

Dangerous Liaisons: A Social Network Model for the Gender Wage Gap^{*}

Maarten Goos¹
Department of Economics
University of Leuven

Anna Salomons²
Department of Economics
University of Leuven

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Abstract

We combine stylized facts from social network literature with findings from the literature on the gender wage gap in a formal model. This model is based on employers' use of social networks in the hiring process in order to assess employee productivity. As a result, there is a persistent gender wage gap, with women being underpaid relative to men after controlling for productivity characteristics. Networks exhibit inbreeding biases by productivity and by gender, which in combination with women's lower network density cause women to be hired less often through referral, as well as receive a lower average referral wage premium. Finally, we use 2001-2006 UK Labour Force Survey data to test the hypotheses implied by our model. We find that networks do indeed account for a significant part of the gender wage gap for newly hired workers.

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¹ Maarten.Goos@econ.kuleuven.be

² Anna.Salomons@econ.kuleuven.be

I. Introduction

The economic literature on the gender wage gap is extensive, yet a significant portion of that gap remains unexplained (e.g. see Blau et al 2006). Several hypotheses have been put forward for this unexplained gap, including preference-based discrimination and statistical discrimination (for an overview, see Altonji and Blank 1999). The most novel approach to the gender wage gap, pioneered by Montgomery (1991), is that of social networks.

Research findings from sociology and economics show that social networks play an important role in labor markets.³ Ioannides and Datcher-Loury (2004) and Calvó-Armengol and Ioannides (2005) distinguish two mechanisms through which social networks influence the functioning of labor markets. Firstly, from the *employee perspective*, social networks provide workers looking for jobs with information about vacancies and job characteristics. Secondly, from the *employer perspective*, networks provide firms looking for workers with information about applicant ability through the job referral mechanism. Hires mediated through such referrals mitigate employer uncertainty about applicants' productivity.

A number of recent papers have used the importance of social networks to model persistent income inequalities among different groups in the labor market (Calvó-Armengol and Jackson 2004; Buhai and van der Leij 2006; Ioannides and Soetevent 2006; Calvó-Armengol and Jackson 2007). All these papers model the impact of networks on income inequalities through the employee perspective. We contribute to this literature in two ways. Firstly, we use the employer perspective to present a simple model with imperfect information that predicts a gender wage gap in equilibrium. Social networks exhibit inbreeding biases by ability and by gender, and women's network density is lower than men's.⁴ Workers hired through referral earn a higher wage

³ For an excellent overview, see Ioannides and Datcher-Loury (2004).

⁴ See Buhai and van der Leij (2006) for the most recent overview of empirical findings on social network composition.

because inbreeding bias by ability reduces the uncertainty about applicant productivity. The gender wage gap arises because women are hired less often through referral, and because the referral wage for women is lower than the referral wage for men. Secondly, we test to what extent our model can account for the empirical gender wage gap. Using UK Labour Force Survey data over 2001-2006, we compare the wages of male and female newly hired workers who have found their job through referral by a friend already employed at the firm with those who have found their job through an advertisement.

The remainder of this paper is organized as follows. Section II presents the network model for the gender wage gap: we describe the assumptions, derive the equilibrium, and discuss the empirically testable implications of the model. In section III, the data is described. Section IV performs the empirical tests by means of individual regression and Oaxaca decomposition. Section V concludes.

II. A social network model for the gender wage gap

II.A Assumed network structure

Assume a continuum of firms employing one of four types of workers: (H,M) , (H,F) , (L,M) , (L,F) where H denotes high-ability, L low-ability, M male, and F female. Also assume only the firm knows the type of its worker because worker ability has been revealed to her after an initial period of employment. Each incumbent worker is associated with a total population of potential hires that is normalized to unity and equally distributed over the four worker types. However, not all workers in the total population of all potential hires are effectively part of the incumbent worker's network. As will become clear below, this assumption is made to allow network structures to differ by gender and ability and to generate the selection of worker types (not) hired through referral that is needed to explain the gender wage gap in equilibrium.

To see this, consider the top and bottom panels of Figure 1, where the equally distanced axes reflect the potential hires of each worker type. The top and bottom panels consider the cases where the incumbent worker is male and female, respectively. The four points connected by dotted lines then reflect the incumbent worker's network. For example, the distance OA reflects the fraction of (i, M) -types in the total population of potential new hires in the network of an (i, M) -type incumbent worker. More generally, the top panel assumes there is inbreeding bias by gender since men are more likely to know men given that $(OA + OD)/(OA + OB + OC + OD) > 1/2$. Also, an incumbent male worker is more likely to know workers of a similar ability type since $(OA + OC)/(OA + OB + OC + OD) > 1/2$, capturing inbreeding bias by ability. Similarly, the bottom panel of Figure 1 shows that there is inbreeding bias by gender since $(OB' + OC')/(OA' + OB' + OC' + OD') > 1/2$ and that there is inbreeding bias by ability since $(OA' + OC')/(OA' + OB' + OC' + OD') > 1/2$. In addition to inbreeding biases by gender and ability, Figure 1 also assumes that $(OA + OB + OC + OD) > (OA' + OB' + OC' + OD')$, i.e. men have bigger social networks compared to women. Finally, note that because the top and bottom panels of Figure 1 are independent of ability type, it is assumed in this simple model that network density does not differ by ability.

