The Old Boy Network: Gender Differences in the Impact of Social Networks on Remuneration in Top Executive Jobs

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Abstract

Using an original dataset describing the career history of some 16,000 senior executives and members of the non-executive board of US, UK, French and German companies, we investigate gender differences in the use of social networks and their impact on earnings. There is a large gender wage gap: women (who make up 8.8% of our sample) earned average salaries of $168,000 in 2008, only 70% of the average $241,000 earned by men. This is not due to differences in age, experience or education levels. Women are more likely than men to be non-executives, whose salaries are lower; nevertheless, a substantial gender gap still exists among executives. We construct measures of the number of currently influential people each individual has encountered previously in his or her career. We find that executive men's salaries are an increasing function of the number of such individuals they have encountered in the past while women's are not. Controlling for this discrepancy, there is no longer a significant gender gap among executives. These findings are robust to the use of different years, to the use of salaried versus non-salaried remuneration, and to the use of panel estimation to control rigorously for unobserved individual heterogeneity. In contrast to executives, the salaries of non-executive board members do not display a significant gender wage gap, nor any gender difference in the effectiveness with which men and women leverage their links into salaries. This suggests that adoption of gender quotas for board membership, as has been enacted or proposed recently in several European countries, is unlikely to reduce the gender gap in earnings so long as such quotas do not distinguish between executive and non-executive board members.

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1 Introduction

1.1 The puzzle: gender gaps in top executive positions

In spite of several decades of substantial increase in women's participation in the labor force in industrialized countries, the representation of women in senior corporate positions remains extremely marginal, and the phenomenon of the "glass ceiling" continues to puzzle researchers and lay commentators alike. Although women represent 51.4% of what the US Bureau of Labor Statistics calls "Management, professional and related occupations", they make up only 15.7% of board members, and just 3% of chief executive officers, of Fortune 500 companies[1]. Apart from the underrepresentation of women at the very top, empirical studies have also shown that, even for those who reach the top, substantial gender differences in earnings still exist. Among the determinants of the gender gap in earnings in top corporate positions, various authors have proposed a gender difference in seniority and in career interruptions (Bertrand and Hallock, 2001; Noonan et al., 2006; Bertrand et al., 2010), a gender difference in the size of firms and their sector (Bertrand and Hallock, 2001; Skalpe, 2007), the existence of discrimination (Selody, 2010), the fact that women are less likely to hold the very top positions (Bertrand and Hallock, 2001; Elkinawy and Stater, 2011) or a gender difference in the structure of compensation (Albanesi and Olivetti, 2006; Yurtoglu and Zulehner, 2009; Kulich et al., 2009).

1.2 A possible explanation: gender differences in the impact of social networks

Social networks and job-related benefits One aspect that has not been sufficiently studied from the point of view of gender is the role of the elite network structure of the individuals holding top corporate positions. A person who sits on a company board may sit on several other boards and may be an executive in one (or several) of the corresponding firms (or may have been an executive at a previous time). Each such individual typically also has personal connections to board members in other companies. Recruitment to board positions often takes place through an informal process, typically involving the role of both professional headhunters and word of mouth recommendations. The pioneering work of Granovetter (1973) has highlighted the importance of social connections in obtaining both jobs and job-related advantages. Recruitment to board-level positions seems particularly likely to give value to such informal connections. According to Granovetter, the social connections that are the most valuable when looking for a job are not the closest ones but the more distant ones. Strong ties, such as close friends and relatives, are more likely to have similar

[1] See Seabright, 2012, chapter 5. The figure of 51.4% is for 2009, the statistics on Fortune 500 companies are for 2010.

information concerning job opportunities, while weak ties, such as acquaintances and coworkers, are more likely to move in different social circles and to have access to different information about job and other opportunities. It seems likely therefore, that the structure of social networks may affect the extent to which individuals may be able to use their connections for professional benefit. The value of such connections for individuals in top corporate positions has been confirmed empirically by a number of studies (Geletkancycz et al., 2001; Brown et al., 2008; Horton et al., 2009; Hwang and Kim, 2009; Engelberg et al., 2009; Liu, 2010; Renneboog and Zhao, 2011; Berardi and Seabright, 2011), though as far as we are aware ours is the first study to examine the impact of gender. As a result, if men and women differ in terms of the size or the composition of their networks (and particularly in terms of the relative importance of strong and weak ties), or in the way in which they use these networks for professional advancement, it seems plausible that this may have a systematic impact on the gender composition of positions for which such networks important in the recruitment process.

Gender differences in social networks The question whether men and women differ in the structure of their social networks has been investigated in the sociological and psychological literatures (Baumeister and Sommer, 1997; Benenson, 1993; Friebel and Seabright, 2011). However, there is little agreement about the extent of any systematic differences (see Seabright, 2012, chapter 7, for an overview). Scholars have also had difficulty distinguishing between the relative importance of gender differences in preferences, as opposed to difference in opportunities and constraints, for forming and using social connections (Moore, 1990; Fisher and Oliker, 1983). Nevertheless, there is suggestive evidence that women may tend to rely relatively more on small social networks of strong relationships, while men will tend to build larger groups with weaker types of relationship. This is consistent with evidence from primatology and evolutionary psychology, based on the hypothesis that coalitions reflect different reproductive strategies in prehistory (Low, 2000, chapter 11). However, even if the hypothesis that male and female networks differ systematically is empirically confirmed, this is compatible with other, cultural explanations for the origin of the divergence.

Gender differences in social networks within firms The idea that there might be gender differences in social network composition and use has received some support from the managerial literature. In the workplace, women's connections seem to be built in order to respond strategically to the different constraints they face, such as a legitimacy problem (Burt, 1998) or their under-representation in top positions (Ibarra, 1993, 1997). There is also evidence that preferences play a role, such as homophily (a preference for interacting with similar others, such as others of same sex (see McPherson and Smith-Lovin, 2001). It seems likely that homophily will compound the effect of female underrepresentation, leading women's networks to differ from males' ones. However, the crucial question is whether women reap different job-related benefits from their connections, or whether the differences from those of men are of little relevance to their career advancement.

Women's connections at the very top Several studies based on interviews of top corporate individuals reveal that women appear lack the relevant informal connections to access top positions (Linehan and Scullion, 2008; Lyness and Thompson, 2000; Metz and Tharenou, 2001) and reap lower benefits in terms of career outcomes from their social networks (Bu and Roy, 2005; Tattersall and Keogh; Forret and Dougherty, 2004). However, studies in this literature mainly rely on surveys (and are thus inevitably subjective). The surveys are also of relatively few individuals, most of the time from a single organization. Our purpose in this paper is to investigate the influence of social networks for men and women in top corporate jobs from a statistical point of view using a substantially larger sample of individuals than has hitherto been possible.

1.3 Methodology, results and outline of the paper

In order to do so, our work is based on a large data set of more than 90 000 individuals working in high positions in almost 4 000 American and European firms over a 12 year period (from 1997 to 2009). This original data set allowed us to create social networks measures based on university ties, association ties and employment ties, contrary to the majority of studies on social networks which only rely on directorship links (Horton et al., 2009; Renneboog and Zhao, 2011). We want to understand whether individuals' links (the number of other individuals with whom they have previously been in contact) affect their career history.

We construct measures of the number of currently influential people each individual has encountered previously in his or her career, and we find evidence that men and women make different use of links with such people. In particular, executive men leverage these links more effectively on average than women, in the sense that men's salaries are an increasing function of the number of such individuals they have encountered in the past while women's are not. This discrepancy explains the full gender gap among executives, in that when we introduce these social network variables in the analysis, the gender dummy is no longer significant in explaining executives' salaries. These findings are robust to the use of different years, to the use of salaried versus non-salaried remuneration, and to cross-section versus panel estimation. The proportion of other women among all links moderates the networking effect: women do benefit from links with other women. In contrast to executives, the salaries of non-executive board members do not display a significant gender wage gap, nor any gender difference in the relation of wages to links. This suggests that adoption of gender quotas for board membership, as has been enacted or proposed recently in several European countries, is unlikely to reduce the gender gap in earnings so long as such quotas do not distinguish between executive and non-executive board members.

The remainder of this paper is organized as follows. Section 2 provides information on the data set and the methodology used. Section 3 presents results. Robustness checks are conveyed in Section 4. A dynamic panel analysis is investigated in Section 5. Finally, Section 6 concludes.

2 Data and Methodology

2.1 Data Description

The analysis is based on an original dataset describing the career history of more than 90 000 executives and members of the non-executive board of US, UK, French and German companies between 1997 and 2009. The dataset was provided to us by BoardEx Ltd, a UK supplier of data to headhunting companies. BoardEx's own proprietary database (which we refer to hereafter as the "main" database) consists of information about some 380,000 individuals who are current or past board members or senior executives of European and US companies. The database provided to us, however, consists of the subset of their main database for which salary data are available at least for some years between 1997 and 2009. For firms to be included in the BoardEx main database, they require a market capitalization above 1 million USD . There are 4940 firms in our dataset, and for each firm we have information about all board members; for firms with fewer than five board members we have information on the five most highly salaried executives where salary information exists. The dataset contains information about individuals' demographic characteristics such as age, nationality and gender, about individuals' employment history such as earnings and position, about individuals' education characteristics such as degree obtained, field and university, and about firms' characteristics such as market capitalization, sector or number of employees.

