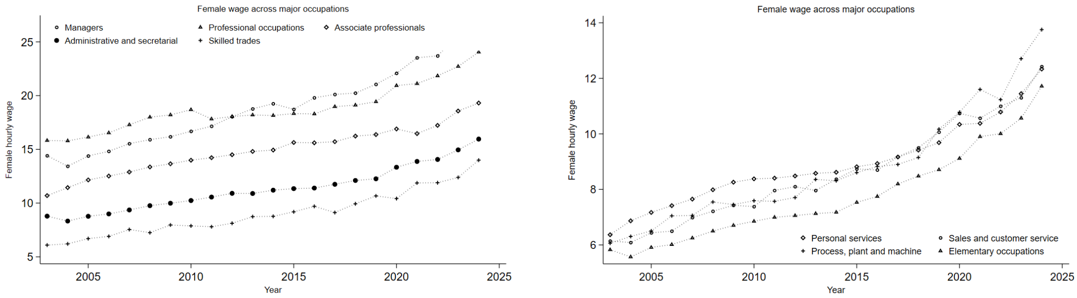
TABLE A.4.—
Educational gender wage gap by regions

	Female					
	North England		London, Midlands		South England	
	Mean	Obs	Mean	Obs	Mean	Obs
Doctorate	22.495	449	21.353	721	24.866	767
Masters	19.024	1,831	19.159	3,070	22.225	3,925
PGCE	17.426	1,378	17.412	2,214	18.384	1,471
Other postgraduate	20.149	623	20.297	955	22.056	832
Not known	14.851	19	14.793	38	18.761	34
Total		4,300		6,998		7,029
	Male					
	North England		London, Midlands		South England	
	Mean	Obs	Mean	Obs	Mean	Obs
Doctorate	25.551	752	24.289	1,141	27.136	1,318
Masters	22.246	2,054	22.905	3,368	26.381	4,547
PGCE	18.091	677	18.271	1,072	20.123	698
Other postgraduate	23.163	485	22.926	667	25.538	736
Not known	17.379	30	18.494	46	20.623	29
Total		3,998		6,294		7,328

NOTE. This Table presents mean and observations of wage by regions and gender across the highest degree already held over the sample period 2003-2024. Data source is the British Quarterly Labour Force Survey.

A.3 Gender Wage Gap Further Descriptive Evidence

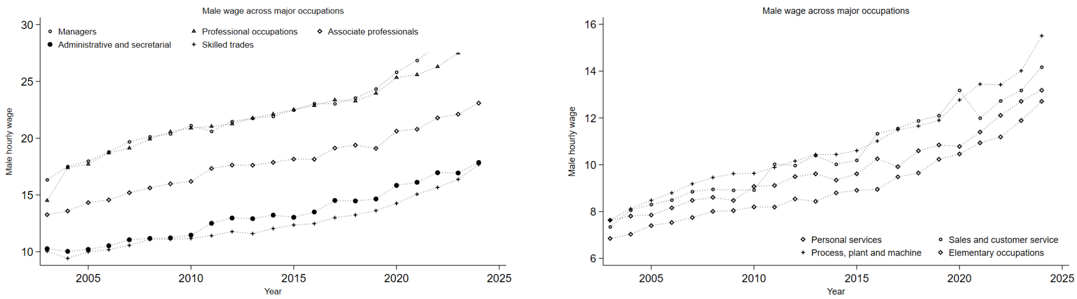
This Section provides further descriptive evidence on the gender wage gap in space, across age bands, educational level, occupation and industry sector.



(A) Female wage by occupation

(B) Female wage by occupation

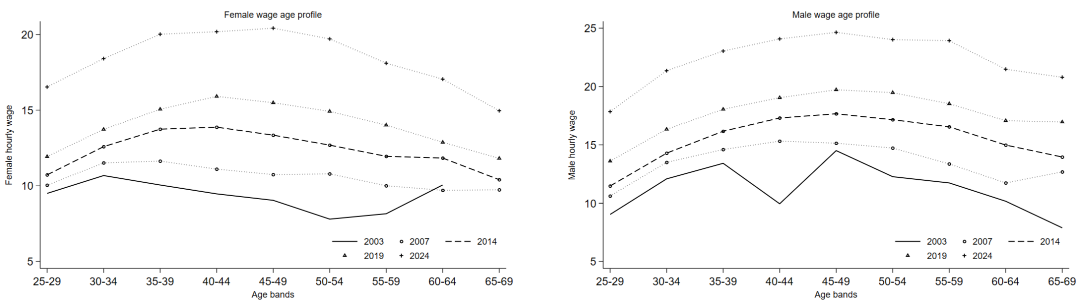
Fig. A.1.—The figure shows female wage over time by major occupation in the UK. The vertical axis depicts the gender wage gap in level. The horizontal axis depicts the period in years from 2003 to 2024. Data source is the British Quarterly Labour Force Survey.