The remainder of Section II is organized as follows. Section II.B more formally introduces the key parameters of the model: inbreeding bias by gender, inbreeding bias by ability and network density. Section II.C then describes the equilibrium hiring strategy and Section II.D derives the equilibrium gender wage gap. Finally, Section II.E derives an estimable expression for the gender wage gap.

II.B Inbreeding biases and network densities

Define the conditional probability $P\{(i, j) | (i, j)\}$ as the probability that a potential new hire of ability i and gender j is connected to a given incumbent worker of type (i, j) . Inbreeding bias by gender, γ , is then given by:

$$(1) \quad \frac{1}{2} < \gamma \equiv \frac{P\{(i, j) | (i, j)\} + P\{(\tilde{i}, j) | (i, j)\}}{P\{(i, j) | (i, j)\} + P\{(i, \tilde{j}) | (i, j)\} + P\{(\tilde{i}, j) | (i, j)\} + P\{(\tilde{i}, \tilde{j}) | (i, j)\}} \leq 1.$$

That is, γ is defined as the probability that a connected potential new hire is of the same gender as the incumbent worker, relative to the probability that any given potential new hire is connected to the incumbent worker. We assume that inbreeding bias by gender is independent of ability and that the degree of gender inbreeding is the same for men and women. Also note that inbreeding bias by gender is complete when γ equals 1 and that there is no inbreeding bias by gender if γ would equal 1/2.

Similarly, inbreeding bias by ability, β , can be defined as:

$$(2) \quad \frac{1}{2} < \beta \equiv \frac{P\{(i, j) | (i, j)\} + P\{(i, \tilde{j}) | (i, j)\}}{P\{(i, j) | (i, j)\} + P\{(i, \tilde{j}) | (i, j)\} + P\{(\tilde{i}, j) | (i, j)\} + P\{(\tilde{i}, \tilde{j}) | (i, j)\}} \leq 1.$$

That is, β is defined as the probability that a connected potential new hire is of the same ability-type as the incumbent worker. Again we assume that inbreeding bias by ability is independent of gender and that the degree of ability inbreeding bias is the same for high and low ability workers.

Define the density of a network as:

$$(3) \quad 0 < \alpha_{i,j} \equiv P\{(i, j) | (i, j)\} + P\{(i, \tilde{j}) | (i, j)\} + P\{(\tilde{i}, j) | (i, j)\} + P\{(\tilde{i}, \tilde{j}) | (i, j)\} < 1.$$

If men have larger networks, we must then have that $\alpha_{i,M} > \alpha_{i,F}$.

II.C The model

In attracting new workers, firms can hire either through the network of an incumbent worker (the referral market) or through other means of job search (the outside market). It does

so either by communicating a referral wage, w_j^R , to its incumbent worker who passes it on to her network or by paying an outside market wage, w^O , through an impersonal channel. Each firm can only offer a single referral or outside market wage that does not discriminate between newly hired men and women but different firms with different (i, j) -types of incumbent workers could offer different referral wages. Also assume the outside market wage which each firm takes as given is unique and equal to the expected productivity of all workers not hired through referral.

Proposition 1: Given that it is optimal for an employer to hire through the network of its incumbent worker, the referral wage will be such that $w^O < w_F^R < w_M^R < w_{\max}^R$ with w^O the outside market wage, w_F^R the referral wage offered to the network of an incumbent female worker, w_M^R the referral wage offered to the network of an incumbent male worker, and w_{\max}^R the network's expected productivity.

In order for a firm to attract connected workers through its incumbent worker's network, a wage above the market wage has to be offered. The lowest referral wage that the firm could offer would therefore be w^O , where the firm extracts the entire surplus associated with the existence of networks. The highest referral wage the firm could offer is w_{\max}^R , where the referred workers extract the entire surplus associated with the existence of networks.

To determine the way the surplus generated by the existence of networks is shared among firms and connected workers, and the effect on referral wages, we assume the following. Each individual in a network has to incur a cost for being part of it. This cost is a monotonically increasing function of network density, since in the network each individual has to maintain contact with each other individual. The incumbent worker only agrees to relay a referral wage

offer to her network ties if each of her ties is compensated for their cost of maintaining the network. In order to remain in the network and generate future referral offers for herself through her network ties, the incumbent worker has to relay a referral wage offer to her network that at least compensates them for the cost incurred in maintaining the network. Therefore, male incumbent workers demand a higher referral wage for their network ties than do female incumbent workers because male incumbent workers have a higher network density. As a result, it holds that $w_M^R > w_F^R$.

Proposition 2: It is an equilibrium that all firms employing (H, j) -type incumbent workers offer a referral wage w_j^R for $j = M, F$ and such that $w_M^R > w_F^R$; and all firms employing (L, j) -type incumbent workers for $j = M, F$ hire workers on the outside market at the outside market wage w^O . (Proof: see Appendix A)

To see that each firm employing an H -type incumbent worker has no incentive to deviate from its equilibrium strategy, consider the following. Given that $w_j^R < w_{\max}^R$ and w_{\max}^R equals the average productivity of an H -type network, firms employing an H -type incumbent worker make a profit by hiring through referral.⁵ In the outside market, on the other hand, the wage equals the average outside market productivity and therefore profits are zero. This is why no single firm employing an H -type incumbent worker has an incentive to deviate from the strategy of only hiring through referral.