The main originality of this data set is that we also have information relevant to individuals' social networks. However, it's important to clarify the characteristics of this information since they affect the inferences that can be drawn from our results. Ideally, in order to study the impact of top business people's social networks on their career, in terms of remuneration or promotion, we would like to have information on their active social contacts. Unfortunately, this kind of information is extremely difficult to obtain for significant numbers of individuals. Most studies of social networks in a business context (see Linehan and Scullion, 2008; Metz and Tharenou, 2001; Tattersall and Keogh, 2006; Forret and Dougherty, 2004) have conducted interviews and collected detailed information about a relatively small number of individuals and their active networks of contacts; these subjects are often employees of the same firm or users of the same professional network (which raises questions about selection). We do not have such data. Instead we have information, based on matching individuals' résumés, about which other members of the BoardEx main database a given individual has overlapped with in the course of his or her career. This is effectively a list of "influential people" with whom any given individual has had an opportunity to interact; whether that interaction has been actively pursued is evidently not something we are in a position to observe. We can observe three categories of overlap: whether two individuals were at university at the same time, whether they worked for the same firm at the same time, and whether they have been involved in not-for-profit organizations at the same time. Definitions of our variables are given in Table 1 and summary statistics in Table 2 for the year 2008. In what follows we use the variable name "Links" to refer to the number of members of the BoardEx main database with whom an individual in our dataset has worked in the same firm at the same time. The main explanatory variable we shall use in the analysis that follows will be called "Weighted links" since we shall weight each link by the reciprocal of one plus the number of years since the two individuals worked together; when we do not use this weighting procedure we shall call our explanatory variable "Unweighted links". Notice that the links are not necessarily to other individuals in our dataset, which would arbitrarily restrict our measure of the size of individuals' networks by whether or not we have salary information about the members of that network.

Data on both salaries and links are frequently missing in our dataset. In particular, educational links and not-for-profit links are more often missing than employment links, so the regression results we report use only employment links. In addition we often find zero reported salaries for some years, and have difficulty knowing whether this means that the data are not available or that the individual concerned literally drew no salary in the year in question. Our main analysis is conducted on a subset of 16204 individuals for whom all salary and employment network data are available in 2004 and 2008 and all salaries are strictly positive in 2008. For our panel estimation we have to restrict attention for reasons of data availability to a subset of 4251 individuals. Table 2 illustrates summary statistics for our sample of 16204 compared to all individuals for whom we have observations for the variable in question. Our sample has slightly higher mean number of links and salary than the rest of the dataset, and a substantially lower proportion of women (8.8% as opposed to 12.4% in the whole dataset). While there is evidently a possibility of selection bias, including survivorship bias, we have no idea of its direction, and no reason to expect the bias to be different for men and women.

For our econometric estimations we use as explanatory variables measures of the overall numbers of links, our principal measure being a weighted sum of links in which each link is weighted by the inverse of the number of years since the individuals last overlapped plus one (other measures of the importance of links could also be envisaged, and will be explored in future work). However, a more complete understanding of the role of social networks on individuals' career, would involve computing more precise network measures such as degree (extent of interaction with other members of the whole network), betweenness (extent to which the individual is a key intermediary) and closeness (extend to which the individual is free from dependence on other members of the network), especially in terms of employment contacts. Studies that have used such measures include those reported in Geletkancycz et al. (2001), Liu (2010) and Renneboog and Zhao (2011).

2.2 Independent and Control Variables

Our measures of individuals' career outcomes for the purposes of this paper are various indicators of remuneration. Individuals' earnings are represented by three components: salary (base annual pay in thousands of USD), liquid wealth (sum of the value of shares held and the intrinsic value of exercisable options in thousands of USD) and total wealth (sum of equity held, estimated value of options held and long term incentive programs held in thousands of USD). For our main outcome regressions we focus on salary. More precisely, because individuals may have several jobs each year, we compute a variable "total salary", corresponding to the sum of salaries of all the jobs for each year for each individual. Total salary is the independent variable in the analysis, mainly because there are fewer ambiguities about its measurement. Nevertheless, we are also interested to know whether our findings are robust to the inclusion of non-salary measures of compensation. As we shall see, there are important differences between men and women in terms of the proportion of total remuneration provided via salary and other mechanisms, a finding that matches what has been reported previously in the literature (Albanesi and Olivetti, 2006; Yurtoglu and Zulehner, 2009; Kulich et al., 2009). As will be seen below, our conclusions are strengthened when the analysis is conducted on non-salary compensation measures.

As control variables, we use demographic variables (gender, age and age squared) and education variables (highest degree obtained and field of study). We describe below our estimation methods that attempt to control for unobserved heterogeneity among individuals.

3 Results

3.1 Descriptive Statistics

We report summary statistics and econometric results principally for the year 2008, the most recent year for which we have relatively complete data (but we also verify robustness of the results using the year 2007). The idea is to understand to what extent differences in individuals' links can explain differences in their salaries, controlling for other explanatory variables. To avoid problems of endogeneity, the links are measured in the year 2004, and we restrict our analysis to the 16,204 individuals for whom we have complete salary and network data in 2004 and strictly positive salary in 2008. 8.8 % of these individuals are women. 47% are executives and 78% held a directorship in 2008 (individuals may be executive board members, non-executive board members or executives who are not board members).

On average, women in our dataset are younger than men (56 years old against 58 years old in 2008). They have a slightly more advanced educational background: 24% of women have a Bachelors degree, 39% have a Masters degree and 28% have a PhD; while the percentages for men are respectively 26%, 37% and 24%. The higher the degree, the higher the percentage of women who hold the degree compared to men. Roughly 68% of men and 78% of women hold at least two degrees. The distribution of men's and women's degrees between business and science subjects are similar, but almost twice as many men as women hold a degree in finance. Overall, the broad human capital of men and women do not seem very different among the individuals in our dataset. A slight educational difference in favor of women is offset by a difference in favor of men in terms of work experience: men have spent an average of just over 11.8 years in the organization as compared to 9.4 years for women. This is not more than would be expected, though, given the average difference in age.

Our measures of links reveal that women in 2008 have somewhat more of these on average than men - 282 links as against 231 for men (the same is true of the lagged values from 2004 we use in the regressions). This may be related to the fact that women tend to work in larger firms than men (a mean of 26,000 employees compared to a mean of 19,000 for men, and with a mean market capitalization around 50% higher than that of the firms in which the men in our sample work)[2]. So women are clearly not at any disadvantage in terms of their overall number of links. See the appendix for more detailed statistics on network measures by gender.

However, there are very striking differences in employment outcomes by gender. In terms of total salary (the sum of salaries from all jobs, where there was more than one), women earned on average $168,000 in 2008, while men earned on average $241,000 (the corresponding median earnings are $89,000 for women and $146,000 for men). Looking at Figure 1 we see that this difference in total salary narrows slightly but remains large over time. These earnings differences are even larger for liquid wealth and total wealth. In common with what has been previously found in the literature, women are less likely to hold executive positions, and very unlikely to hold senior positions such as CEO or Chairman of the Board. 4% of our women board members (already a small minority of the dataset) hold CEO positions as against 15% of the men.

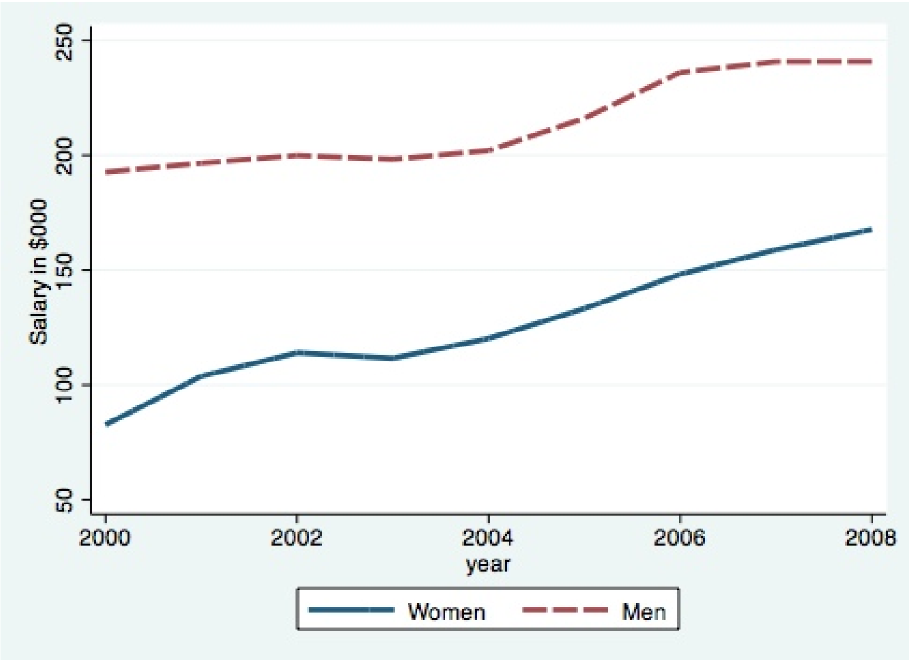

Figure 1: Total salary evolution by gender

[2]The corresponding median figures are 6778 employees for women as against 4000 for men, and $2.2 billion capitalization as against $1.4 billion for men.