(A) Male wage by occupation

(B) Male wage by occupation

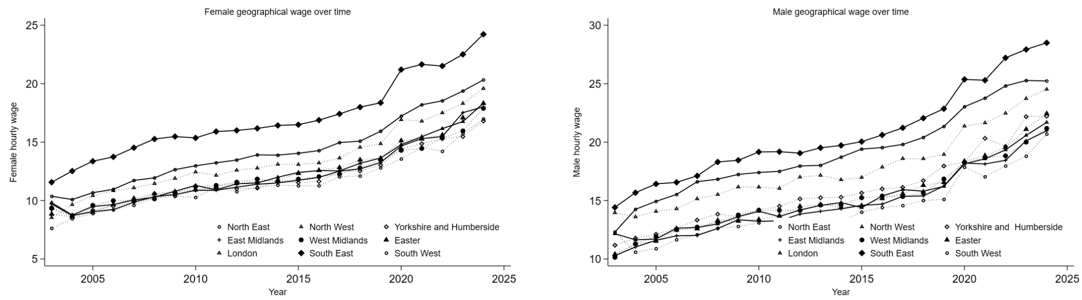
Fig. A.2.—The figure shows male wage over time by major occupation in the UK. The vertical axis depicts the gender wage gap in level. The horizontal axis depicts the period in years from 2003 to 2024. Data source is the British Quarterly Labour Force Survey.



(A) Female wage age profile

(B) Male wage age profile

Fig. A.3.—The figure shows female and male wage profile over the lifecycle in the UK. The vertical axis depicts the gender wage gap in level. The horizontal axis depicts the age bands. Data source is the British Quarterly Labour Force Survey.



(A) Female wage (B) Male wage

FIG. A.4.— The figure shows the path of female and male wage over time from 2003 to 2024 across geographical regions in the UK. The vertical axis depicts the gender wage gap in level. Data source is the British Quarterly Labour Force Survey.

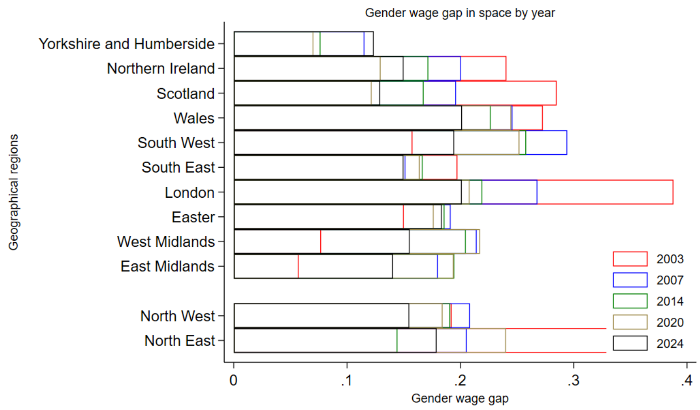


FIG. A.5.—Gender wage gap in space over time

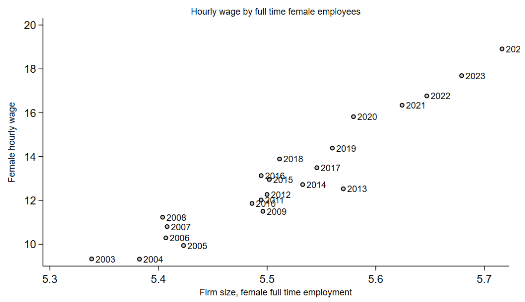
NOTE. The x-axis reports gender wage gap in levels, the y-axis depicts the geographical regions considered in the UK. Data source is the British Quarterly Labour Force Survey.