To see that each single firm employing an L -type incumbent worker has no incentive to deviate from its equilibrium strategy, consider the following. Firms employing an L -type

⁵ Note that profit per worker is lower for firms employing a male high-ability incumbent worker than for firms employing a female high-ability incumbent worker. On the other hand, the difference in total profit is not determined a priori.

incumbent worker have to offer $w_j^R > w^O$ in order to hire through referral. Therefore, for these firms to break even or make a profit, the average productivity of the L -type network has to be higher than the average productivity in the outside market. However, in Appendix A it is proven that in the assumed separating equilibrium, the average productivity in the outside market exceeds the average productivity in L -type networks.

That is, in this separating equilibrium the expected productivity from an H -type network is higher and the expected productivity from an L -type network is lower compared to the outside market which is what makes this equilibrium stable.

Proposition 3: The equilibrium described in Proposition 2 is unique. (Proof: see Appendix B)

Given the assumptions made, three other scenarios are possible, none of which can be an equilibrium:

1. *No networks are used.* In this case each firm employing an H -type incumbent worker has an incentive to deviate since this will increase profits given Proposition 1.
2. *All networks are used.* In this case each firm employing an L -type incumbent worker has an incentive to deviate since the average ability in the market equals the population wide average, whereas L -type networks exhibit inbreeding bias by ability. Given Proposition 1, a firm employing an L -type incumbent worker makes losses by not deviating: hiring through the market instead of through referral raises profits to zero.
3. *Only L -type networks are used.* In this case each firm has an incentive to deviate. Each firm employing an H -type incumbent worker has an incentive to deviate since this will increase profits given Proposition 1. Also, each firm employing an L -type incumbent worker makes losses by not deviating: hiring through the market instead of through referral raises profits to zero.

II.D Equilibrium gender wage gap for new hires

Proposition 4: In the unique equilibrium, the mean wage of male hires exceeds the mean wage of female hires.

Proof:

The mean male wage for new hires, \bar{w}_M , can be written as:

$$(4) \quad \bar{w}_M = \frac{1}{2} \left[\gamma \alpha_{H,M} w_M^R + (1-\gamma) \alpha_{H,F} w_F^R + (2 - \gamma \alpha_{H,M} - (1-\gamma) \alpha_{H,F}) w^O \right]$$

Note that the number of male workers hired through referral is given by $\gamma \alpha_{H,M} + (1-\gamma) \alpha_{H,F}$, where the first term is male workers referred by a male incumbent worker (receiving w_M^R), and the second term those referred by a female incumbent worker (receiving w_F^R). Also, since the male population of new hires has been normalized to 2, the term $2 - \gamma \alpha_{H,M} - (1-\gamma) \alpha_{H,F}$ gives the number of male workers not hired through referral (receiving w^O). Equation (4) therefore shows that the mean male wage is given by the weighted average of the two referral wages and the market wage, where the weights are the proportion of the male population that receives each of the three wages earned in the economy.

The mean female wage can be derived analogously

$$(5) \quad \bar{w}_F = \frac{1}{2} \left[(1-\gamma) \alpha_{H,M} w_M^R + \gamma \alpha_{H,F} w_F^R + (2 - (1-\gamma) \alpha_{H,M} - \gamma \alpha_{H,F}) w^O \right]$$

Taking the difference between (5) and (4) gives the expression for the gender wage gap:

$$(6) \quad \bar{w}_F - \bar{w}_M = \frac{1}{2} \left\{ (1-2\gamma) (\alpha_{H,M} w_M^R - \alpha_{H,F} w_F^R) + (2\gamma-1) (\alpha_{H,M} - \alpha_{H,F}) w^O \right\}$$

Denoting $w_F^R = w_M^R - \varphi$, where φ captures the gender difference in referral wages offered through male and female incumbent workers, equation (6) can be rewritten as

$$\begin{aligned}
(7) \quad \bar{w}_F - \bar{w}_M &= \left\{ \left[\frac{1}{2}(1-2\gamma)(\alpha_{H,M} - \alpha_{H,F}) \right] [w_M^R - w^O] \right\} + \left\{ \varphi \frac{1}{2} \alpha_{H,F} (1-2\gamma) \right\} \\
&= \left\{ \frac{1}{2} [\gamma\alpha_{H,F} + (1-\gamma)\alpha_{H,F} - \gamma\alpha_{H,M} - (1-\gamma)\alpha_{H,F}] [w_M^R - w^O] \right\} - \left\{ \varphi \frac{1}{2} [\gamma\alpha_{H,F} - (1-\gamma)\alpha_{H,F}] \right\} < 0
\end{aligned}$$

It follows from (7) that there is a gender wage gap for new hires in equilibrium, since $1/2 < \gamma < 1$, $\alpha_{H,M} > \alpha_{H,F}$ and $w_M^R > w_F^R > w^O$. The first expression in square brackets multiplied by $1/2$ is the difference between the fraction of female hired through referral $1/2[\gamma\alpha_{H,F} + (1-\gamma)\alpha_{H,F}]$ and male workers hired through referral $1/2[\gamma\alpha_{H,M} + (1-\gamma)\alpha_{H,F}]$. The second expression in square brackets is the referral wage premium earned by the workers in the network of an incumbent (H, M) -type worker. Finally, the last expression in curly brackets is the fraction of female workers hired through referral by an incumbent (H, F) -type worker, $1/2\gamma\alpha_{H,F}$, minus the fraction of male workers hired through referral by an incumbent (H, F) -type worker, $1/2(1-\gamma)\alpha_{H,F}$, pre-multiplied by φ .

