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Social capital as a partial explanation for gender wage gaps

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Abstract

Despite a long record of research on the sources of the gender wage gap, a large fraction of gender wage differences remains unexplained. In this paper, we propose gender differences in social capital as a novel explanation for the gender wage gap. We use British data from the Understanding Society (UKHLS) survey and wage decompositions to estimate the contribution of social capital derived from network homophily, that is, the similarity to one's peer group, to the gender wage differential. Our results show that differences in network structure explain as much as 15% of the overall gender wage gap. This finding is largely driven by gender differences in the number of males among closest friends, while other social capital measures used in this study hardly matter. We further show that differences in returns to social capital are not statistically significant.

KEYWORDS

decomposition, gender wage gap, social networks, UK

1 | INTRODUCTION

The causes and consequences of gender (in)equality have raised attention in a variety of settings, from newspaper articles on corporate America (Fuhrmans, 2019) to scientific research on female representation in news coverage (Shor et al., 2019). One of the most prominent indicators for these differences in the labor market

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is the gender wage gap, which, even if adjusted for a large set of observable characteristics, is still substantial (Blau & Kahn, 2017; Boye et al., 2017). Research has identified many different factors contributing to the gender wage gap, such as human resource practices (Huffman et al., 2017), overtime work (Cha & Weeden, 2014), personality traits (Nyhus & Pons, 2012), and motherhood (e.g., Budig & England, 2001; Kleven et al., 2019; Villanueva & Lin, 2019). But even net of these characteristics, a large unexplained gap remains. We propose gender differences in the composition of social capital as a new explanation for a substantial part of the gender wage gap.

Anecdotal evidence (Tufts Now, 2018) as well as research (Cullen & Perez-Truglia, 2019; McDonald, 2011) suggest that there are *old boys' clubs*, that is, informal, homophilous male networks in key positions that function as gatekeepers in the workplace. More generally, the literature identifies gender differences in both the structure of social networks as well as the utilization of these networks (e.g., Burt, 1998; McDonald, 2011; Son & Lin, 2012). Thus, females can either be disadvantaged in terms of wages because they have different networks and thus they lack important information and influence or because they have lower returns from their networks compared to males. But despite social network analysis' long-standing tradition in sociology (e.g., Burt, 1976; Granovetter, 1973; Lin et al., 1981) and many empirical studies on the connection between social networks and labor market outcomes (e.g., McDonald, 2015; Mouw, 2003), to the best of our knowledge, social networks have never explicitly been investigated as a factor that contributes to the gender wage gap.

We are aware of only two studies that relate closely to this topic. Day and Devlin (1997) investigate the connection between volunteering and gender wage gaps with data from a survey on volunteering in the US, arguing that volunteering may affect wages either through human capital accumulation or networking effects. They find a negligible contribution of volunteering to the explained gender gaps, that is, no differences in endowments between the genders, but differential returns. In their study, differences in terms of the returns to volunteering can explain 33% of the unexplained gender gap gaps and thus 24% of the overall gender wage gap.

Cullen and Perez-Truglia (2019) investigate the impact of managers' gender on employees' career advancement using data from a financial firm. They identify the effect through changes in the manager assigned to employees, thus claiming causality. The study finds that male managers boost the career advancement—in terms of promotions and wages—of male employees in contrast to female managers, while managerial gender has no impact on female employees' career advancement. They argue that this is the effect of socializing as the effects are only present when manager and employee work in close proximity. In a back of the envelope calculation, they find that removing this advantage for males would reduce the gender pay gap by 38%.

In this paper, we focus on gender differences in the labor market due to homophily in friend networks (McPherson et al., 2001) or, in other words, the level of diversity in ones' network. Thus, in our case, a diverse network mainly describes a network of friends consisting of people who differ from one's own characteristics. Gender-homophilous ties create disadvantages especially for females as females have on average lower status (Ibarra, 1992; McPherson et al., 2001; Ridgeway & Smith-Lovin, 1999; Son & Lin, 2012). In contrast, males could profit from homophily in certain aspects, such as the number of male contacts, because males are, in general, more likely to hold key positions that can further career advancement (McDonald, 2011). While these findings do not directly tie to the impact of social networks on gender wage gaps, the literature implies a large gendered impact of social networks on labor market success (e.g., Lin & Ao, 2008; Lutter, 2015; McDonald, 2011).

Thus, we investigate the contribution of friendship social capital and the level of homophily within these networks to gender wage differences using data from the Understanding Society (UKHLS) survey for the UK. We draw on information from a module on the homophily of the friends network and investigate the impact of these measures on the gender wage gap using wage decompositions (Blinder, 1973; Kitagawa, 1955; Oaxaca, 1973). This allows us to investigate whether gender differences in wages arise either through different levels of network diversity or through different returns to network characteristics (i.e., the utilization of networks).

2 | SOCIAL NETWORKS, LABOR MARKET OUTCOMES, AND THE GENDER WAGE GAP

In this section, we discuss the connection between social networks, social capital and labor market outcomes and tie it to gender wage gaps. Social networks provide access to social capital, which can be defined as a resource in which people invest because they expect returns to pursue their own goals (Coleman, 1988; Lin, 1999).[1] In general, social capital can affect labor market outcomes, like wages, through three different channels: information, influence, and status (Lin, 2001).

First, information on job opportunities plays an important role in the labor market. Contacts can provide access to novel information, for example, about job openings, which can help individuals to find jobs (Granovetter, 1973). In general, this mostly implies that a diverse network is helpful (Son & Lin, 2012), because it is more likely to provide novel information, in contrast to a homophilous network, which would then provide redundant information.