B The Gender Wage Gap Reporting and the Equality Act 2010

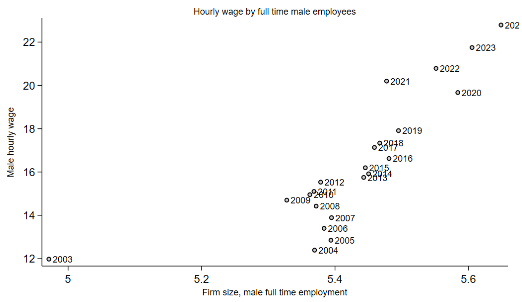
In March 31, 2017 the UK Government introduced the Gender Wage Gap Reporting Policy as part of the The Equality Act 2010 (Specific Duties and Public Authorities) Regulations 2017 regulation in an effort to align with the Public Sector Equality Duty. The policy regards employers with equal or more than 250 employees and requires them to report information on variables related to female and male wages on a mandatory basis. This annual information release includes among a list of 14 metrics the difference in means of the hourly wage between males and females relative to the mean hourly wage of men in percentages, the distribution of females and males in each quartile of the distribution as well as the proportion of female and male receiving bonuses.[9]

The Equality Act 2010 (Specific Duties and Public Authorities) Regulations 2017 puts for-

[9]Detailed information on the Equality Act 2010 with regards to the Gender Pay Gap Regulation 2017 is available at the following website: https://www.legislation.gov.uk/uksi/2017/353/contents/made.

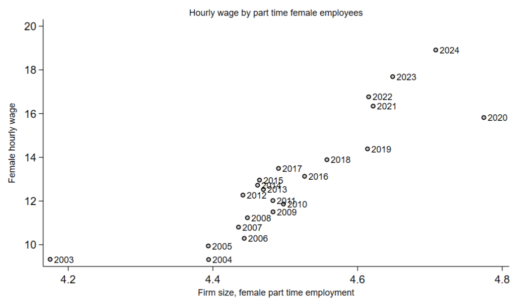


(A) Female wage full-time employment

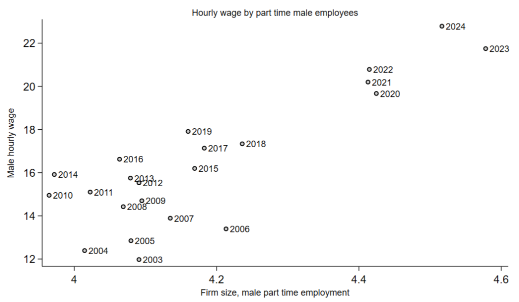


(B) Male wage full-time employment

FIG. A.6.— The figure shows the path of female and male wage in Panel A and B, respectively, over time as a function of firm size for full-time jobs. The vertical axis depicts the hourly wage in level, the horizontal axis is the average number of employees. Data source is the British Quarterly Labour Force Survey.



(A) Female wage part-time employment



(B) Male wage part-time employment

FIG. A.7.— The figure shows the path of female and male wage in Panel A and B, respectively, over time as a function of firm size for part-time jobs. The vertical axis depicts the hourly wage in level, the horizontal axis is the average number of employees. Data source is the British Quarterly Labour Force Survey.

ward legislative steps to raise transparency in pay information between females and males and a fair treatment in pays. The UK government has made efforts to reach equity in pays by imposing public disclosure of pays contextualized to the organization and providing guidance to employers to understand and reduce their gender pay gap thereby creating a more inclusive workplace structure. The policy aims to support women's career progressions in the workplace, ensuring that they are not paid less given the same talent with men. Information on closing the UK gender pay gap is available at the following websites: https://www.gov.uk/government/publications/gender-pay-gap-reporting-guidance-for-employers/closing-your-gender-pay-gap, and at this website: https://www.gov.uk/government/publications/womens-progression-in-the-workplace-actions-for-employers/what-works-to-reduce-the-gender-pay-gap-womens-progression-in-the-workplace-action-note.[10]

In a recent report published in March 2025, the Competition and Markets Authority−who has undertaken the Gender Wage Gap Reporting Policy−has documented a reduction in its gender wage gap in the period 2023-2024 from 6.8% to 4.9% particularly because of the increase of female representations in senior and leadership positions.[11] While these figures are encouraging in terms of the policy changes that have been taking place, a non indifferent figure in the gender wage gap remains and calls for further research and actions to close the workforce wage gap. In this direction the UK Statistics Authority has launched the Women into Leadership Programme helping female to progress into more senior positions.[12]