Note that the equilibrium gender wage gap is driven by the two terms in curly brackets. Firstly, a smaller fraction of female than of male hires receives a referral wage offer, despite there being no gender differences in the productivity distribution. In other words, women are underrepresented in the referral market, where wages are higher; and overrepresented in the outside market, where wages are lower. Secondly, a larger fraction of the women that *are* hired through referral receives the lower referral wage w_F^R , in comparison to men hired through referral. The lower referral wage for workers in the network of an incumbent (H, F) -type worker is caused by incumbent women's lower network density. More female than male new hires receive this lower referral wage, due to inbreeding bias by gender. This implies that the second term increases the absolute value of the gender wage gap.

II.E Empirical implications of the model

Consider a sample of newly hired individuals such that:

$$(8) \quad w = \beta_0 + \beta_1 sex + \beta_2 referral + \beta_3 (sex * referral) + \beta_4' X + \varepsilon$$

where w reflects log hourly wages, sex is a gender dummy equal to 1 if a person is female, $referral$ is a dummy equal to 1 if a person has been hired through referral, and X is a vector of person-specific and job related controls. The final term reflects sampling error assumed to be independently and identically distributed with mean zero.

The overall mean male and female wages of newly hired individuals are then given by:

$$(9) \quad E[w|sex=1] = \beta_0 + \beta_1 + (\beta_2 + \beta_3)E[referral|sex=1] + \beta_4' E[X|sex=1]$$

$$(10) \quad E[w|sex=0] = \beta_0 + \beta_2 E[referral|sex=0] + \beta_4' E[X|sex=0]$$

such that the overall gender wage gap for new hires can be written as:

$$(11) \quad E[w|sex=1] - E[w|sex=0] = \beta_1 + \beta_2 (\overline{ref}_F - \overline{ref}_M) + \beta_3 \overline{ref}_F + \beta_4' (\overline{X}_F - \overline{X}_M)$$

In equation (11), \overline{ref}_F is defined as the fraction of all newly hired women that are hired through referral and \overline{ref}_M is the fraction of all newly hired men that are hired through referral.

Note that equation (7) showed that the gender wage gap among new hires with identical person-specific and job related characteristics was defined as:

$$(12) \quad \begin{aligned} \bar{w}_F - \bar{w}_M &= (w_M^R - w^O) (\overline{ref}_F - \overline{ref}_M) - \varphi (\overline{ref}_F^{HF} - \overline{ref}_M^{HF}) \\ &= (w_M^R - w^O) (\overline{ref}_F - \overline{ref}_M) - \varphi \overline{ref}_F + \varphi (\overline{ref}_F^{HM} + \overline{ref}_M^{HF}) \end{aligned}$$

where the last equation can be deduced using that $\overline{ref}_F^{HF} = \overline{ref}_F - \overline{ref}_M^{HF}$, with \overline{ref}_F^{HM} the fraction of female workers hired through an (H, M) -type incumbent worker, and \overline{ref}_M^{HF} the fraction of male workers hired through an (H, F) -type incumbent worker.

If there is *complete* inbreeding bias by gender, \overline{ref}_F^{HM} and \overline{ref}_M^{HF} are equal to zero, since there would be no women (men) in the network of an (H, M) -type ((H, F) -type) incumbent worker. In that case, β_2 and β_3 from equation (8) are equal to $(w_M^R - w^O)$ and $-\varphi$, respectively. However, if there is *incomplete* inbreeding bias by gender, there is no longer a one-to-one correspondence between β_2 and β_3 and the parameters of equation (12). In this case, β_2 is interpreted as the wage premium for the average referred male hire, and $\beta_2 + \beta_3$ as the wage premium for the average referred female hire.

In our model, male workers hired through referral earn a premium, which implies β_2 has a positive sign. In addition, β_3 has a negative sign, but such that $\beta_2 + \beta_3 > 0$ since the average female worker hired through referral still earns a premium, albeit lower than the average male worker. This lower premium is due to women being overrepresented in (H, F) -type incumbent workers' networks, where the referral wage is lower. Equation (11) furthermore shows that the overall gender wage gap can be decomposed into an unexplained part β_1 ; the importance of networks $\beta_2(\overline{ref}_F - \overline{ref}_M) + \beta_3\overline{ref}_F$; and differences in person-specific and job related characteristics, $\beta_4(\overline{X}_F - \overline{X}_M)$.