Second, contacts can influence the job hiring process by vouching for a certain job candidate. Especially contacts higher up in the hierarchy (e.g., individuals with a high status) are helpful in reaching a higher position because these contacts are more able to influence the hiring process (Lin, 1999). This influence could thus increase ones' wages by providing better career perspectives.

Third, contact to a high-status person can signal positive characteristics (Lin, 2001). In contrast to influence, it is not necessary for contacts to influence the hiring process directly, but just to know high-status persons, which then serves as a signal. This signal can help to achieve higher status positions, which also increase wages. In this context, close friends, not acquaintances, could matter, because a connection to a high-status individual is a strong signal. Thus, contacts can matter for labor market outcomes both in terms of a diverse network as well as in terms of close contacts (e.g., McDonald, 2011).

But how can the previously described mechanisms contribute to the gender wage gap? Lin (2001, p. 100) describes two processes that can explain social capital inequalities between different groups: *capital deficit* and *return deficit*. A *capital deficit* results from different investments or opportunities for certain groups, which constrain the social capital acquisition. For example, females can invest less in labor market relevant social capital than males due to gender-specific tasks like informal care (Eberl, 2020).

A *capital deficit* can also occur if females are embedded in different (segregated) networks than males, and therefore, have different labor market opportunities (Burt, 1998). Due to physical segregation (e.g., workplace segregation), resources are clustered by gender (Burt, 1998; McDonald, 2011; McDonald & Day, 2010). Studies show that on average networks of females have a higher proportion of kin ties (Marsden, 1987; Moore, 1990) and have less access to high-status contacts (McGuire, 2000; Smith, 2000). Females may focus more on ties that provide friendship and emotional support, whereas males focus on ties that provide job-related information (e.g., van Emmerik, 2006). In this context, Brashears (2008) concludes that males can bridge larger social capital space than females. Therefore, it is likely that males accumulate larger amounts of labor market relevant social capital than females. Empirically, Cullen and Perez-Truglia (2019) find that men are more likely to socialize with superiors of the same gender, which results in promotions, a finding that supports the theoretical considerations. Blommaert et al. (2019) show that women in general have less diverse occupational networks and are less likely to know managers than men, which are important network features for job authority. Thus, women are less well endowed with social capital that provides individuals with information, influence, and status.

Additionally, network segregation is reinforced by homophily, that is, the tendency to connect with people who have similar characteristics (McPherson et al., 2001). Research shows that social networks members are similar in their characteristics and that homophily tendencies exist regarding gender (e.g., Brashears, 2008; Ibarra, 1992; Kossinets & Watts, 2009; McPherson et al., 2001, 2006), thus supporting network segregation. The structure of everyday interactions, which provide opportunities to connect with same-gender individuals, further strengthens homophily (Ridgeway & Smith-Lovin, 1999). The result are gender-homophilous networks that lead to disadvantages for females, because especially male contacts are important for labor market success (McDonald, 2011; Son & Lin, 2012).

However, a diverse network helps to overcome in-group constraints on resources (McPherson & Smith-Lovin, 1987) and is especially helpful for females (Lutter, 2015; Son & Lin, 2012; Stoloff et al., 1999). As a consequence, network diversity builds bridges to non-connected parts and once again highlights the importance of bridging structural holes (Burt, 1992). This can be especially important for females, as they do not profit from homophilous groups the same way that men do (Burt, 1998; Son & Lin, 2012). In this context, Lutter (2015) shows that female actors have better career perspectives if they are embedded in open and diverse networks. Thus, females suffer from cohesive networks but can benefit from diverse networks by optimizing their flow of information through diverse networks.

Overall, for the reasons discussed in the previous paragraphs, we expect **a social capital deficit for females compared to males, that is, females being less well endowed with social capital that supports career advancement. This capital deficit could then produce a gender wage gap (H1)**.

Another cause for the gender wage gap could be a *return deficit* regarding females' social capital. A *return deficit* describes that a certain quality generates a differential return or outcome. Thus, even if males and females have the exact same quantity of social capital, they could receive different returns from that capital (Lin, 2001, p. 100). McDonald et al. (2009) show that although White males and White females have very similar levels of social capital, White females receive fewer job leads than White males.

Different mechanisms can explain the occurrence of return deficits (Lin, 2001; McDonald & Day, 2010). First, females may utilize certain ties differently than males. For example, males may be more prone asking friends about job leads than females. Second, contacts are less supportive for females than for males (Huffman & Torres, 2002; McDonald, 2011; McGuire, 2002). Thus, males are more likely to receive support from their network, even with the same endowment with social capital. Third, firms value recommendations given by females lower than recommendations made by males (Bjerk, 2008; Lin, 2001). Given the theoretical considerations, **we hypothesize that women are more likely to experience a return deficit than males, which contributes to the gender wage gap (H2)**.

3 | THEORETICAL IDENTIFICATION

As previously described, social capital can affect wages through various channels and it is likely that the structures of one's social network plays a role in explaining gender wage gaps. However, to identify the connection between social capital and wages (and, in the next step, the contribution of networks to gender wage gaps), we need to think about endogeneity problems (Mouw, 2006). At this point, we want to clarify that we do not tie to the literature that investigates the general causal effects of social capital on wages (e.g., Dustmann et al., 2016; Krug et al., 2020). Rather, we are interested in gender differences in wages through social capital. Regarding causality, we are confident that we can rule out several potential factors that could bias an estimation of the effect of social networks on gender wage gaps. Thus, even if we do not precisely identify the magnitude of the causal impact of social capital on gender wage gaps, we can still provide evidence for an underlying mechanism.