3.2 Preliminary Analysis

We want to understand whether social networks have an impact on individuals' career outcomes. We focus on the year 2008 and on the impact of employment links on earnings. There is a risk of simultaneity bias because of reverse causality. For example, while those individuals with more links in 2008 might as a result have higher salaries in 2008, it might also be true that individuals changing employment in pursuit of higher salaries in 2008 acquire a larger network of contacts in 2008. We therefore use lagged explanatory variables, with employment links in 2004 instead of employment links in 2008[3].

Table 3 reports regressions of total salary in 2008 on links in 2004 plus a gender dummy and controls for age, age squared, degree level and degree field (in fact, we use dummy variables for bachelors, masters and PhD degrees and for the fields of business, science, social science and finance). We do not use sectoral controls or controls for firm size or other characteristics since these are likely to be endogenous to individual choices and constitute part of the outcomes that we are seeking to explain (if, for example, women earn lower salaries because they work for firms of a certain kind we would like to know why they work for relatively low-paying firms)[4].

The model specification is then:

$$\begin{aligned} ln(salary_i) &= \beta_1 + \beta_2 ln(lagged\_salary_i) + \beta_3 ln(lagged\_links_i) + \beta_4 female_i \\ &+ \beta_5 female_i * ln(lagged\_links_i) + \beta_6 age_i + \beta_7 age_i^2 + \beta_8 degree_i \\ &+ \beta_9 degree\_field_i + \epsilon_i \end{aligned} \quad (1)$$

The first column shows that links are very significantly correlated with total salary. The elasticity of 8.8% implies that, of two otherwise identical individuals one of whom has 250 links while the other has 350 (an increase of 33 log points, less than half a standard deviation more), the individual with 350 links should have a 3% salary advantage over the individual with 250. This is not a very large effect but as we shall see, this average hides significant variations among sub-groups, for some

[3]We have also undertaken IV regressions with similar results, using employment links in 2004 as an instrument for employment links in 2008.

[4]We did not include country dummies in the regressions as we consider that the market for executives and board members is international. However, including country dummies does not change the overall picture of the results.

of whom the effect may indeed be large.

Although our use of lagged links instead of current links should remove endogeneity problems due to reverse causality, we cannot rule out the possibility that there are unobserved characteristics of individuals that determine both the size of their networks and the size of their salary. Suppose, for instance, that job mobility is related to entrepreneurial dynamism: then individuals who accumulate more links through more frequent changes of job may also independently have the talent to earn higher salaries. There is no perfect way of dealing with this problem, which has not been fully resolved to our knowledge in previous studies of the impact of networks on labor market outcomes[5]. We shall report results from estimation strategies of two main kinds, which yield qualitatively similar results though with some differences as to the magnitude of the respective coefficients. One possibility, explored in the second and third columns of Table 3, is to enter the lagged salary in 2004 as an independent control variable in the regression of salary in 2008, on the theory that the unobserved individual characteristics that affect salaries in 2008 will also have influenced salaries in 2004. There are disadvantages to this, which introduce possible biases. First, salaries in 2004 may already be influenced by individual networks, so using this as a control variable may remove too much of the influence of networks from the estimation, thereby biasing downward the coefficients. Secondly, even if salaries in 2004 are related to unobserved characteristics, they contain substantial measurement error so they will be imperfect proxy variables. Third, there may be separate dynamics of individual salaries over time (they might, for instance, be mean-reverting because of idiosyncratic shocks), so using lagged salary will not be able both to control for these dynamics and control of unobserved individual heterogeneity. We return to this issue below in discussing our second estimation strategy, namely dynamic panel estimation. Nevertheless, we report specifications both with and without controlling for salaries in 2004 in the results that follow.

In order to see whether there are different returns from links for men and women, we introduce the interaction variable female*links. The second column of Table 3 includes only the gender dummy, while the third column also includes the interaction with the links variable. Table 4 reports the same three specifications as Table 3 but using the weighted measure of links, in which links are weighted by the reciprocal of the number of years since the two individuals worked together plus one. This variable is plausibly a more effective measure of the real importance of a person's links

[5] Of the papers that have recognized this difficulty, Hwang and Kim (2009) use past performance as a proxy for ability, which raises similar issues to our own procedure. Engelberg et al. (2009) use school and industry fixed-effects, but these are not equivalent to individual fixed-effects, and in any case would have little relevance to gender differences. Renneboog and Zhao (2011) use random effects estimation, which is unlikely to capture the unobserved talent differences we are concerned with here.

than the unweighted measure. In Tables 3 and 4 we report both measures but in subsequent Tables we report only the results using weighted measures as these appear to be preferable on principle.

The central messages of Tables 3 and 4 are as follows. Using weighted rather than unweighted links increases the measured influence of network opportunities by around 50%. Controlling for lagged salary reduces the coefficient on links by about a third, so that the two adjustments more or less cancel out, leaving the estimated elasticity of salary with respect to links at a little over 8%. However, there is no evidence at all of different impacts of networks for women and men, since the coefficient on the interaction of the gender dummy with links is both statistically insignificant and economically negligible.

It appears, therefore, that the hypothesis that men and women leverage their links very differently is not supported by the data *at this level of aggregation.* On the contrary, the negative coefficient on the female dummy, which lies between 33 and 45 log points according to the particular specification, seems to indicate the presence of a major salary disadvantage for women, controlling for their other characteristics as far as we are able. However, the aggregation masks some important differences between groups in the dataset, differences we shall now explore in more detail.

3.3 The Importance of Executive Status

Executives and non-executive directors are two very different populations among the senior employees of a company; they have very different roles within the company and also very different salaries. Non-executives typically work part-time and may often hold several directorships simultaneously. Although non-executive directors of one firm may hold executive positions in another, there is a substantial population (making up over 50% of our dataset in fact) of individuals who hold only non-executive positions. They have much lower salaries on average than executives (see Figure 2 for year 2008 and Figure 3 for evolution over time). And many more of them are women (see Figure 4 and Figure 5). When comparing the salaries of men and women in our sample, it is essential to take into account the fact that part of the gender gap is a composition effect: women are more likely to be non-executives, who are in a lower-paid category. We cannot, of course, determine using these data *why* women are more likely to be non-executives. It is possible that different preferences are involved, since non-executive positions typically involve much more flexible working conditions. It is also possible that discrimination is more significant in respect of executive positions, since it is here that real power is exercised in the firm.

As Table 5 reveals, only 32% of women in our dataset in 2008 are executives while 49% of men are executives. Since non-executives earn only 28% as much on average as executives, this indicates that it is important to examine gender differences separately within categories. Indeed, female executives earn on average 17% less than their male counterparts, while the difference is only 2% when we consider female non executives (see Figure 3 for a graphical representation); the initial gender difference for non-executives clearly disappears over the period of the sample[6].

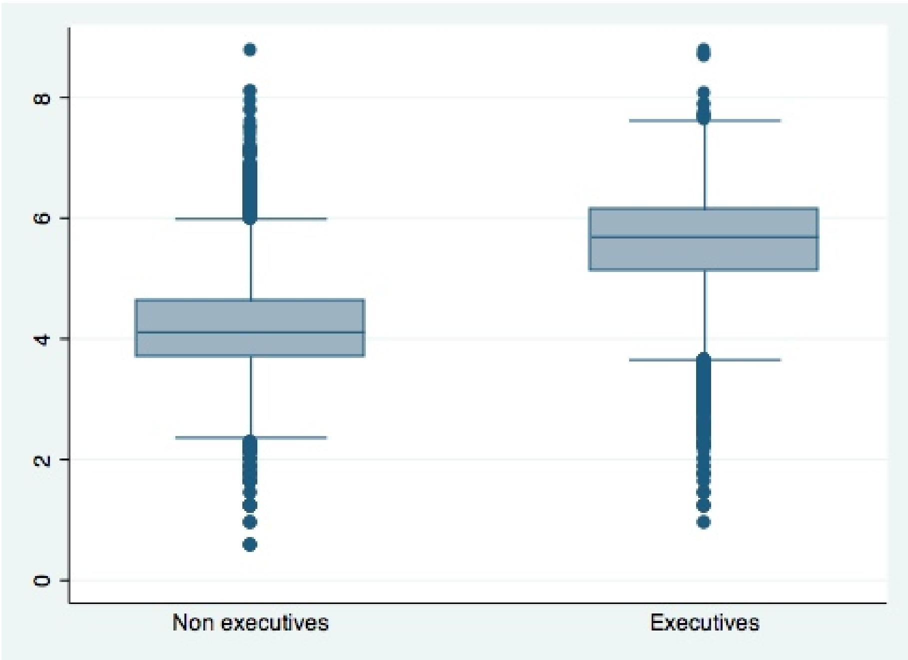

Figure 2: Logarithm of total salary in 2008 by executive status

[6]It appears in Figure 3 as though the gender gap in earnings is declining over time for both executives and non-executives. Unfortunately it is difficult to test this rigorously since there are different numbers of individuals in different years due to missing observations. It is hard to know whether the apparent decline is a real effect or an artefact of sample composition (for instance because in later years firms are included that may have smaller gender gaps). We have tried plotting gender gaps for those individuals who are observed for all years over a given period, and it appears overall that there is a real decline in the gap for non-executives and no decline for executives. However, this is at the cost of substantially restricting the numbers of individuals, so we hesitate to generalize from these tentative findings.