III. Data

We use quarterly UK Labour Force Survey (LFS) data from 2001 to 2006. Our data set contains newly hired individuals, defined as those workers (excluding the self-employed) who have been employed with their current employer for three months or less. The LFS has a question called *Howget*, which asks respondents how they obtained their current job, conditional on them having found a new job in the past 3 months. Respondents can select one of the

following eight channels: reply to a job advertisement; job centre, jobmarket or training and employment agency office; careers office; jobclub; private employment agency or business; hearing from someone who worked there; direct application; or some other way. Of these channels, “hearing from someone who worked there” is exactly the referral mechanism that we analyze in our model. On the other hand, “reply to a job advertisement” is most similar to firms hiring on an impersonal outside market. Table 1A displays the percentages of the use of these various channels for newly hired men and women between 2001 and 2006. Referral and advertisement are the two most important hiring channels, both for men and women. We only retain these two channels because they provide the most direct test of our model.⁶ Restricting our attention to these two channels leaves 10,174 observations. Table 1B shows that 40.9 percent of the women in our sample found their current job through a referral, against 51.1 percent of men.

Our dependent variable is the log hourly wage, calculated as the log of the gross weekly salary over total usual weekly hours. We also use a number of person-specific and job related variables available in the LFS. Firstly, we generate a scale for individuals’ education by assigning the LFS educational qualifications into three categories: below A-level qualifications; above A-level, but below college degree qualifications; and college degree or higher qualifications.⁷ Establishment size is coded from 1 (establishments under 25 workers) to 3 (establishments over 500 workers). The dummy for part-time work is equal to one when the respondent reports working part-time.⁸ The occupational classification used is the 2000 Standard Occupational Classification; the industry classification is the 1992 Standard Industry Classification.

Table 2 presents the mean values of the person-specific and job related characteristics by gender. It can be seen that the female new hires in our sample are on average slightly younger,

⁶ Including the other channels through which jobs are found into the analysis does not qualitatively change results.

⁷ We have also calculated years of education using age and the year at which continuous full-time education was completed. Substituting years of education for the three-category educational variable in the regressions does not qualitatively change our results.

⁸ In our sample, the average usual weekly hours worked by individuals reporting to work part-time is 16.9 hours; for individuals reporting to work full-time, it is 41.3 hours.

less educated, more likely to work part-time, and more likely to work in a smaller establishment than the male new hires.

IV. Empirical analysis

Table 3 presents regression results of equation (8). The first column gives the raw gender wage gap for newly hired workers, which is 11.7 percent.⁹ The second column controls for a number of person-specific and job related characteristics: education, age, age squared, establishment size, a dummy for part-time work, and one-digit occupation and industry codes. These controls reduce the gender wage gap to 7.6 percent. Column 3 includes the referral dummy, and the referral dummy interacted with sex. It can be seen that both have the expected sign, such that a male worker hired through referral on average earns 5.3 percent more than a worker hired through an ad, and a female worker hired through referral on average earns 1.5 (=5.3-3.8) percent more than a worker hired through an ad. More importantly, column 3 shows that the inclusion of the referral terms reduces the unexplained gender wage gap by 1.9 percentage points, or 25 percent ($= [0.076 - 0.057] / 0.076 * 100$) of its total size.

Columns 4 and 5 of Table 3 repeat the procedure of the previous two columns, but looking at the unexplained gender wage gap within the most disaggregated occupation and industry categories that are available in the LFS. These regression results show that the signs on referral and referral interacted with sex do not change, and neither does the effect on the unexplained gender wage gap. A male worker hired through referral on average earns 3.6 percent more than a worker hired through an ad, and a female worker hired through referral on average earns 1.9 percent more than a worker hired through an ad. The referral terms reduce the

⁹ For the entire sample of workers in the LFS between 2001 and 2006, the raw gender wage gap is 23.0 percent. After controlling for person-specific and job related characteristics, the remaining gender wage equals 12.4 percent.

unexplained gender wage gap by 14 percent ($= [0.063 - 0.054] / 0.063 * 100$). In sum, Table 3 shows that networks do indeed explain a significant portion of the unexplained gender wage gap.

Table 4 further investigates the explanatory power of the referral terms by showing the results of an Oaxaca decomposition. Column 1 decomposes the gender wage gap into a part attributable to gender differences in person-specific and job related characteristics and a part attributable to differences in returns to those characteristics. In column 2, the referral terms, differences in referral opportunity and differences in returns to referral, are included in the decomposition. Column 2 shows that women's lower referral opportunity contributes 0.6 percentage points to the gender wage gap, whereas women's lower referral wage premium contributes 2.9 percentage points to the gender wage gap. Also, it is clear that referral explains part of the gender difference in returns to person-specific and job related characteristics. In total, the referral terms constitute 24 percent ($= 0.0296 / 0.123 * 100$) of the predicted gender wage gap.

In Table 5, we provide information on another implication of our network model, namely that the effect of referral on wages depends on the importance of unobserved ability. After all, networks are the channel through which employers can more accurately estimate worker productivity on the job. For some jobs, the ability of workers required to perform the job is more difficult to observe at the time of hiring than for other jobs. This implies that the referral wage premium should be larger in those jobs where output is more dependent on the ability to perform the job.¹⁰ We expect that to be the case for jobs that have high education requirements: if ability, observed and unobserved, is important for worker productivity, the firm will employ more highly educated workers and will be more willing to pay for hiring through networks.

¹⁰ In our model, we have assumed high-ability and low-ability workers to have productivities of 1 and 0, respectively. Making these values more similar makes output less ability-dependent, thereby decreasing the value of the information transmitted by referral and thus the referral wage premium. Since the referral wage must lie somewhere in between the cost of maintaining the network to the worker and the expected productivity of the network to the employer, a higher expected network productivity (as is the case in ability-sensitive jobs) leads to a higher referral wage.