One likely confounder are personality traits. Personality traits correlate with wages (Heineck & Anger, 2010) and could also affect social networks, as males and females could form diverging social networks due to gender differences in specific personality traits (Staiano et al., 2012). Thus, we need to control for personality traits in the empirical specification. Furthermore, health could be a confounder. It is likely that health problems are linked to lower wages and health problems could also affect the social network structure (Smith & Christakis, 2008), for example, because certain health problems prevent individuals from various social activities and hinder social integration. Further, studies show gender differences in health (e.g., Denton et al., 2004). Thus, we also control for health problems.

Additionally, the place of residence, especially concerning an urban/rural divide, could affect both, wages (if cities provide more job opportunities and thus potentially higher wages) and social networks (cities potentially provide more contact opportunities). Further, it could affect female wages differently compared to males (Nisic, 2017). Thus, we also need to control for the place of residence. We also control for sociodemographic characteristics that could affect the social network structure as well as wages (Moore, 1990) and could contribute to gender wage differentials (Blau & Kahn, 2017). This set of variables includes education, employment characteristics, ethnicity, and age.

We also control for marital status and the existence of a child in the household. It is well documented that motherhood goes along with wage penalties (e.g., Budig & England, 2001) while some studies even report a fatherhood premium (e.g., Killewald, 2013). The pattern of motherhood penalty also shows up in the context of social networks. Studies show that having children affects social networks and that this correlation differs by gender (e.g., Munch et al., 1997; Song, 2012). In line with the motherhood penalty literature, Song (2012) shows that parenthood negatively affects the quality of social capital for women. Further, the author reports a positive effect of parenthood for men. Thus, controlling for these differences in our analysis is important to account for differences with regard to parenthood.

Finally, we have to account for gender-specific selection into jobs. For example, males could select themselves into high paying firms and jobs, whereas females tend to select into low paying workplaces. This is supported by research, which shows that the share of females within an occupation is negatively correlated with wages (e.g., Kilbourne et al., 1994; Levanon et al., 2009). Therefore, we control for industry, occupation, and firm size (the specific measures are described in Section 4) to tackle the issue of sorting into certain firms by gender. Even if there are still omitted variables in our estimation, they should not bias the results of the decomposition approach as long as the confounding factors work the same way for men and women.

However, we would also like to acknowledge that selection into jobs and thus the job characteristics could also be outcomes of social networks and thus social capital. A priori, it is unclear whether selection into jobs confounds the results by affecting networks (i.e., workplace characteristics lead to new friendships) or whether we miss a part of the effects of networks by conditioning on job characteristics (i.e., if social networks affect wages through job choice). We thus conduct the estimation with and without controlling for sorting into occupations.

Another concern that could pose a problem for us is selection into employment. We only observe wages conditional on being employed and previous evidence (Cappellari & Tatsiramos, 2015; McDonald, 2011) suggests that social capital affects employment. This poses a problem for our analysis if these selection patterns differ by gender, for example, if females' employment reacts more strongly to social capital while males work, no matter the network structure. However, if this is the case, our estimation results provide a lower bound of the total impact of social capital on the gender wage gap, because females in the sample would be positively selected. Furthermore, we provide several robustness checks (Section 6.2) to alleviate concerns regarding biases through selection into jobs.

4 | DATA, SAMPLE, AND DESCRIPTIVE STATISTICS

We use data from Understanding Society (also known as UK Household Longitudinal Study, UKHLS) from 2009 to 2015 in our analysis (University Of Essex, 2019). The UKHLS is the follow-up survey to the British Household Panel Study (BHPS) and contains items on labor market variables, sociodemographic characteristics as well as wave-specific modules. Waves 3 and 6 contain a module on social integration that also surveys the homophily of the friendship network in various dimensions as well as a resource generator. We apply several restrictions on the data and keep only individuals that (a) are between 19 and 65 years old who are (b) not in education, (c) report positive wages, and (d) gave valid responses in each variable in the regression. This leaves us with an analysis sample of 17,590 observations.

The dependent variable of interest is the natural logarithm of hourly wages. We calculate hourly wages from usual monthly pay and regular weekly working hours. The median hourly wage is GBP 13.78 for men and GBP 11.05 for women, which implies an unadjusted gender wage gap of 19.8% which is consistent with official figures (Office for National Statistics, 2019).

Our main regressors of interest are measures for network homophily, which we take from the social integration module of the BHPS. This part of the survey asks what share of friends is similar in terms of age, education, ethnicity, what share of friends lives in the local area, and what share of friends has a job. Furthermore, respondents are also asked what share of their friends are also family members. Even though the data also contain a question on what share of friends is similar in terms of income, we do not use this item, as we do not know whether similarity in this case means that friends have a higher or a lower income. Each of these items is surveyed on a 4-point scale from "less than half" to "all." Since all variables refer to friends, the measures reflect strong ties rather than weak ties (Granovetter, 1973). The distribution of each variable is shown in Figure 1. Overall, there seem to be relatively few differences in the network structure between men and women. This is especially interesting with regards to the share of friends that are family members, as the literature shows that females tend to have more kin ties (Marsden, 1987; Moore, 1990). However, it could be the case that this measure is too crude to grasp small gender differences, as over 70% of both males and females report that less than half of their friends are family members.

Due to the nonlinearity of these variables, we generate binary indicators for each of the variables indicating whether more than half or half and less of the friend network are similar in each dimension.[2] In the empirical analysis, we subsume these coefficients under the term homophily as this set of variables capture whether one's network is homophilous.