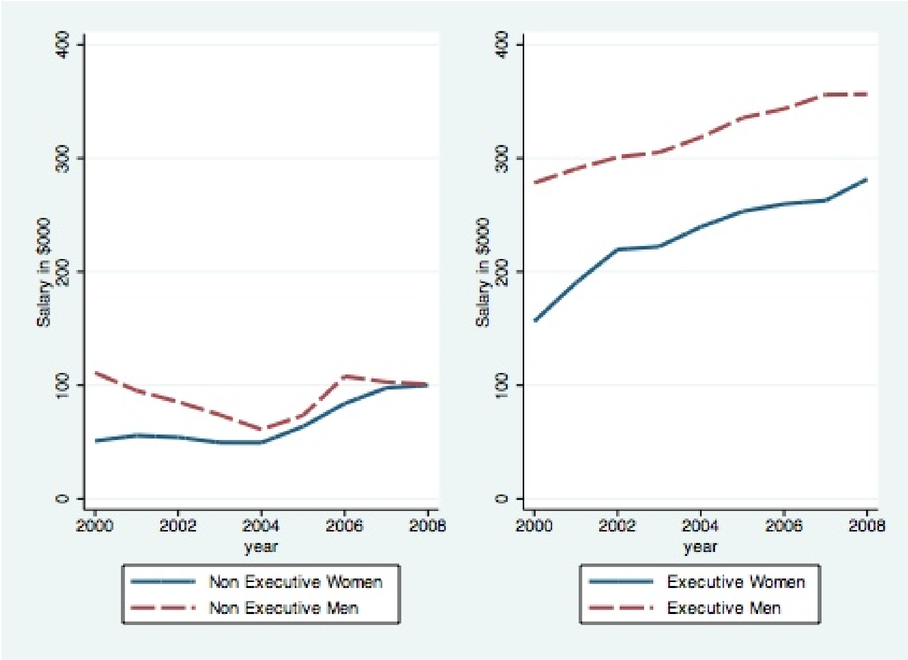

Figure 3: Total salary evolution by executive status

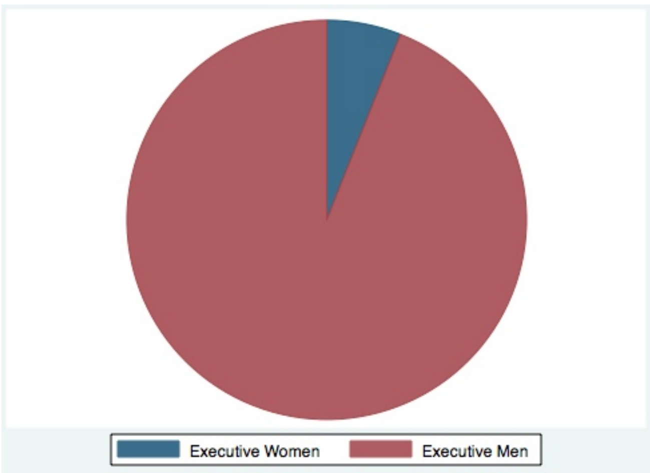

Figure 4: Executive men and women in 2004

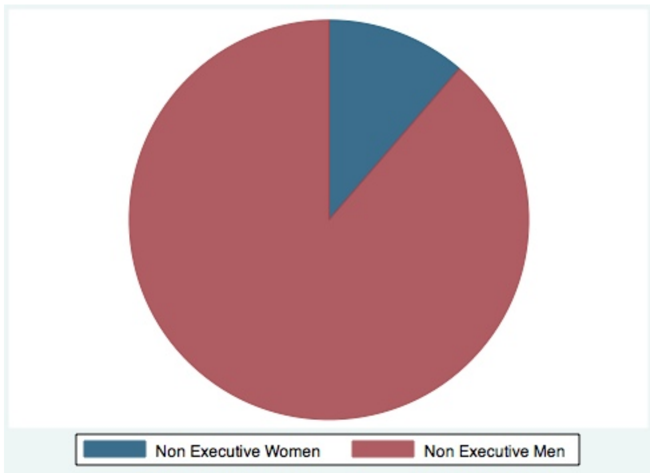

Figure 5: Non executive men and women in 2004

The influence of employment links might be very different for executives and non executives. In particular, if they play a different role for men and women, it is among executives (where the real gender gap exists) that we should expect to find the evidence. Figure 6 provides a striking confirmation of this hypothesis. We have divided the sample of executive individuals first by gender and secondly according to their network size, with ”Large Network” referring to those individuals who have weakly more than the median of the link distribution of all individuals in 2004, and ”Small Network” referring to those who have strictly less than the median. For each group we plot the mean annual salary for each year from 2000 to 2008. First, for a given size of network, men always have higher salary than comparable women. Secondly, the size of networks makes much more difference to the salaries of men than to those of women. Women with large networks earn a little more than women with small networks, whereas men with large networks earn a lot more than men with small networks[7].

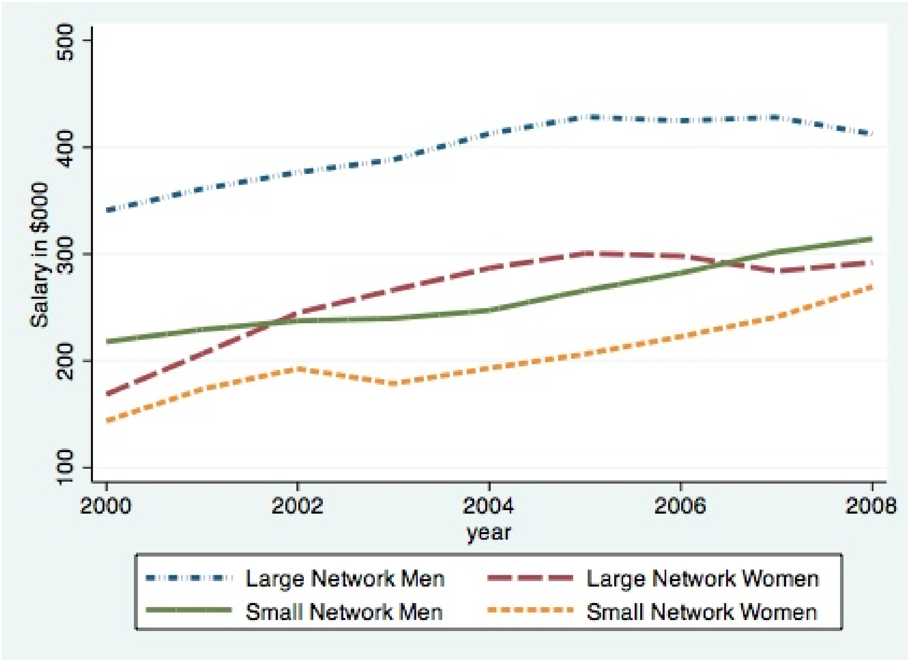

Figure 6: Salary evolution by network size and gender

Tables 6 and 7 test these findings econometrically by reporting the results of separate estimation of the determinants of salaries in 2008 for executives and non-executives. Four points stand out from these tables.

- First, even without taking different number of links into account, the gender dummy for non-executives is is completely insignificant. If there is a discrepancy between men and women in respect of salaries, it is concentrated among executives. Indeed, it seems possible that in the light of public discussion of gender imbalance in the boardroom, a number of firms may be actively recruiting and advancing women to non-executive positions, without doing so to anything like the same extent in respect of executive positions. It is among executives that the gender gap is really striking, with a gap of 33 log points to women's disadvantage.

[7]In case these average salary figures are distorted by the presence of a few very large earners in the sample we have plotted the equivalent of Figure 6 (as well as Figures 7 and 8 below) using median earnings for each group. These are available from the authors on request and show qualitatively similar results.

- Secondly, the influence of links on salaries is substantially more important for non-executives than for executives, with an estimated elasticity of 33% without controlling for lagged salary and over 20% when lagged salary is controlled for. The elasticity on links for executives is around 10% (and this is hardly affected at all by controlling for lagged salary). Being a non-executive board member evidently requires and benefits from contacts to a substantially greater extent than being an executive.
- Thirdly, among executives the interaction of the female dummy with links is now negative and significant at the 10% level, and nearly cancels the positive coefficient on the uninteracted network term. Put simply, this means that while executive men appear to transform their employment links into higher salaries, women do not.
- Fourthly, once these differences in the effect of links are taken into account, the gender dummy becomes insignificant in the executive equation as well.

Overall, therefore, it seems as though the extent of individuals' networks makes a difference to their salaries in a way that is unaffected by gender among non-executives but among executives is beneficial only to men (consistently with the view that firms are making more efforts at recruitment and advancement of female board members in non-executive than in executive roles; see Daily et al.(1999) and Helfat et al.(2006)). One natural question is whether it makes a difference to what extent women have networks composed of other women. A number of studies have highlighted a positive impact of women in top positions on other women's positions and earnings (Bell, 2005; Cohen and Huffman, 2007; Cardoso and Winter-Ebmer, 2010), though they are not able to determine the mechanism by which such an impact occurs. A possible explanation might appeal to the role of social networks (for example, women in top positions might be mentoring and helping other women in lower positions). Tables 8 and 9 therefore report the same specification as Tables 6 and 7, but with the addition of a variable representing the ratio of women among each individual's links.