Therefore, from our model we would expect the referral wage premium to increase with education.

Table 5 therefore repeats the analyses of Table 3 but includes the interaction of referral with years of education. It can be deduced from column 3 that there is a positive average referral premium for men and for women. Since the average number of years of education is around 12 for both men and women, the average male hired through referral receives a wage premium of 4.8 percent ($[0.014*12]-0.12$), and the average female one of 1.6 percent ($[0.014*12]-0.12-0.032$). Moreover, the referral premium for both men and women increases with 1.4 percent for each additional year of education. Therefore, in line with the predictions of our model, the referral premium for both men and women increases with education.

V. Conclusions

In this paper, we have drawn from the emerging social network literature to account for the part of the gender wage gap that remains unexplained after controlling for person-specific and job related characteristics.

We have presented a simple network model for the gender wage gap of newly hired workers where inbreeding biases and women's smaller network density combine to an equilibrium gender wage gap. In specific, two factors cause the gender wage gap: women have fewer opportunities to be hired through referral and women receive a lower referral wage premium than men on average.

We test our theoretical model using 2001-2006 UK Labour Force Survey data and find that networks contribute between 14 to 25 percent to the unexplained gender wage gap. Of the two contributing factors, men receiving a higher average referral wage premium is more important than men being hired more often through referral. In line with predictions from our

model, we also find that the referral wage premium for both men and women increases with years of education.

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Figure 1: The Assumed Network Structure

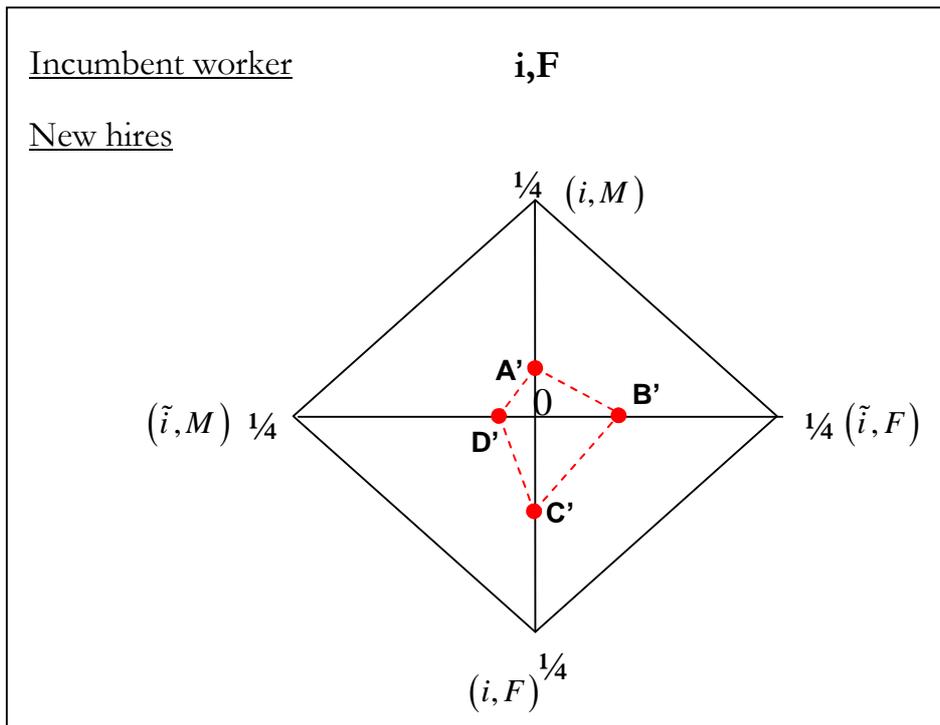
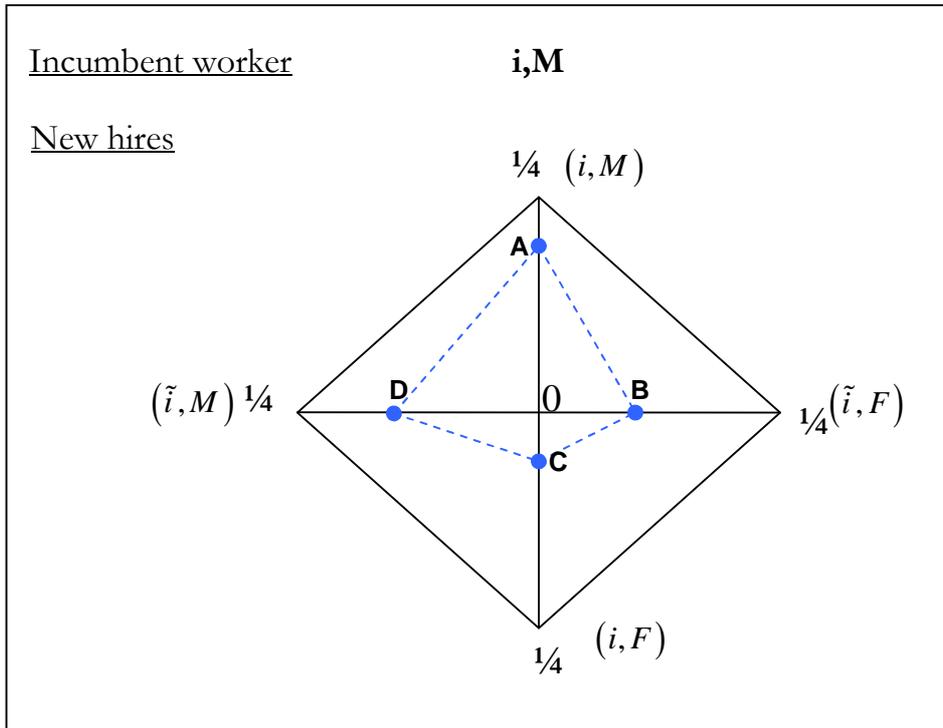