Beyond these items, the UKHLS also provides information on clubs memberships as well as a resource generator for close friends. Respondents are asked for the number of organizations, in terms of sports clubs or voluntary organizations, in which they participate. Volunteering is often used as a measure for social capital in the literature (e.g., Eberl & Krug, 2020; Ruiter & De Graaf, 2008) and is the only measure that does not focus on friends in our analysis. The UKHLS further contains an item battery that serves as a resource generator. In this battery, respondents are asked to provide information on their three closest friends, for example, concerning gender.

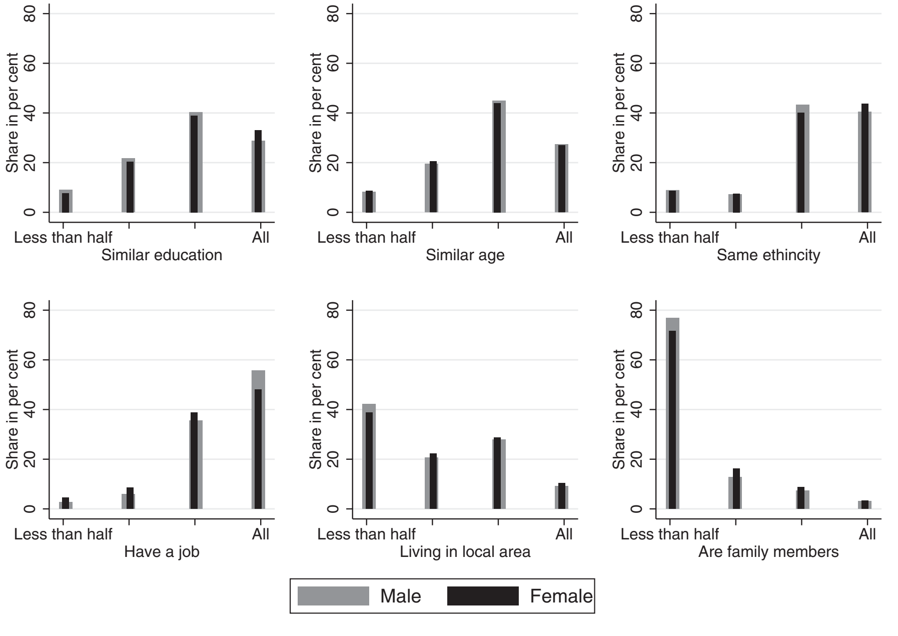

FIGURE 1 Distribution of network diversity measures by gender

Resource generators are commonly used in social networks analysis (e.g., Cappellari & Tatsiramos, 2015; Stoloff et al., 1999). From these items, we calculate the number of male and female friends among the three closest contacts. Previous studies (McDonald, 2011) show that having male contacts can be advantageous in terms of labor market outcomes and this is what we want to measure with these variables. Furthermore, we can investigate return deficits by comparing the coefficients of the number of male and female friends from separate regressions by gender in the decomposition analysis. Figure 2 shows the distribution of club memberships and friends by gender. As can be seen, around 70% of females report no male as one of their closest friends; this is matched by around 60% of males concerning female friends. Unfortunately, the data do not contain even a raw measure of the overall size of the social network, such as number of friends. We thus do not capture effects of the overall size of the friendship network.

Table 1, panel A shows descriptive statistics for our variables of interest, that is, wages and network measures, for males and females in our analysis sample. As can be seen, there is hardly any difference between males and females in either of the network homophily measures, suggesting that differences in the structure of the network in terms of homophily hardly seem to matter. This holds also true for the number of club memberships. As expected, close friends are mostly of the same gender and this holds true for males and females. Thus, we observe homophily in terms of gender.

The UKHLS also contains a broad set of control variables that we draw on to eliminate biases through confounders. We include standardized measures of the big five personality traits, as they could be omitted variables in the empirical estimations. As the big five are only surveyed in wave 3, we follow the literature (Collischon, 2020; Heineck & Anger, 2010) and assume that these traits are mostly time constant within individuals, but can change with age. We thus use the measures from wave three, regress each trait on age and age squared and use the residuals from these estimations as measures of personality traits that are free of age effects for wave 6 as well. Additionally, we standardize each trait (Table 1, panel B shows the corresponding descriptives).

Furthermore, we control for age, age squared, education, ethnicity, marital status, the existence of children in the household under the age of 16, full-time employment status, a dummy for a temporary employment contract, a dummy for a self-reported good health status (4 or 5 on a 1 to 5-scale), a dummy for ever doing overtime work,