The inclusion of this variable does not make much difference to the remaining coefficients (men's network opportunities still appear to benefit them while women's do not). Non-executives appear if anything to be harmed by having female contacts, but this effect disappears when we control for lagged salary. Intriguingly, however, executives of either gender benefit from having women among their contacts. Women appear to benefit more than men from this effect, but the standard errors are high and the difference, though economically important, is not statistically significant. It's not at all clear what may be causing this effect. It may be that individuals with more women among their links have for various reasons tended to work for firms that have a stronger team ethic and whose members are more likely to look after the interests of former colleagues. In the absence of further evidence this can only remain a conjecture.

We now proceed to test the robustness of these findings in a variety of respects.

4 Robustness Checks

4.1 Year 2007

Table 10 shows that we get very similar results for salaries in the year 2007. The negative coefficient on the interaction of links with the gender dummy is now significant at the 5% level.

4.2 Liquid Wealth and Total Wealth in 2008

Liquid wealth is the sum of the value of shares held and the intrinsic value of exercisable options in thousands of USD. Total wealth is the sum of equity held, estimated value of options held and long term incentive programs held in thousands of USD. We consider here again the totals from all jobs held by individuals in 2008.

Figures 7 and 8 display the equivalents of Figure 6 for liquid and total wealth. Women with large networks are at essentially no advantage compared to women with small networks, and both are indistinguishable from men with small networks. For men with large networks, though, the advantage is huge.

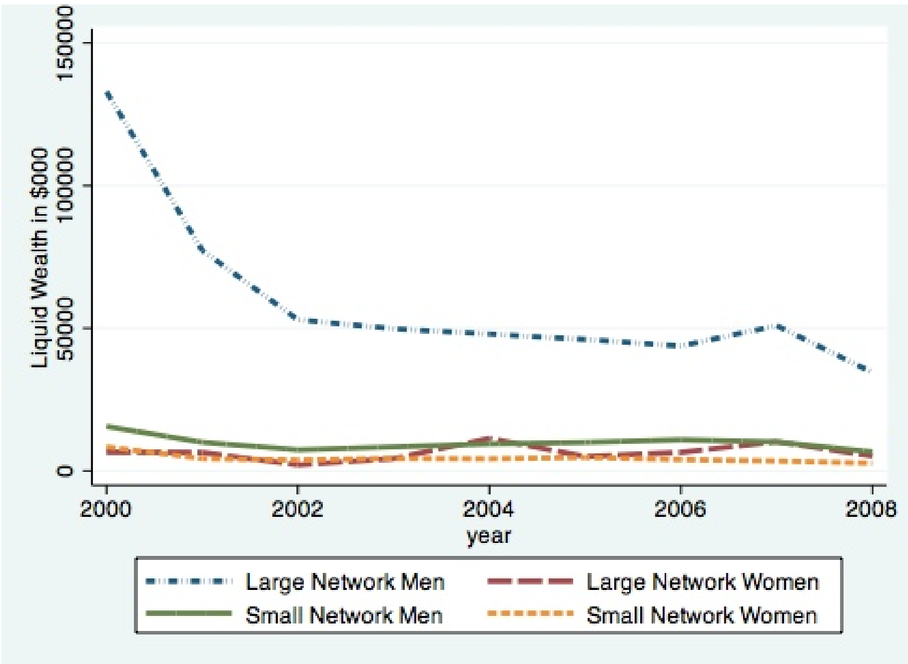

Figure 7: Liquid wealth evolution by network size and gender

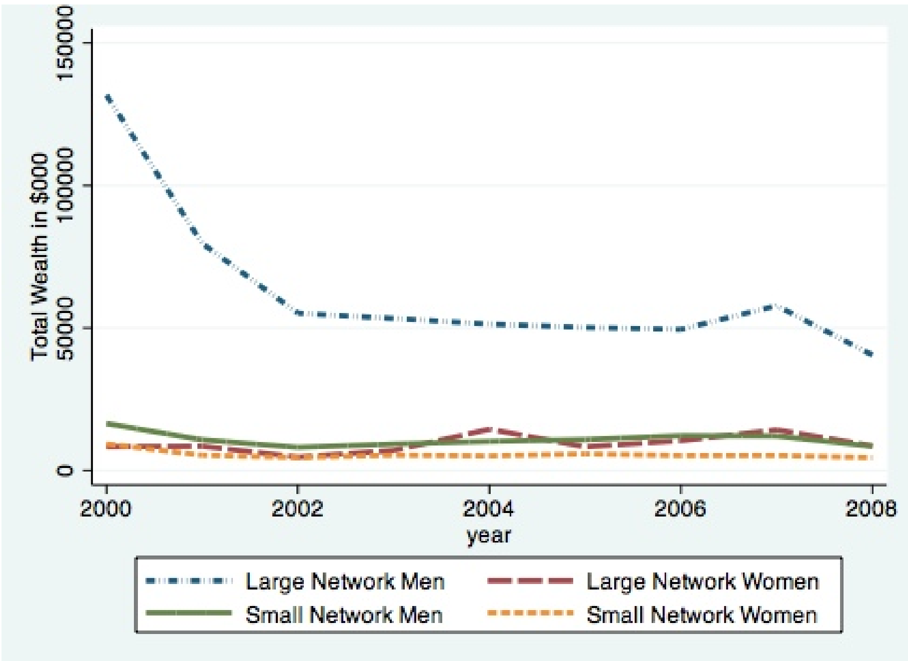

Figure 8: Total wealth evolution by network size and gender

Tables 11 through 14 test these findings econometrically, and confirm that they are even more striking than those for salaries. Without controlling for lagged salaries or wealth, the elasticity of liquid wealth with respect to links is 32% for executives and 40% for non-executives; these elasticities fall to 23% and 16% respectively when lagged wealth is controlled for (controlling for lagged salary has a milder effect). The corresponding figures for total wealth are 61% and 55%, falling to 40% and 27% when lagged wealth is controlled for. To put this in perspective, an elasticity of 40% would imply that an executive with 350 links instead of 250 would have 14% higher remuneration.

The negative coefficients on the interaction of links with the gender dummy in the equations for executives are statistically significant at the 5% level for liquid wealth and at the 1% level for total wealth, and large enough to offset most of the effect for males so that women's return to links is statistically indistinguishable from zero. This confirms once again a striking gender disparity in the value of networks for remuneration among executives.

One potential reason why these gender disparities are even larger for liquid and total wealth than for salary may lie lie in the way non-salary components of remuneration are determined. Generally, the salary part of executive compensation is more transparently determined and often tied to some market level reference. Liquid and total wealth are more likely to be determined by a relatively opaque process of ad hominem bargaining (for once the gender-asymmetric term "ad hominem" appears justified). Following the argument of Babcock and Laschever (2003), women may tend to negotiate less hard than men, so that gender differences in delayed compensation may be larger than differences in the fixed part of compensation. Some corroboration of this conjecture may be noted in the finding in Table 13 that the coefficient on the interaction of the gender dummy with links is negative and about two-thirds the magnitude of the uninteracted coefficient. Although it is statistically significant at only 15%, this is the first time we have found even mild evidence of any gender gap among non-executives, and it is striking that this should be with respect to that part of compensation that is determined by the most opaque and individual bargaining.

4.3 Oaxaca Decomposition

We use the Oaxaca decomposition technique in order to recover the part of the gap in total salary which is due to gender differences in the magnitudes of the determinants of total salary (such as links among others), from the part which is due to gender differences in the effects of these determinants on total salary. These two parts are known as the "endowment" and the "coefficient" effects respectively. The main difference with our estimations so far is that the Oaxaca technique estimates separate equations for each group whereas our previous technique estimated a common equation except for the gender dummy and its interactions. Tables 15 to 18 present the results. The gap in total salary seems to be explained mainly by different returns from determinants (such as links) for executives, while for non executives, the gap in total salary seems to be mainly explained by different magnitudes of the determinants themselves (age being the more important). For men, returns to links are positive and significant at the 1% level while for women they are positive but small and statistically completely insignificant. Again this reinforces strongly the conclusions of our estimations so far.

5 Panel analysis

5.1 Model Specification

Using the panel nature of the data allows us to consider a more complex model in which we take potential unobserved individual heterogeneity into account through individual fixed effects, and also to separate this out from the intrinsic dynamics of salaries over time.

The model specification is now (for both executive and non-executive subsamples):

$$
\begin{aligned}
salary_{it} &= \alpha salary_{i,t-1} + \beta female\_links_{i,t-1} + \gamma male\_links_{i,t-1} + \delta gender_i \\
&+ \zeta human\_capital_{it} + \sigma time_t + u_{it} \qquad (2)
\end{aligned}
$$

with

$$u_{it} = \eta_i + v_{it} \qquad (3)$$

where η_i are the (unobserved) individual fixed effects.

The network variables are lagged to avoid simultaneity bias (due for instance to individuals' changing jobs in pursuit of a higher salary and thereby acquiring larger networks). However, it remains likely that the network and human capital variables, as well as the lagged salary term, will be correlated with the individual fixed effects. Under these conditions the OLS estimator will not be consistent and we shall need to use alternative estimators such as difference and system GMM estimators. For these to be consistent, we need the idiosyncratic disturbances (apart from the fixed effects) to be uncorrelated across individuals, so we include time dummies in order to remove as much as possible of this correlation from the data. However, the disturbance terms may have individual-specific patterns of heteroskedasticity and serial correlation. We undertake the analysis on the years 2000 to 2008 inclusive, so T is relatively small and the number of observations N is relatively large (the executive sample is composed of 1,768 individuals, the non executive sample is composed of 2,483 individuals).