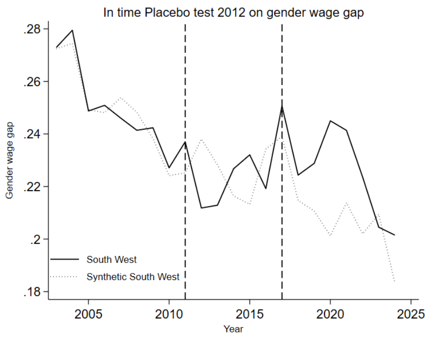
Moreover, sectors with high gender wage gap figures such as the banking, finance and insurance sector and the technology sector have introduced mentorship programmes that allow women to take leadership roles and undertaken pay transparency practices. Flexible working arrangements help women to maintain the full-time positions, however at more senior roles this option may not be available preventing women from promotions and obtaining wage rises. In addition, flexible working arrangements can have a positive impact on the gender wage gap only if the flexible option is standardised for both female and male, by contrast with only women taking flexible working patterns the flexible time option can limit female career progressions. Since part-time work and term time work are more prevalent amongsts women, they contribute to raise wage disparities as the carry lower earnings.

In this paper I am interested in the impact of the Gender Wage Gap Reporting Policy which has been implemented nationwide in the UK, therefore to identify the effect of the treatment I need to pose strong assumptions on the choice of the control group. To deal with this problem,

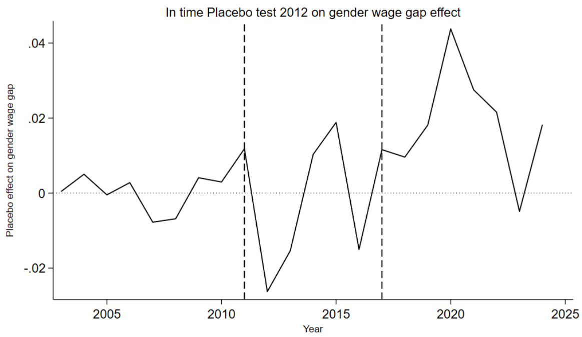
[10] The UK legislative aspect of the Equality Act 2010 (Gender Pay Gap Information) Regulation 2017 is also available at this link: https://www.gov.uk/government/publications/gld-gender-pay-gap-report-and-data-2017/gld-gender-pay-gap-report-2017.

[11] Details on the gender wage gap regarding the Competition and Markets Authority are available at this website: https://www.gov.uk/government/publications/gender-pay-gap-report-2023-to-2024/gender-pay-gap-report-1-april-2023-to-31-march-2024.

[12] Details on the actions taken by the UK Statistics Authority including the Women into Leadership programme are available at the following website: https://uksa.statisticsauthority.gov.uk/publication/gender-pay-gap-report-2024/pages/6/.



(A) Path wage gap in time placebo test 2012



(B) Placebo wage gap effect 2012

FIG. C.1.—The figure shows the in time placebo path of the wage gap between the South West and Synthetic South West (Panel A), and the effect on the gender wage gap (Panel B). The vertical lines in 2012 and 2017 are the year used for placebo test and the year when the Gender Wage Gap Reporting was introduced, respectively. The vertical axis is shown in level. The horizontal axis reports the period in years. Data source is the British Quarterly Labour Force Survey.

I use as control group a group of individual that operates in the same labour market but for whom the policy has been taking longer to be fully implemented. The identification assumption considers the fact that individual unit of treatment are regions and the effect of the policy on the gender wage gap is meant to be an aggregate effect on the individual geographical regions.

Moreover, in this study I am concerned with the impact of the policy in reducing the gender wage gap. I focus on the outcome variable of the difference in means between males and females wages relative to males wage instead of the median. The choice of the mean in place of the median is dictated by the fact that by sorting female and male hourly wage, the median cannot show inequalities in the top and bottom pays of the distribution and women are often over represented at the bottom tail of the wage distribution in contrast to men who are mainly over represented in the top tail of the wage distribution. To assess the quantitative importance of the estimation I evaluate the methodology in the period prior to the policy implementation. I then test the quantitative significance of the estimates by conducting a series of in space and in time placebo tests.