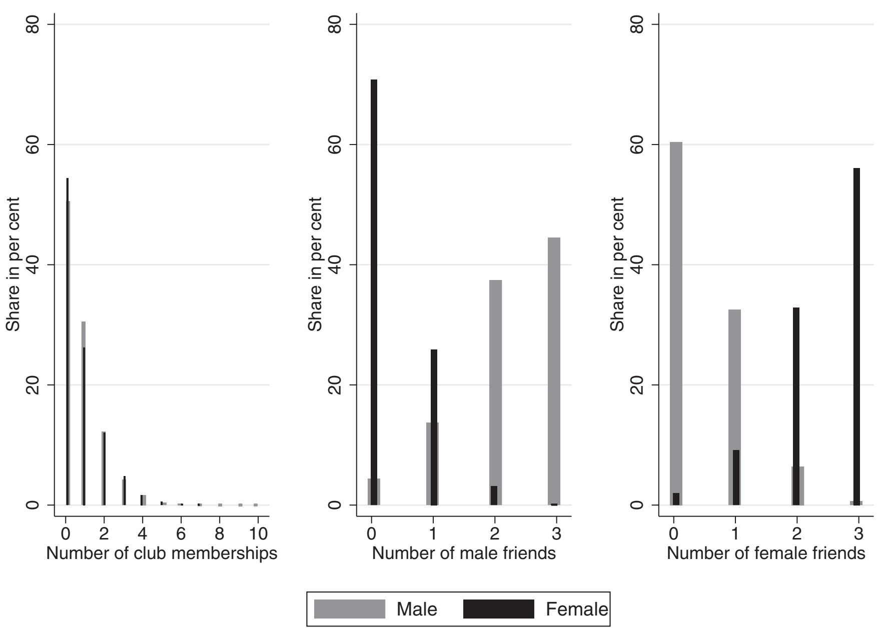

FIGURE 2 Distribution of club memberships and number of friends by gender

TABLE 1 Sample descriptives

	Males		Females	
	Mean	*SD*	Mean	*SD*
(A) Variables of interest				
Ln(wage)	2.63	0.60	2.44	0.55
Most friends similar education	0.69	0.46	0.72	0.45
Most friends similar age	0.72	0.45	0.71	0.45
Most friends same ethnicity	0.84	0.37	0.84	0.37
Most friends have a job	0.91	0.28	0.87	0.34
Most friends live in local area	0.48	0.50	0.49	0.50
Most friends family members	0.60	0.49	0.61	0.49
Number of club memberships	0.37	0.48	0.39	0.49
Number of male friends	0.10	0.31	0.12	0.33
Number of female friends	0.79	1.04	0.76	1.06
(B) Standardized personality traits				
Agreeableness	−0.14	0.99	0.17	0.90
Conscientiousness	−0.03	0.91	0.21	0.87
Extraversion	−0.08	0.95	0.15	0.96
Neuroticism	−0.29	0.91	0.11	0.94
Openness to experience	0.14	0.88	−0.01	0.92
(C) Covariates				
Age	40.28	11.74	40.55	11.60
Caucasian (0/1)	0.75	0.43	0.78	0.41
Married (0/1)	0.57	0.50	0.53	0.50
Child (0/1)	0.38	0.49	0.41	0.49
Full-time employed (0/1)	0.91	0.28	0.64	0.48
Temporary contract (0/1)	0.06	0.24	0.07	0.26
Overtime work (0/1)	0.50	0.50	0.42	0.49
Urban area (0/1)	0.79	0.40	0.77	0.42
Good health (0/1)	0.66	0.47	0.65	0.48
Observations	7,390		10,200	

Notes: N = 17,590. Not displayed in the table: Firm size (3 categories), education (16 categories), ISCO (2-digit dummies), Industry (SIC 2007 top-level codes).

a dummy for living in an urban area, firm size dummies (seven categories), as well as occupation (2-digits-ISCO88) and industry (SOC-2007 top groups) indicator variables. Table 1, panel C shows sample means.

5 | ECONOMETRIC APPROACH

We investigate the contributions of both a potential capital deficit as well as a return deficit to the gender wage gap using a Kitagawa–Oaxaca–Blinder (Blinder, 1973; Kitagawa, 1955; Oaxaca, 1973) style decomposition. In contrast to previous analyses that use regressions with interaction terms of the relevant regressors by gender (e.g., Smith, 2000), decomposition methods allow for explicitly calculating the contribution of certain variables to group differences in terms of differential endowments and returns. Thus, we cannot only estimate whether there are gender differences in social capital, but also their exact contribution to the gender wage gap. As the basis for the decomposition analysis, we estimate the following regression model:

$$\ln\left(wage_{it}\right) = \beta_{0g} + \beta_{1g} networks'_{it} + \beta_{2g} X'_{it} + u_{it} \tag{1}$$

This estimation mirrors the theoretical model derived in Section 3. In this regression model, *networks* is a set of variables that measures the structure of the social network (as displayed in Table 1, panel A) and X is a set of control variables described previously as well as survey year dummies. We estimate this equation for male and female subsamples, indicated by the g subscript for each coefficient which can take m for males and f for females. We use these regressions in the decomposition analysis.

In the classical KOB-decomposition, the wage gap depends on the choice of the reference group, that is, the KOB-decomposition assumes that the wage structure of either males or females is nondiscriminatory and thus altering the reference wage structure affects the results. This problem is known as the index number problem (Oaxaca, 1973). To account for this problem, we use the pooled decomposition in the version proposed by Fortin (2008) to decompose the gender wage gap (Fortin et al., 2011) This version of the decomposition also estimates a pooled regression, including males and females, and uses the parameter estimates from this regression as the nondiscriminatory wage structure.[3]

The case of a wage decomposition (with the natural logarithm of wages (*lnw*) as the outcome of interest) with males as the omitted group in the pooled regression can be written as:

$$\begin{aligned} \overline{lnw_m} - \overline{lnw_f} = \Delta X \hat{\beta}_p &+ \left[\overline{X}_m\left(\hat{\beta}_m - \hat{\beta}_p\right) + \left(\hat{\beta}_{0m} - \hat{\beta}_{0p}\right)\right] \\ &- \left[\overline{X}_f\left(\hat{\beta}_f - \hat{\beta}_p\right) + \left(\hat{\beta}_{0f} - \hat{\beta}_{0p}\right)\right] \end{aligned} \tag{2}$$

where $\hat{\beta}$ are the estimated coefficients and $\hat{\beta}_0$ are the constants from pooled (p) and gender-specific (m and f) regressions. X is a set of regressors. $\Delta X\hat{\beta}_p$ is the difference in explained characteristics. The terms in brackets are used to assign proportions of the unexplained gap to variables in X.