5.2 Estimation Strategy

2SLS estimation To obtain a consistent estimate, one possibility is to apply a first-difference transformation to the equation to eliminate the individuals' fixed effects:

$$\Delta salary_{it} = \alpha \Delta salary_{i,t-1} + \beta \Delta female\_links_{i,t-1} + \gamma \Delta male\_links_{i,t-1} + \Delta X'_{it}\delta + \Delta v_{it} \qquad (4)$$

where X'_{it} include all the other exogenous regressors.

If we apply OLS regression on this transformed equation, we will still obtain inconsistent estimates of α, β and γ. In fact, even if individuals' fixed effects η_i are removed, the lagged salary is still endogenous to the errors, since the $y_{i,t-1}$ in $\Delta y_{i,t-1}$ is correlated with the $v_{i,t-1}$ in Δv_{it} (the same is true for the lagged links regressors). However, deeper lags of the lagged salary and lagged links regressors remain orthogonal to the error and are available as instruments. We could then apply a 2SLS estimation to the equation (Anderson and Hsiao, 1981). One additional assumption is needed here (additionally to the assumption that the v_{it} are independent across individuals and serially uncorrelated): the initial conditions $salary_{i1}$, $female\_links_{i1}$ and $male\_links_{i1}$ have to be uncorrelated with subsequent errors (initial conditions have to be predetermined). However, the 2SLS estimator is a good estimator only under homoskedasticity (and after differencing, Δv_{it} are probably far from i.i.d.). Moreover, it is not asymptotically efficient, while the GMM estimator will be.

GMM difference estimation The GMM difference estimator (Holtz-Eakin, Newey and Rosen, 1988; Arrellano and Bond, 1991) is based on the fact that all the past lags available in the data are used as instruments for the endogenous variables. To implement the feasible efficient GMM estimator, we have to estimate the covariance matrix of the transformed errors. For the one-step GMM estimator, the estimate of the covariance matrix is based on the assumption that the v_{it} are i.i.d. However, it can be shown that the GMM estimator is still consistent under this (potentially false) assumption. For the two-step GMM, we run the GMM regression twice, first assuming homoskedasticity of errors and second, using the residuals from the first GMM regression to obtain the estimate of the covariance matrix. In practice, researchers have more often used the one-step estimator because efficiency gains from the two-step estimator are shown to be low even if errors are heteroskedastic (Arellano and Bond, 1991; Blundell and Bond, 1998; Blundell et al., 2001) and the asymptotic distribution is less reliable due to the fact that the weighting matrix is based on estimated parameters (Windmeijer, 1998 proposes a finite-sample correction for the asymptotic variance of the two-step GMM estimator). As a result, it is not possible to make a choice between the estimators on *a priori* grounds, so we report both one-step and two-step estimators.

GMM system estimation Blundell and Bond (1998) showed that if the variable salary (or the links variables) is close to a random walk, then the GMM difference estimator performs poorly because past levels provide little information about future changes, so that untransformed lags are weak instruments for transformed variables. Let us rewrite the differenced model in the following way:

$$\begin{aligned}\Delta salary_{it} &= \alpha^{t-2}\Delta salary_{i2} + \sum_{s=0}^{t-3}\alpha^{s}\beta\Delta female\_links_{i,t-s} + \sum_{s=0}^{t-3}\alpha^{s}\gamma\Delta male\_links_{i,t-s} \\ &+ \sum_{s=0}^{t-3}\alpha^{s}\delta\Delta X_{i,t-s} + \sum_{s=0}^{t-3}\alpha^{s}\Delta u_{i,t-s} \end{aligned} \tag{5}$$

where X' again include all the other exogenous regressors.

Here again, the main problem is the individual fixed effects η_i. However, we observe that $\Delta salary_{it}$ will be uncorrelated with η_i if and only if $\Delta salary_{i2}$ is uncorrelated with η_i. Notice that the same has to be true for the links variables as well. This will be satisfied if salary and links variables follow a mean stationary process. As a result, the system GMM estimation (Arrellano and Bover, 1995; Blundell and Bond, 1998) combines the linear moment conditions for the differenced model with the linear moment conditions for the model in levels. In other words, both equations 2 and 4 are simultaneously estimated in order to provide estimates of coefficient α, β, γ and δ.

5.3 Results

We first test AR(1) models for salary and social network in order to see whether these processes are close to random walks:

$$salary_{it} = \lambda^1 salary_{i,t-1} + \xi^1_(i) + \mu^1_{it} \tag{6}$$

$$network_{it} = \lambda^2 network_{i,t-1} + \xi^2_(i) + \mu^1_{it} \tag{7}$$

Table 19 presents the results. We observe that links seem to be a persistent series, especially for executives and also, to some extent, for non executives. Salary seems also to be fairly persistent for the non executive sample. We thus need to use GMM system estimators. We present four different GMM system estimators for the two subsamples of executives and non executives: one-step GMM system estimator where all lags of salary and links instrument both equations (the one in difference and the one in levels), one-step GMM system estimator where all the lags of salary instrument the equation in difference and all the lags of links instrument both equations and their counterpart two-step GMM estimators.

Tables 20 and 21 present the results for salary in 2008, for executive and non-executive samples only. Table 22 presents one-step GMM system estimation for liquid and total wealth. The key features of the panel results are as follows:

- The coefficient on links for male executives in the salary equations is significant at the 1% level and large, with elasticities ranging from 13% to 33% depending on the instrument set used.

- The coefficient on links for male executives in the wealth equations is significant at the 5% level for liquid wealth and 10% level for total wealth and relatively large, with elasticities of 52% for liquid wealth and 55% for total wealth.

- The coefficient on links for female executives is positive but insignificant in the salary equations, and negative and not significant in the wealth equations.

- The coefficient on links for non-executives is positive and significant at 1% for both women and men, with the coefficients slightly larger for women in the salary equations and substantially larger in the wealth equations but not significative.

- The tests of autocorrelation indicate that the series meet the requirements for GMM estimation. In particular, the first order serial correlation of the error differences is negative by construction (since each error term enters negatively into the difference of its successor with itself and positively into its own difference with its predecessor). But the second order serial correlations are insignificantly different from zero, suggesting that errors are serially uncorrelated, as required by GMM estimation.
- However, all specifications reject the null under the Sargan test.

The results of the Sargan tests mean that we cannot take these results as conclusive. The most likely reason is that some of the lagged values of the links variables are invalid instruments in the sense that they should properly be included in the main estimating equation. This would be plausible if, for example, some of the additions to an individual's network of contacts do not lead to career advantages for that individual until several years later. If so, this is an inherent limitation of the data and there is nothing we can really do to estimate the system consistently[8].

Overall, the results of the panel estimation are nevertheless broadly supportive of our earlier findings, in the sense that panel estimation strengthens the conclusion that male executives reap remuneration benefits from their links while female executives do not, though the precise magnitude of the elasticities varies from a low of just under 13% to a high of just over 55% according to the specification and to the measure of remuneration used.

6 Discussion and Conclusions

Using both cross-section and panel estimation we have found substantial evidence that employment links matter for the remuneration of top executives and non-executive board members, in the sense that controlling for other factors, individuals who have overlapped professionally with a larger number of currently influential people have higher salaries and non-salary remuneration. We have further found evidence that this effect is very different for executives as compared to non-executive board members. For non-executives the impact of networks is large but there is no gender difference (and no apparent gender gap in remuneration). For executives, however, the effect of links is restricted to men. Broadly speaking, executive men in our sample do not have more links than women, but they manage to leverage the opportunities they do have into higher

[8] We have experimented with different lags for the instruments and the Sargan test rejects the null in all specifications.

remuneration while women do not. Men's salaries are influenced by their links, with an elasticity lying from just under 8% to 33% depending on the specification, and their liquid and total wealth are influenced even more strongly, with elasticities of around 23% to over 61% depending on the measure used. The effect of links on the remuneration of executive women, however, is significantly lower than that for men, and is statistically indistinguishable from zero. Furthermore, once the different impact of networks is taken into account, there is no further statistical evidence of a gender gap in remuneration.

Two different types of phenomena might explain such results. First, there might exist gender differences in preferences for social contacts or for forms of interaction with those social contacts. For instance, as has previously been conjectured, women might be more inclined to build and rely on a few "strong ties", while men might have a preference for a large number of "weak ties". As a result, when considering career evolution, men will be aware of a larger number of job opportunities than comparable women and obtain better labor market outcomes (this is exactly the "strength of weak ties" hypothesis of Granovetter (1973)). Alternatively, even if the structure of men's and women's networks were the same, women might be less willing to approach their weak ties for help in seeking job opportunities (this would be a variant of the "women don't ask" hypothesis of Babcock and Laschever (2003)). Under either hypothesis men and women in similar initial position, and given similar numbers of opportunities to meet influential people, might end up with very different currently employment outcomes due to their different preferences. The second type of phenomenon might be exclusionary behavior on the part of men, whether consciously through a preference for not admitting women to positions of real power, or unconsciously as a side effect of the greater conspicuousness of other men among the networks of people that predominantly male recruiters turn to when seeking to fill such positions. Either way, old boy networks may exclude women, either through the explicit or implicit preferences of the women or the explicit or implicit preferences of the men.