C Robustness

This Appendix reports complementary results on the synthetic control estimation performed in Section 4.2 in the main text.

Table A.5.—
Structural workforce wage inequality in space with Blinder-Oaxaca decomposition

	2024			All sample		
	North	London, Midlands	South	North	London, Midlands	South
Coefficients						
Highest qual	-1.406	-0.901	-2.424***	-0.855***	-0.876***	-1.456***
Experience	2.647***	0.415	-0.394	0.919***	0.671***	0.298
Age qual	0.681	1.777	-3.463	0.985***	0.537**	-1.922***
Hours	-0.353	0.143	-3.852**	-1.250***	-0.705***	-1.165***
Flexible job	1.616	-1.117	-0.175	1.270***	0.441	0.851
Part-time	-0.315	-0.255	-0.731	-0.498***	-0.291***	-0.148
Sector	-1.800	-0.795	-1.770	-0.522*	0.853***	2.988***
Occupation 2	0.594	-0.534*	0.482	-0.024	-0.055	0.211***
Occupation 3	0.392	-0.307*	-0.021	-0.067*	-0.012	0.063
Occupation 4	-0.115	-0.547**	-0.254	-0.265***	-0.205***	-0.192**
Occupation 5	0.017	-0.005	-0.004	-0.003	0.008	-0.000
Occupation 6	-0.104	-0.406**	-0.041	-0.131***	-0.238***	-0.173***
Occupation 7	0.062	-0.209*	-0.138	-0.078**	-0.044	-0.015
Occupation 8	0.031	-0.020	-0.003	-0.007	-0.002	-0.004
Occupation 9	-0.129	-0.227	-0.130	-0.112***	-0.102***	-0.089***
Kids < 2	0.051	0.007	0.041	-0.034**	-0.032	-0.117***
Kids 2-4	0.075	-0.116	-0.060	-0.001	-0.064***	-0.081***
Kids 5-9	-0.150	-0.091	-0.016	0.073**	0.060**	0.017
Kids 10-15	0.274	0.086	0.635***	0.193***	0.190***	0.259***
Constant	0.183	4.994	14.237***	1.721**	1.462**	3.005***
Interactions						
Highest qual	-0.079	-0.075	0.001	-0.002	-0.018***	0.014*
Experience	-0.024	0.029	0.011	0.036***	0.029***	0.004
Age qual	-0.007	-0.065	0.040	-0.009**	-0.002	-0.004
Hours	-0.063	0.030	-0.734**	-0.327***	-0.206***	-0.296***
Flexible job	0.023	-0.019	-0.001	0.032***	0.007	0.008
Part-time	0.251	0.211	0.606	0.418***	0.248***	0.125
Sector	0.292	0.147	0.207	0.095*	-0.157***	-0.361***
Occupation 2	-0.021	0.048	0.014	0.001	0.002	0.015***
Occupation 3	0.013	-0.006	-0.001	-0.005	-0.000	0.004
Occupation 4	0.081	0.413**	0.186	0.191	0.155	0.143**
Occupation 5	0.185	-0.067	-0.031	-0.028	0.066	-0.000
Occupation 6	0.079	-0.312**	0.031	0.101***	0.189***	0.134***
Occupation 7	-0.027	-0.108*	0.022	0.044**	0.027	0.007
Occupation 8	0.174	-0.221	-0.015	-0.061	-0.013	-0.028
Occupation 9	-0.047	-0.002	0.002	-0.014***	-0.008**	-0.015***
Kids < 2	0.044	0.003	0.029	-0.021**	-0.020***	-0.088***
Kids 2-4	0.002	0.014	-0.001	-0.000	-0.007***	-0.017***
Kids 5-9	0.005	0.003	0.001	-0.011**	-0.006**	-0.000
Kids 10-15	-0.037	-0.010	-0.115*	-0.033***	-0.028***	-0.043***

Note. This Table presents of the Blinder-Oaxaca decomposition between female and male wage across different spatial regions in 2024 and all sample period. Significance is ***p< 0.01, **p< 0.05 and *p< 0.10 critical values. Data source is the British Quarterly Labour Force Survey.