Table 1A: Summary Statistics - Hiring Channels for Men and Women, %

	Male	Female
Reply to advertisement	25.0	33.7
Job centre	8.16	6.90
Careers office	0.68	0.45
Jobclub	0.07	0.11
Private employment agency	11.46	8.70
Hearing from someone who worked there	26.2	23.3
Direct application	16.2	16.9
Some other way	12.1	9.88
Observations	8787	9941

UK Labour Force Survey 2001-2006. Newly hired workers with tenure of 3 months or less. Total percentages may not add to 100 because of rounding errors.

Table 1B: Summary Statistics - *Howget* for Men and Women, %

	Male	Female
Reply to advertisement	48.9	59.1
Hearing from someone who worked there	51.1	40.9
Observations	4502	5672

UK Labour Force Survey 2001-2006. Newly hired workers with tenure of 3 months or less.

Table 2: Summary Statistics - Mean Person Specific and Job Related Characteristics by Gender

	Male	Female
Mean age	31.7	31.4
Mean education	2.91	2.84
Mean value of <i>ftpt</i> dummy	1.22	1.51
Mean establishment size	1.71	1.66
Observations	4502	5672

UK Labour Force Survey 2001-2006. Newly hired workers with tenure of 3 months or less.

Table 3: Networks and the Gender Wage Gap
Dependent Variable: ln(hourly wage)

	Raw Gender Wage Gap	1-digit Occupation and Industry Codes	4-digit Occupation and 3-digit Industry Codes		
	(1)	(2)	(3)	(4)	(5)
Female	-0.117 (0.010)	-0.076 (0.008)	-0.057 (0.011)	-0.063 (0.009)	-0.054 (0.011)
Referral	-	-	0.053 (0.011)	-	0.036 (0.011)
Female x referral	-	-	-0.038 (0.015)	-	-0.017 (0.015)
Education	-	0.089 (0.005)	0.091 (0.005)	0.071 (0.006)	0.072 (0.006)
Age	-	0.041 (0.000)	0.042 (0.001)	0.040 (0.001)	0.040 (0.001)
Age2	-	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
Adjusted R ²	0.012	0.437	0.438	0.496	0.497

UK Labour Force Survey 2001-2006. Newly hired workers with tenure of 3 months or less. The number of observations for each column is 10174. Columns (2) to (5) also control for establishment size and a dummy for part-time work.

Table 4: Oaxaca Decompositions of the Gender Wage Gap

	no referral	referral
	(1)	(2)
Raw gender wage gap	0,127	0,127
Predicted gender wage gap	0,122	0,123
Predicted difference due to differences in :		
Characteristics	0,034	0,035
Fraction referred	-	0,006
Returns to characteristics	0,087	0,052
Difference in referral premium	-	0,029

UK Labour Force Survey 2001-2006. Newly hired workers with tenure of 3 months or less. The decompositions use male returns to premultiply gender differences in person-specific and job related characteristics. Using female returns does not change results. The decomposition of predicted differences may not exactly sum up to the total predicted gender wage gap due to rounding errors.

Table 5: Networks and the Gender Wage Gap by Years of Education
Dependent Variable: ln(hourly wage)

	Raw	Controls	Controls + Referral
	(1)	(2)	(3)
Female	-0.132 (0.009)	-0.086 (0.008)	-0.071 (0.010)
Referral	-	-	-0.120 (0.035)
Female x referral	-	-	-0.032 (0.014)
Yrs educ x referral	-	-	0.014 (0.002)
Adjusted R ²	0.017	0.430	0.432
Observations		10833	

UK Labour Force Survey 2001-2006. Newly hired workers with tenure of 3 months or less. The controls in columns (2) and (3) are 1-digit occupation and industry codes, establishment size and a dummy for part-time work.

Appendix A

Proposition 2: It is an equilibrium that all firms employing (H, j) -type incumbent workers offer a referral wage w_j^R for $j = M, F$ and such that $w_M^R > w_F^R$; and all firms employing (L, j) -type incumbent workers for $j = M, F$ hire workers on the outside market at the outside market wage w^O . (Proof: see Appendix A)

Proof:

No single firm has an incentive to deviate from its hiring strategy: we consider firms by incumbent worker ability-type.

No single firm employing an (H, j) -type worker has an incentive to deviate by hiring through the market. For a firm employing an (H, j) -type worker, profits in the equilibrium are positive (see Proposition 1) and when deviating by hiring through the market profits are lowered to zero since average labor market productivity in the outside market equals the market wage.