We cannot conclude from these findings which of these two phenomena is more important in explaining our results. If the preferences of women were the sole explanation it would be hard to see why they should not apply to non-executive women as well, whereas we can clearly reject the hypothesis that non-executive men and women behave differently. But it does not follow that the preferences of men are therefore the sole cause. Much more likely is that the preferences and behaviors of women interact with those of men, and that men's networks are more likely to exclude women in respect of recruitment to positions of real power in the firm (there may even be a deliberate "window-dressing" policy on the part of some firms, to appoint women to non-executive positions as a substitute for appointing them to executive jobs). If so this suggests that quota policies that fail to distinguish between executive and non-executive positions may have little effect on the distribution of real power within firms. These suggestions remain conjectural, however, and are an important subject for further research.

7 Appendix

Table 1: Network variables

Variables	Description
Links-Employment	Number of employment contacts with whom the opportunity to link arose
Weighted Links-Employment	Links weighted by the reciprocal of one plus the number of years since the overlapping ended
Sex Ratio-Employment	Proportion of females contacts out of all male and female contacts
Average Job Level-Employment	Average job level for executive contacts
Standard Deviation Job Level-Employment	Standard deviation of job level for executive contacts
Higher Job Level Ratio-Employment	Proportion of higher job level executives out of all executive links
Higher Board Level Ratio-Employment	Proportion of higher board level board members out of all board members contacts
Executive Ratio-Employment	Proportion of executive contacts
Board Ratio-Employment	Proportion of board members contacts
Number of Colleagues-Employment	Number of current employment contacts
Links-Education	Number of education contacts with whom the opportunity to link arose
Number of Classmates-Education	Number of education contacts who graduated the same year in the same university for the same degree
Links-NFP	Number of non for profit organizations contacts with whom the opportunity to link arose
Links-Other	Number of other organizations contacts with whom the opportunity to link arose

Table 2: Sample representativeness for 2008

Variables	Our sample		Whole dataset	
	Mean (Std. Dev.)	Observations	Mean (Std. Dev.)	Observations
Age	58.23 (9.07)	16 204	55.62 (10.33)	72 434
Percentage women	8.84%	16 204	12.36%	92 278
Links	235.71 (271.91)	16 204	153.64 (208.75)	89 550
Weighted links	99.46 (111.84)	16 204	65.12 (87.12)	89 550
Total salary	234.37 (271.94)	16 204	101.83 (201.29)	51 598
Total salary (excluding zero total salary)	234.37 (271.94)	16 204	218.80 (247.93)	24 014
Total liquid wealth	11 051.08 (350 748)	16 204	4 586.67 (204 428.2)	51 598
Total liquid wealth (excluding zero total (liquid wealth)	11 051.08 (350 748)	16 204	10 503.87 (309 265.5)	22 531
Total total wealth	13 121.52 (351 510.3)	16 204	5 353.39 (204 844.5)	51 598
Total total wealth (excluding zero total total wealth)	13 121.52 (351 510.3)	16 204	12 300.15 (310 368.5)	22 457
Number employees*	19 327.47 (73 280.41)	15 772	22 496.81 (78 738.84)	49 644
Market capitalization*	7 893.91 (23 937.71)	15 786	9 751.39 (28 477.03)	50 146

*not included in regressions (this is why the number of observations for our sample differ)

Table 3: Determinants of salary 2008 (unweighted links)

Variables	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Ln salary (2004)		0.209***	0.209***
		(0.004)	(0.004)
Ln links (2004)	0.088***	0.052***	0.050***
	(0.008)	(0.007)	(0.007)
Female*ln links (2004)			0.024
			(0.024)
Female	-0.441***	-0.319***	-0.433***
	(0.029)	(0.026)	(0.116)
Intercept	-51.039***	-25.233***	-25.168***
	(4.150)	(3.820)	(3.820)
N	16204	16204	16204
R^2	0.147	0.288	0.288

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 4: Determinants of salary 2008 (weighted links)

Variables	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Ln salary (2004)		0.209***	0.209***
		(0.004)	(0.004)
Ln weighted links (2004)	0.121***	0.085***	0.083***
	(0.011)	(0.010)	(0.010)
Female*ln weighted links (2004)			0.018
			(0.024)
Female	-0.454***	-0.330***	-0.416***
	(0.029)	(0.026)	(0.115)
Intercept	-50.352***	-24.627***	-24.590***
	(4.151)	(3.818)	(3.818)
N	16204	16204	16204
R^2	0.147	0.289	0.289

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 5: Gender by executive status in 2008

Gender	Non executives	Executives	Total
Men	7 604 (51,48%)	7 168 (48,52%)	14 772 (91,16%)
Women	972 (67,88%)	460 (32,12%)	1 432 (8,84%)
Total	8 576 (52,93%)	7 628 (47,07%)	16 204 (100%)

Table 6: Determinants of salary in 2008 for executives

Variables	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Ln salary (2004)		0.092***	0.092***
		(0.004)	(0.004)
Ln weighted links (2004)	0.101***	0.091***	0.096***
	(0.014)	(0.013)	(0.014)
Female*ln weighted links (2004)			-0.066*
			(0.036)
Female	-0.386***	-0.330***	-0.029
	(0.042)	(0.041)	(0.169)
Intercept	-64.752***	-57.646***	-57.825***
	(5.647)	(5.516)	(5.516)
N	8625	8625	8625
R^2	0.049	0.096	0.097

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 7: Determinants of salary in 2008 for non executives

Variables	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Ln salary (2004)		0.236***	0.236***
		(0.007)	(0.007)
Ln weighted links (2004)	0.328***	0.209***	0.205***
	(0.011)	(0.011)	(0.011)
Female*ln weighted links (2004)			0.027
			(0.024)
Female	-0.015	-0.021	-0.151
	(0.029)	(0.026)	(0.118)
Intercept	-12.748**	-3.027	-3.097
	(5.561)	(5.140)	(5.140)
N	7578	7578	7578
R^2	0.118	0.249	0.249

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 8: Determinants of salary in 2008 for executives

Variables	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Ln salary (2004)		0.092***	0.092***
		(0.004)	(0.004)
Ln weighted links (2004)	0.086***	0.075***	0.076***
	(0.014)	(0.014)	(0.014)
Female*ln weighted links (2004)	-0.061*	-0.059^{+}	-0.063*
	(0.037)	(0.036)	(0.036)
Sex ratio (2004)	0.870***	0.882***	0.842***
	(0.125)	(0.122)	(0.126)
Female*sex ratio (2004)			0.607
			(0.487)
Female	-0.133	-0.088	-0.149
	(0.173)	(0.168)	(0.175)
Intercept	-64.617***	-57.492***	-57.410***
	(5.632)	(5.500)	(5.500)
N	8625	8625	8625
R^2	0.055	0.102	0.102

Significance levels : $+$: 15% $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 9: Determinants of salary in 2008 for non executives

Variables	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Ln salary (2004)		0.236***	0.236***
		(0.007)	(0.007)
Ln weighted links (2004)	0.326***	0.205***	0.206***
	(0.012)	(0.012)	(0.012)
Female*ln weighted links (2004)	0.042^{+}	0.027	0.023
	(0.026)	(0.024)	(0.024)
Sex ratio (2004)	-0.262*	0.017	-0.034
	(0.144)	(0.133)	(0.141)
Female*sex ratio (2004)			0.469
			(0.421)
Female	-0.211*	-0.152	-0.187^{+}
	(0.128)	(0.118)	(0.122)
Intercept	-13.001**	-3.085	-3.038
	(5.561)	(5.141)	(5.141)
N	7578	7578	7578
R^2	0.119	0.249	0.249

Significance levels : $+$: 15% $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 10: Determinants of salary in 2007

Variables	**Executives**	**Executives**	**Non executives**	**Non executives**
	Coefficient (Std. Err.)	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Ln salary (2003)		0.104***		0.256***
		(0.004)		(0.007)
Ln links (2003)	0.122***	0.120***	0.292***	0.181***
	(0.012)	(0.012)	(0.012)	(0.012)
Female*ln weighted	-0.060*	-0.070**	0.064**	0.031
links (2003)	(0.033)	(0.032)	(0.028)	(0.026)
Female	-0.105	0.008	-0.322**	-0.179
	(0.154)	(0.149)	(0.138)	(0.126)
Intercept	-59.315***	-51.532***	-14.236**	-3.9566
	(5.002)	(4.849)	(6.192)	(5.676)
N	9 896	9 896	7 479	7 479
R^2	0.046	0.107	0.107	0.252

Significance levels : $+$: 15% $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 11: Determinants of liquid wealth 2008 for the executive sample

Variables	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Ln salary (2004)		0.209***	
		(0.012)	
Ln liquid wealth (2004)			0.301***
			(0.007)
Ln weighted links (2004)	0.315***	0.292***	0.226***
	(0.040)	(0.039)	(0.037)
Female*ln weighted links (2004)	-0.276**	-0.262**	-0.216**
	(0.105)	(0.103)	(0.096)
Female	0.465	0.569	0.502
	(0.490)	(0.482)	(0.450)
Intercept	-7.140	8.999	-10.930
	(15.990)	(15.763)	(14.675)
N	8 625	8 625	8 625
R^2	0.032	0.063	0.185

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 12: Determinants of total wealth 2008 for the executive sample