Table C.1.—
Mean Value of Regressors and Weights for the Synthetic South West

	South West	Synthetic South West	Region	Weight
Hours 2013-2017	22.842	21.690	North East	0.000
Experience	24.665	23.499	North West	0.000
Experience squared	769.326	714.595	Yorkshire and Humberside	0.130
Age qualification	20.470	20.514	East Midlands	0.042
Hours	21.957	20.767	West Midlands	0.391
Wealth index	2.260	2.297	Eastern	0.136
Degree held	1.820	1.821	London	0.000
Qualif held	8.287	8.946	South East	0.028
Female	0.559	0.556	Wales	0.273
Kids < 2	0.065	0.068	Scotland	0.000
Kids 2-4	0.114	0.118	Northern Ireland	0.000
Kids 5-9	0.190	0.202		
Kids 10-15	0.241	0.241		
Flexible time	1.872	1.883		
full-time	0.707	0.741		
Part-time	0.293	0.259		
Married	0.623	0.602		
Separated	0.029	0.031		
Divorced	0.116	0.111		
Widowed	0.023	0.025		
Occupation managers	0.144	0.131		
Professionals	0.181	0.171		
Associate professionals	0.147	0.135		
Administrative	0.132	0.130		
Skilled Trades	0.088	0.090		
Personal Service	0.082	0.082		
Sales and Customer	0.067	0.069		
Process, plant, machine	0.063	0.085		
Agriculture	0.009	0.007		
Transport	0.076	0.078		
Banking	0.149	0.136		
Public administration	0.347	0.342		
Distribution	0.174	0.168		
Construction	0.055	0.055		
Manufacturing	0.129	0.153		
Other sectors	0.042	0.042		
No. female flexitime	5.843	5.895		
No. female full-time	5.269	5.478		
Managers	2.277	2.347		
Female wage 2017	12.663	12.761		
Female Wage 2007	10.096	10.162		
Female Wage 2004	8.623	8.751		

Note. This Table presents the mean value of the regressors for the South West of England and the Synthetic South West and the weights attached to each region to construct the synthetic control group. Industry sectors, occupations and marital status are introduced with dummy variables of which one dummy is excluded for each category. Data source is the British Quarterly Labour Force Survey.

Table C.2.—

Mean Value of Regressors and Weights for the Synthetic South West Workforce Wage Gap

	South West	Synthetic South West	Region	Weight
Hours 2013-2017	22.842	23.234	North East	0.000
Experience	25.116	24.260	North West	0.000
Experience squared	797.057	752.541	Yorkshire and Humberside	0.062
Age qualification	20.544	20.496	East Midlands	0.130
Hours	22.028	22.464	West Midlands	0.000
Wealth index	2.278	2.312	Eastern	0.487
Degree held	1.808	1.818	London	0.000
Qualif held	6.394	6.664	South East	0.209
Female	0.558	0.556	Wales	0.113
Kids < 2	0.065	0.070	Scotland	0.000
Kids 2-4	0.117	0.122	Northern Ireland	0.000
Kids 5-9	0.189	0.204		
Kids 10-15	0.237	0.236		
Flexible time	1.872	1.894		
Full-time	0.707	0.744		
Part-time	0.292	0.256		
Married	0.617	0.611		
Separated	0.029	0.031		
Divorced	0.117	0.110		
Widowed	0.022	0.022		
Occupation managers	0.138	0.140		
Professionals	0.193	0.192		
Associate professionals	0.149	0.147		
Administrative	0.127	0.129		
Skilled Trades	0.086	0.081		
Personal Service	0.085	0.081		
Sales and Customer	0.066	0.064		
Process, plant, machine	0.062	0.068		
Agriculture	0.009	0.009		
Transport	0.079	0.093		
Banking	0.150	0.161		
Public administration	0.353	0.331		
Distribution	0.171	0.165		
Construction	0.054	0.056		
Manufacturing	0.124	0.127		
Other sectors	0.041	0.041		
No. female flexitime	5.774	5.847		
No. female full-time	5.301	5.496		
Managers	2.274	2.286		

Note. This Table presents the mean value of the regressors for the South West of England and the Synthetic South West and the weights attached to each region to construct the synthetic control group for the workforce wage gap. Industry sectors, occupations, marital status and country of birth are introduced with dummy variables of which one dummy is excluded for each category. Data source is the British Quarterly Labour Force Survey.