No single firm employing an (L, j) -type worker has an incentive to deviate. For a firm employing an (L, j) -type worker, profits in the equilibrium are zero, but will be negative when deviating by hiring through referral. In order to prove that profits of hiring through referral are negative, we need to show that the average productivity in the (L, j) -type networks is lower than the average productivity in the market.

To show this we use that the average productivity in the outside market is a monotonically increasing function of the fraction of H -type workers in the outside market. The number of H -type workers in the outside market (H^O) is:

$$H^o = 2 - \beta(\alpha_{H,M} + \alpha_{H,F})$$

In the equilibrium, the number of L -type workers in the outside market (L^o) equals:

$$L^o = 2 - (1 - \beta)(\alpha_{H,M} + \alpha_{H,F})$$

such that the fraction of H -type workers in the outside market is given by

$$\frac{H^o}{L^o + H^o} = \frac{2 - \beta(\alpha_{H,M} + \alpha_{H,F})}{4 - (\alpha_{H,M} + \alpha_{H,F})}$$

The fraction of H -type workers in (L, j) -type networks equals $1 - \beta$.

Since $1/2 < \beta \leq 1$, it holds that

$$\frac{2 - \beta(\alpha_{H,M} + \alpha_{H,F})}{4 - (\alpha_{H,M} + \alpha_{H,F})} > 1 - \beta$$

In sum, the average ability in the outside market is higher than in (L, j) -networks, and no single firm employing an (L, j) -type worker will want to deviate by hiring through referral, given Proposition 1.

Appendix B

Proposition 3: The equilibrium described in Proposition 2 is unique.

Proof:

In order to prove Proposition 3, we need to examine the other possible equilibria and show that firms have incentives to deviate. We discuss each of the three alternative equilibrium scenarios in turn.

1. No networks are used.

All workers offer their labor in the outside market. As a result, the mean ability in the market equals the population-wide mean ability. In this case each firm employing an (H, j) -type worker has an incentive to deviate since this will increase profits given Proposition 1.

2. All networks are used.

For a firm employing an (L, j) -type worker, profits are negative, but will be zero when deviating by hiring through the outside market. In order to prove that profits of hiring through referral are negative, we need to show that the average productivity in the L -type networks is lower than the average productivity in the market, given Proposition 1.

The average ability in the outside market is a monotonically increasing function of the fraction of H -type workers. The number of H -type workers in the outside market is given by

$$H^o = 2 - \beta(\alpha_{H,M} + \alpha_{H,F}) - (1 - \beta)(\alpha_{L,M} + \alpha_{L,F})$$

The number of L -type workers the outside market is given by

$$L^o = 2 - (1 - \beta)(\alpha_{H,M} + \alpha_{H,F}) - \beta(\alpha_{L,M} + \alpha_{L,F})$$

Thus, the fraction of H -type workers the outside market equals:

$$\frac{H^o}{L^o + H^o} = \frac{2 - (\alpha_{i,M} + \alpha_{i,F})}{4 - 2(\alpha_{i,M} + \alpha_{i,F})} = \frac{1}{2}, \text{ since } \alpha_{H,M} = \alpha_{L,M} \text{ and } \alpha_{H,F} = \alpha_{L,F}$$

Hence, the average ability in the outside market equals the population wide average ability.

The fraction of H-type workers in L -type networks equals $1 - \beta$. Since $1/2 < \beta \leq 1$, the average ability in L -type networks is lower than the average ability in the outside market. Given this, each firm employing an L -type worker has an incentive to deviate.

3. Only L -type networks are used.

In this case each single firm has an incentive to deviate. The average ability in the outside market is a monotonically increasing function of the fraction of H -type workers. The number of H -type workers in the outside market is given by

$$H^o = 2 - (1 - \beta)\alpha_{L,M} - (1 - \beta)\alpha_{L,F}$$

The number of L -type workers in the outside market is given by

$$L^o = 2 - \beta\alpha_{L,M} - \beta\alpha_{L,F}$$

Calculating the fraction:

$$\frac{H^o}{L^o + H^o} = \frac{2 - (1 - \beta)(\alpha_{L,M} + \alpha_{L,F})}{4 - (\alpha_{L,M} + \alpha_{L,F})} > \frac{1}{2} \text{ since } 1/2 < \beta \leq 1 \text{ and } \alpha_{L,j} > 0.$$

Thus it has been shown that the average productivity in the outside market is higher than the population wide productivity.

This gives each single firm employing an H -type worker an incentive to deviate given Proposition 1. They break even in the outside market, whereas they would make a profit by deviating and hiring through referral because the average ability the deviating firm can obtain is higher than the average ability in the outside market. This is true since $1/2 < \beta \leq 1$ such that

$$\frac{2 - (1 - \beta)(\alpha_{L,M} + \alpha_{L,F})}{4 - (\alpha_{L,M} + \alpha_{L,F})} < \beta.$$

Also, any single firm employing an L -type worker has an incentive to deviate, because each firm employing an L -type worker makes a loss, given Proposition 1. The reason for this is that the firms have to offer a referral wage above the market wage, but the fraction of H -type workers is lower in the L -type network than in the outside market. Given that $1/2 < \beta \leq 1$ it holds that

$$\frac{2 - (1 - \beta)(\alpha_{L,M} + \alpha_{L,F})}{4 - (\alpha_{L,M} + \alpha_{L,F})} > 1 - \beta.$$