The decomposition method allows for a detailed decomposition of wage differentials, thus showing how certain variables contribute to the explained and unexplained wage gaps.[4] Thus, in the following empirical analysis, we can use the decomposition approach to show how social capital contribute to the gender wage gap, either in terms of mean differences between men and women (e.g., men having a more favorable network), which allows us to make statements on a capital deficit, or in terms of different returns (e.g., men reaping higher gains from their networks compared to women), which relates to a return deficit. Thus, the detailed decomposition also allows us to pinpoint which variables are especially important for gender wage differences.[5]

Note that the impact of social networks on wage gaps derived from the detailed decomposition is not necessarily equal to the overall change in unexplained wage gaps because other control variables (e.g., full-time employment) may implicitly control for the effect of social networks if they are correlated.

6 | RESULTS

6.1 | Decomposition analysis

As described in the previous section, we use a KOB style decomposition in the version suggested by Fortin (2008) as our main analysis. This method allows us to decompose the overall gender wage gap into explained (by differences in observable characteristics) and unexplained (by differences in returns to certain variables) shares. Table 2

TABLE 2 Results from the decomposition analysis of the gender wage gap with the UKHLS waves 3 and 6; controlling for occupations, full set of controls, using dummy variables

	Mean gap		
	Log points	**Percentage**	***p* value**
Mean male	2.627		
Mean female	2.441		
Difference	0.186	100.00	.000
Explained	0.075	40.52	.000
Unexplained	0.110	59.48	.000
Detailed decomposition			
Explained: social networks	0.029	15.77	.000
Homophily	0.002	1.05	.000
Number of club memberships	0.000	0.27	.153
Number of male friends	0.058	31.06	.000
Number of female friends	−0.031	−16.61	.012
Unexplained: social networks	−0.006	−3.16	.915
Homophily	0.003	1.69	.899
Number of club memberships	0.002	0.97	.761
Number of male friends	−0.001	−0.51	.945
Number of female friends	−0.010	−5.31	.549

Notes: Dependent variable: ln(wage); N = 17,590. Fortin (2008) decomposition. p values are obtained from F tests of the joint significance of the respective set of parameter estimates. Estimates are conditional on personality traits, age, age^2, ethnicity (dummy), married (dummy), child in household (dummy), full time (dummy), temporary contract (dummy), overtime work (dummy), urban area (dummy), good health (dummy), occupation (dummies), industry (dummies), firm size (dummies), and education (dummies).

shows the results of this analysis.[6] Overall, our model can explain 40% of the 19 log points overall gender wage gap. 15.77% (2.9 log points) of the overall gap are explained by differences in social capital endowments, that is, men having a more favorable social network compared to females.[7] While this figure may seem large at first, the magnitude of this finding is consistent with Day and Devlin (1997) who find that gender differences in volunteering accounts for 24% of the overall gender wage gap. Furthermore, Cullen and Perez-Truglia (2019) approximate that gender differences in socializing could account for around 38% of the gender wage gap. Thus, our finding is well within the magnitude of the literature on gender wage differences and social networks.

Compared to other variables in the analysis, the share of the gender wage gap explained by social networks (i.e., better endowments of men compared to women) is around thrice as large as the contribution of personality traits to the gender wage gap (4.8%) and comparable to the share explained by the 2-digit-ISCO88 dummies (14.8%) in our estimation as well as to the contribution of sorting into occupations in the US (which accounts for 17.6% of the wage gap, Blau and Kahn (2017)). Thus, social capital seem to play an important role for the gender wage gap.

Next, we investigate which specific variables drive the contribution of social capital to the explained gender wage gap, thus differing between social capital derived from homophily, the number of club memberships and the structure of close friends.

We begin by investigating whether there is a capital deficit, as hypothesized in Hypothesis 1 (H1). Table 2 shows the contribution of social network measures to the explained gap, that is, mean differences between males and females multiplied by the estimate of the coefficient corresponding to the respective variable from the pooled regression model. The difference explained by social capital measures is statistically significant for the variables measuring homophily (i.e., the set of dummy variables generated from the variables in Figure 1) as well as for the number of male friends in the close friends network. The gap explained by different endowments is almost entirely driven by the structure of close contacts, which is measured by the number of male and female friends among the three closest friends, respectively. Differences in the number of male friends can explain around 30% of the overall wage gap, since males tend to have more male friends. The number of female friends can partly compensate this effect (and reduces the gender wage gap by 3.1 percentage points), but because an additional female friend has a smaller correlation with wages, female friends cannot fully compensate the gap due to the number of male friends. Thus, having more close contacts—male or female—correlates with higher wages, but the marginal effect of one additional male friend is larger compared to one additional female friend. In contrast, the other measures can hardly explain wage gaps.

Overall, we find that a capital deficit among females compared to males explains a non-negligible share of the gender wage gap, thus supporting Hypothesis 1 (H1). This capital deficit is overwhelmingly driven by gender differences in the number of close male friends, which almost completely accounts for the overall effect of social capital endowments. In contrast, the measures with regards to homophily and club memberships hardly seem to matter for gender wage differences. This finding is also in line with the literature (e.g., McDonald, 2011) that suggests that especially contacts to friends in powerful positions—which tend to be males—matters for wages.