Table C.3.—

Mean Value of Regressors and Weights for the Synthetic South West Wage Gap, continuation

	South West	Synthetic South West	Region	Weight
Scotland	0.018	0.017		
Wales	0.021	0.086		
Norther Ireland	0.005	0.004		
UK Not Known	0.001	0.001		
Republic of Ireland	0.004	0.005		
Hong Kong	0.000	0.000		
China	0.000	0.000		
Wage gap 2017	0.251	0.245		
Wage gap 2007	0.246	0.253		
Wage gap 2004	0.279	0.271		
Wage gap 2010	0.227	0.214		
Wage gap 2013	0.213	0.224		
Wage gap 2015	0.232	0.228		
Wage gap 2009	0.242	0.249		

Note. This Table presents the mean value of the regressors for the South West of England and the Synthetic South West and the weights attached to each region to construct the synthetic control group for the workforce wage gap. Industry sectors, occupations, marital status and country of birth are introduced with dummy variables of which one dummy is excluded for each category. Data source is the British Quarterly Labour Force Survey.

Table C.4.—

Mean Value of Regressors and Weights for the Synthetic South West Workforce Wage Gap in Full Optimisation

	South West	Synthetic South West	Region	Weight
Wage	12.737	13.587	North East	0.000
Experience	24.665	23.909	North West	0.000
Experience squared	769.326	730.979	Yorkshire and Humberside	0.019
Age qualification	20.470	20.415	East Midlands	0.138
Hours	21.958	22.094	West Midlands	0.000
Wealth index	2.260	2.278	Eastern	0.425
Degree held	1.820	1.816	London	0.000
Qualif held	8.287	8.548	South East	0.220
Female	0.559	0.556	Wales	0.198
Kids < 2	0.065	0.069	Scotland	0.000
Kids 2-4	0.114	0.119	Northern Ireland	0.000
Kids 5-9	0.190	0.203		
Kids 10-15	0.241	0.239		
Flexible time	1.872	1.888		
Full-time	0.707	0.743		
Part-time	0.293	0.257		
Married	0.623	0.618		
Separated	0.029	0.031		
Divorced	0.117	0.110		
Widowed	0.023	0.023		
Occupation managers	0.144	0.147		
Professionals	0.179	0.179		
Associate professionals	0.147	0.145		
Administrative	0.132	0.132		
Skilled Trades	0.088	0.083		
Personal Service	0.082	0.081		
Sales and Customer	0.067	0.063		
Process, plant, machine	0.064	0.071		
Agriculture	0.009	0.009		
Transport	0.076	0.087		
Banking	0.149	0.157		
Public administration	0.347	0.331		
Distribution	0.174	0.165		
Construction	0.055	0.057		
Manufacturing	0.129	0.134		
Other sectors	0.042	0.043		
No. female flexitime	5.843	5.871		
No. female full-time	5.269	5.248		
Managers	2.277	2.284		

Note. This Table presents the mean value of the regressors for the South West of England and the Synthetic South West and the weights attached to each region to construct the synthetic control group for the workforce wage gap using a full optimisation technique. Industry sectors, occupations, marital status and country of birth are introduced with dummy variables of which one dummy is excluded for each category. Data source is the British Quarterly Labour Force Survey.

TABLE C.5.—

Mean Value of Regressors and Weights for the Synthetic South West Wage Gap in Full Optimisation, continuation

	South West	Synthetic South West	Region	Weight
Scotland	0.018	0.017		
Wales	0.022	0.146		
Norther Ireland	0.005	0.004		
UK Not Known	0.001	0.001		
Republic of Ireland	0.004	0.005		
Hong Kong	0.000	0.000		
China	0.000	0.000		
Wage gap 2017	0.251	0.245		
Wage gap 2015	0.232	0.223		
Wage gap 2013	0.213	0.216		
Wage gap 2010	0.227	0.205		
Wage gap 2009	0.242	0.245		
Wage gap 2007	0.246	0.250		
Wage gap 2004	0.279	0.268		

NOTE. This Table presents the mean value of the regressors for the South West of England and the Synthetic South West and the weights attached to each region to construct the synthetic control group for the workforce wage gap using a full optimisation technique. Industry sectors, occupations, marital status and country of birth are introduced with dummy variables of which one dummy is excluded for each category. Data source is the British Quarterly Labour Force Survey.