Next, we turn to differences in returns to investigate a potential return deficit, as proposed by Hypothesis 2 (H2). Overall, differences in returns to social networks hardly contribute to the overall gender wage gap, with a contribution of close to 0 log points. If anything, differences in the returns to these variables even work in favor of females. Due to the small magnitude of the effect and due to its statistical insignificance, we reject H2.[8]

Nevertheless, we would like to be cautious when interpreting this finding, as our social capital measures are relatively coarse and could contain measurement error, which then leads to statistically insignificant differences between the returns by gender. For this reason, we abstain from definitely ruling out return deficits.

6.2 | Robustness

One concern described in Section 3 is reverse causality in the sense that high-earning males might work in workplaces with other high-earning males and thus, their job characteristics might affect their network. To rule out this problem, we account for 2-digit ISCO-codes as well as industry classifications and firm size dummies in our main specification. However, there could still be a selection problem if this selection takes places on a lower level, for example, within firms. Unfortunately, we cannot control for, for example, firm fixed effects with the data and thus rule out differential selection into firms as an explanation for the correlation patterns we observe. Thus, we approximate these differences by adding interaction terms between the ISCO and industry dummies (225 categories) as well as interaction terms between industry and firm size dummies (30 categories). Because this potentially adds multicollinearity to our estimation and thus causes imprecision, we abstain from using this model as our baseline.

Table 3 shows the results of this estimation. Compared to the baseline results, the estimation hardly changes: differences in the network structure can still explain around 15% of the overall gender wage gap. This result is also consistent with another descriptive in our data: both males and females report that they have known their first best friend for longer than 10 years at a rate of around 65%. If reverse causality as discussed previously would pose a problem, we would expect the close friend network to be younger relationships.

It is also possible that we underestimate the impact of social networks on gender wage gaps assuming that network structure might also affect the job characteristics. For example, individuals with many male friends could be more likely to choose jobs in male-dominated occupations, which also correlates with wages. In this case, the individual job choice would be an outcome of social networks and part of the path from networks to wages and

TABLE 3 Results from the decomposition analysis of the gender wage gap with the UKHLS waves 3 and 6; controlling for industry X occupation as well as industry X firm size dummies, full set of controls

	Mean gap		
	Log points	Percentage	*p* value
Mean male	2.627		
Mean female	2.441		
Difference	0.186	100.00	.000
Explained	0.076	40.77	.000
Unexplained	0.110	59.23	.000
Detailed decomposition			
Explained: social networks	0.027	14.77	.000
Homophily	0.002	1.12	.000
Number of club memberships	0.001	0.27	.137
Number of male friends	0.056	30.19	.000
Number of female friends	−0.031	−16.81	.000
Unexplained: social networks	−0.002	−0.92	.000
Homophily	0.001	0.37	.000
Number of club memberships	0.002	1.30	.000
Number of male friends	−0.001	−0.38	.000
Number of female friends	−0.004	−2.21	.000

Notes: Dependent variable: ln(wage); *N* = 17,590. Fortin (2008) decomposition. *p* values are obtained from *F* tests of the joint significance of the respective set of parameter estimates. Estimates are conditional on personality traits, age, age^2, ethnicity (dummy), married (dummy), child in household (dummy), full time (dummy), temporary contract (dummy), overtime work (dummy), urban area (dummy), good health (dummy), occupation (dummies), industry (dummies), industry X occupation (dummies), firm size (dummies), industry X firm size (dummies), and education (dummies).

thus should not be included in the model. However, it could also be the case that the share of males or females in a given occupation (that is implicitly controlled for by using occupation dummies) affects one's friend network and thus, our baseline estimation would suffer from overcontrol bias. In any case, it is important for us to investigate whether selection into occupations and industries moderates the effect of social capital on wages. Therefore, Table 4 shows the results from the decomposition analysis without controlling for the ISCO categories.[9] As can be seen, the share of the gender wage gap explained by social networks slightly increases, which is mostly driven by a large increase in the share of the wage gap explained by the number of male close friends. This finding suggests that job characteristics correlate with the networks structure. However, we abstain from using this result as our baseline model, because we still might capture biases through reverse causality as discussed in the previous paragraphs. Nevertheless, both robustness checks show that the impact of social network structure on gender wage gaps is remarkably stable and ranges between 15% and 18%, depending on the assumptions one makes.

7 | DISCUSSION AND CONCLUSION

This article decomposes the impact of friend networks and the resulting social capital, in terms of network structure as well as returns to this structure, on gender wage gaps. Our results indicate that systematic differences in the network composition between males and females explain around 15% of the overall gender wage gap. This finding further highlights the importance of research on differences in social capital due to gender (e.g., McDonald, 2011). The results are supportive of a capital deficit of women, which is especially driven by diverging

TABLE 4 Results from the decomposition analysis of the gender wage gap with the UKHLS waves 3 and 6; full set of controls, no occupation, using dummy variables

	Mean gap		
	Log points	Percentage	*p* value
Mean male	2.627		
Mean female	2.441		
Difference	0.186	100.00	.000
Explained	0.067	35.87	.000
Unexplained	0.119	64.13	.000
Detailed decomposition			
Explained: social networks	0.033	17.67	.000
Homophily	0.002	1.32	.000
Number of club memberships	0.001	0.34	.148
Number of male friends	0.075	40.65	.000
Number of female friends	−0.046	−24.64	.000
Unexplained: social networks	−0.027	−14.52	.844
Homophily	0.007	3.67	.976
Number of club memberships	0.003	1.77	.593
Number of male friends	−0.010	−5.29	.499
Number of female friends	−0.027	−14.66	.118

Notes: Dependent variable: ln(wage); *N* = 17,590. Fortin (2008) decomposition. *p* values are obtained from *F* tests of the joint significance of the respective set of parameter estimates. Estimates are conditional on personality traits, age, age^2, ethnicity (dummy), married (dummy), child in household (dummy), full time (dummy), temporary contract (dummy), overtime work (dummy), urban area (dummy), good health (dummy), firm size (dummies), and education (dummies).

access to male contacts. Gender differences in the number of males and females among close contacts almost completely explain the contribution of social capital differences to the gender wage gap. While having additional female friends is positively correlated with wages as well, the marginal effect of male friends is larger. Thus, our results closely align with previous findings (McDonald et al., 2009; Son & Lin, 2012) that show that especially male contacts are important for labor market outcomes.

We further investigate whether return deficits, that is, males and females using social capital differently or being treated differently by their contacts, also contribute to the gender wage gap. In this case, our analysis rejects the notion of a return deficit. Differences in returns overall even work in favor of females, thus closing the gender wage gap by 0.6 log points, but this figure is not significantly different from zero. However, as described in Section 5, measurement errors due to the relatively coarse measures of social networks could lead to increasing standard errors as well as attenuation bias toward zero and thus render gender differences in returns insignificant. Thus, while our empirical results reject the notion of a return deficit, we still urge readers to take this finding with a grain of salt. Overall, the share of the gender wage gap due to social capital in our analysis is largely in line with previous evidence by Day and Devlin (1997) and Cullen and Perez-Truglia (2019).

Our findings hold regardless of accounting for job characteristics, suggesting that our results are not mechanically driven by men working in high-wage occupations where only men work and thus their network consisting of men. This finding also suggests that the problem of social networks being an outcome of job characteristics, differing by gender seems relatively limited. This notion is also in line with previous studies (Cappellari & Tatsiramos, 2015) that do not find large differences in the effect of social capital on employment, depending on the empirical method.

The most salient finding in our study is in line with the literature: male contacts are beneficial, regardless of the individual's gender. This strongly supports the notion of the existence of *old boys' clubs* in key positions that are gatekeepers in the labor market. Consequently, gender-homophily in the friend network is beneficial for males, while diversity is beneficial for females, which is in in line with findings from the literature (e.g., Lutter, 2015).

Nevertheless, we want discuss several limitations of this study. The social capital measures in this analysis mainly reflect strong ties, as they focus on the characteristics of friends. We know that weak ties are important especially in the labor market (e.g., Bian et al., 2015; Granovetter, 1973). However, this means that we potentially underestimate the overall contribution of social networks and the resulting social capital on the gender wage gap. Thus, we present a conservative estimation, which highlights the importance of follow-up studies that also include weak tie measures to fully exploit the importance of social capital on the gender wage gap that is suggested by the theoretical framework. Another drawback of this study is that our social network/social capital measures are rather coarse. This hinders us to identify the exact mechanisms that lie in between the stock social capital and wage formation.

Furthermore, even with regards to strong ties, the data unfortunately do not contain measures that could be important as well, for example, whether close friends work in supervisory or managerial jobs. This could potentially lead us to underestimating the total contribution of social capital to the gender wage gap, if we miss certain aspects of networks.

Another limitation of our study is that we cannot account for potentially different patterns of selection into employment due to social capital by gender. It is possible that the women in our sample are positively selected and work due to their social network structure. Consequently, we could underestimate the true impact of social networks on the gender wage gap. In this case, our results provide a lower bound of the real effect and are a conservative estimate. Another drawback is that we cannot use exogenous variation in social capital measures, which hinders us to pinpoint the exact causal effects of social capital measures on gender wage differences. Nevertheless, we can show the importance of social capital, especially the number of male friends among the closest contacts for gender wage gaps net of a large number of potential confounders.

Overall, our results suggest that differences in friend networks between men and women are an important driver of gender wage differentials. This finding further highlights the importance of studies on the exact channels and provide many potential directions for future research. For example, future studies could investigate the gendered consequences of having children for social networks and how they relate to gender wage gaps and motherhood penalties.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available upon registration at https://www.understandingsociety.ac.uk/.

The programs to reproduce the findings of the analyses are available from the authors upon request.

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ENDNOTES

[1] See also Portes (1998) for an overview.

[2] We also ran additional analyses in which we included all four dummies per item in the decomposition analyses. However, as the results hardly differ from the binary indicators, we decided to use these as they are more intuitive to interpret.

[3] This decomposition circumvents some problems compared to the more widely known version introduced by Oaxaca and Ransom (1994) by including a gender dummy in the estimation of the pooled model. Fortin et al. (2011) provide a comprehensive overview over various decomposition methods for further reading.

[4] Because the results of the detailed decomposition are sensitive to the choice of the reference group when using dummy variables, we apply the normalizing approach by Yun (2005) to overcome this problem for the homophily measures. As the number of club memberships as well as the number of friends by gender contain natural zeros, we abstain from using dummies and the normalization procedure for these variables.

[5] We use the Oaxaca STATA ado (Jann, 2008).

[6] Furthermore, Appendix Table A1 shows the results of the regressions used in the decomposition analysis. For brevity, we only report the coefficients of the network measures as well as the gender variable.

[7] Arithmetically, this figure represents the sum of the mean differences in the social network measures between men and women times the estimated βs corresponding to these variables in the pooled regression.

[8] Appendix Table A1, column 5 also shows that there are no statistically significant differences in the coefficients of social network variables between males and females, providing further support against a return deficit.

[9] We still control for industry because we think that the broad industry categories should not capture the effects of social networks as do individual jobs.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the Supporting Information section.

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