Variables	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Ln salary (2004)		0.185***	
		(0.015)	
Ln total wealth (2004)			0.457***
			(0.007)
Ln weighted links (2004)	0.605***	0.584***	0.398***
	(0.048)	(0.048)	(0.040)
Female*ln weighted links (2004)	-0.360***	-0.356***	-0.277***
	(0.127)	(0.126)	(0.105)
Female	1.121*	1.214**	1.075**
	(0.595)	(0.590)	(0.491)
Intercept	-37.320*	-23.028	-34.048**
	(19.416)	(19.288)	(16.021)
N	8 625	8 625	8 625
R^2	0.042	0.058	0.348

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 13: Determinants of liquid wealth 2008 for the non executive sample

Variables	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Ln salary (2004)		0.191***	
		(0.021)	
Ln liquid wealth (2004)			0.483***
			(0.008)
Ln weighted links (2004)	0.397***	0.302***	0.156***
	(0.036)	(0.038)	(0.030)
Female*ln weighted links (2004)	-0.062	-0.074	-0.102^{+}
	(0.080)	(0.079)	(0.066)
Female	0.032	0.084	0.371
	(0.391)	(0.389)	(0.323)
Intercept	4.559	12.430	-0.232
	(16.991)	(16.927)	(14.047)
N	7 578	7 578	7 578
R^2	0.042	0.052	0.345

Significance levels : + : 15% $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 14: Determinants of total wealth 2008 for the non executive sample

Variables	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**	**Coefficient (Std. Err.)**
Ln salary (2004)		0.178***	
		(0.020)	
Ln total wealth (2004)			0.459***
			(0.008)
Ln weighted links (2004)	0.547***	0.459***	0.271***
	(0.035)	(0.036)	(0.029)
Female*ln weighted links (2004)	0.039	0.028	-0.047
	(0.076)	(0.076)	(0.063)
Female	-0.159	-0.110	0.270
	(0.372)	(0.370)	(0.311)
Intercept	-11.733	-4.386	-6.913
	(16.170)	(16.113)	(13.503)
N	7 578	7 578	7 578
R^2	0.061	0.070	0.345

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 15: Decomposition Results

	Executives	Non executives
Mean prediction (men)	5.538	4.273
Mean prediction (women)	5.234	4.188
Raw differential	0.303	0.085
Due to endowments	-0.021	0.105
Due to coefficients	0.330	-0.024
Due to interaction	-0.005	0.004

Table 16: Oaxaca Decomposition

Variables	**Executives**		**Non executives**	
	Men	**Women**	**Men**	**Women**
Ln salary (2004)	0.090***	0.109***	0.240***	0.198***
	(0.005)	(0.017)	(0.007)	(0.021)
Ln weighted links (2004)	0.094***	0.061	0.202***	0.265***
	(0.014)	(0.059)	(0.012)	(0.032)
N	8 092	533	6679	899
R^2	0.092	0.102	0.248	0.261

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 17: Decomposition Results (including sex ratio)

	Executives	Non executives
Mean prediction (men)	5.538	4.273
Mean prediction (women)	5.234	4.188
Raw differential	0.303	0.085
Due to endowments	-0.074	0.104
Due to coefficients	0.355	-0.029
Due to interaction	0.022	0.010

Table 18: Oaxaca Decomposition (including sex ratio)

Variables	**Executives**		**Non executives**	
	Men	**Women**	**Men**	**Women**
Ln salary (2004)	0.090***	0.109***	0.240***	0.198***
	(0.004)	(0.017)	(0.007)	(0.021)
Ln weighted links (2004)	0.075***	0.026	0.202***	0.260***
	(0.014)	(0.060)	(0.012)	(0.033)
Sex ratio (2004)	0.840***	1.588***	-0.023	0.349
	(0.125)	(0.531)	(0.142)	(0.381)
N	8 092	533	6679	899
R^2	0.097	0.118	0.248	0.262

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Control not reported: age, age squared, degree, degree field

Table 19: AR(1) specification for salary and links

	Executives	**Executives**	**Non executives**	**Non executives**
	GMM diff	**GMM syst**	**GMM diff**	**GMM syst**
λ^1	0.727***	0.779***	0.911***	0.847***
	(0.026)	(0.025)	(0.011)	(0.009)
a1 (first order serial correlation)	-7.03***	-7.06***	-21.00***	-22.76***
a2 (second order serial correlation)	1.50^+	1.48^+	-1.65*	-1.69*
Sargan (p-values)	0.00	0.00	0.00	0.00
N	1 768	1 768	2 483	2 483
λ^2	1.325***	1.089***	0.904***	0.982***
	(0.050)	(0.033)	(0.034)	(0.028)
a1 (first order serial correlation)	-14.88***	-14.07***	-13.94***	-13.06***
a2 (second order serial correlation)	3.29***	3.33***	2.43**	2.36**
Sargan (p-values)	0.00	0.00	0.00	0.00
N	1 768	1 768	2 483	2 483

Significance levels: $+$: 15% $*$: 10% $**$: 5% $***$: 1%

Asymptotic standard errors are in parentheses (heteroskedasticity-consistent estimates of the asymptotic standard errors).

a1 and a2 test for first-order and second-order serial correlation, asymptotically N(0,1). They test the first-differenced residuals.

Sargan tests the overidentifying restrictions, asymptotically χ^2. This test uses the minimized value of the corresponding two-step GMM estimators.

One-step and two-step GMM estimators are based on the same set of moment conditions, so that the overidentifying restrictions are the same for both estimators.

GMM diff are one-step GMM difference estimators; GMM syst are one-step GMM system estimators.

Table 20: Alternative GMM system estimators for executive sample

	GMM (syst)	GMM2 (syst)	GMM (syst)	GMM2 (syst)
Ln salary (t-1)	0.409***	0.414***	0.233***	0.231***
	(0.045)	(0.048)	(0.042)	(0.043)
Female*ln weighted	0.026	0.021	-0.371	-0.354
links (t-1)	(0.193)	(0.160)	(0.292)	(0.266)
Male*ln weighted	0.330***	0.221***	0.233***	0.129***
links (t-1)	(0.061)	(0.052)	(0.066)	(0.050)
Female	0.844	0.485	1.906*	1.448^{+}
	(0.740)	(0.534)	(1.074)	(0.992)
Intercept	117.884***	97.019***	84.655***	62.828***
	(18.782)	(18.807)	(18.765)	(15.673)
a1 (first order serial correlation)	-5.63***	-5.47***	-5.15***	-4.78***
a2 (second order serial correlation)	1.34	1.33	1.03	1.01
Sargan (p-values)	0.00	0.00	0.00	0.00
Dif-Sar (p-values)			0.211	0.211
Instruments	all lags	all lags	all lags of salary for equation in diff all lags of links for equation in diff and in levels	all lags of salary for equation in diff all lags of links for equation in diff and in levels
N	1 768	1 768	1 768	1 768

Significance levels: $+ : 15\%$ $* : 10\%$ $** : 5\%$ $*** : 1\%$

Asymptotic standard errors are in parentheses (heteroskedasticity-consistent estimates of the asymptotic standard errors).

Years dummies are included in all models. Controls not reported: age, age squared, degree, degree field.

a1 and a2 test for first-order and second-order serial correlation, asymptotically N(0,1). They test the first-differenced residuals.

Sargan tests the overidentifying restrictions, asymptotically χ^2. This test uses the minimized value of the corresponding two-step GMM estimators. One-step and two-step GMM estimators are based on the same set of moment conditions, so that the overidentifying restrictions are the same for both estimators.

Dif-Sar is the Difference Sargan test, which is asymptotically χ^2 and tests the validity of the additional moment conditions used in the former case.

We use GMM-style instruments for lagged salary and lagged social network (i.e. deeper lagged values); IV-style instruments for the other regressors (i.e. available exogenous regressors or, as it is in our case, they instrument themselves).

GMM syst are one-step GMM system estimators; GMM2 syst are two-step GMM system estimators.

Table 21: Alternative GMM system estimators for non executive sample

	GMM (syst)	GMM2 (syst)	GMM (syst)	GMM2 (syst)
Ln salary (t-1)	0.666***	0.666***	0.695***	0.689***
	(0.017)	(0.021)	(0.018)	(0.025)
Female*ln weighted links (t-1)	0.497***	0.360***	0.462***	0.312***
	(0.091)	(0.081)	(0.089)	(0.078)
Male*ln weighted links (t-1)	0.433***	0.351***	0.417***	0.314***
	(0.044)	(0.039)	(0.052)	(0.048)
Female	-0.315	-0.046	-0.234	-0.001
	(0.421)	(0.384)	(0.409)	(0.370)
Intercept	192.387***	184.557***	195.950***	192.586***
	(21.356)	(21.538)	(22.067)	(22.421)
a1 (first order serial correlation)	-21.07***	-18.43***	-20.37***	-17.81***
a2 (second order serial correlation)	-0.40	-0.40	-0.34	-0.35
Sargan (p-values)	0.00	0.00	0.00	0.00
Dif-Sar (p-values)			0.534	0.534
Instruments	all lags	all lags	all lags of salary for equation in diff all lags of links for equation in diff and in levels	all lags of salary for equation in diff all lags of links for equation in diff and in levels
N	2 483	2 483	2 483	2 483

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Asymptotic standard errors are in parentheses (heteroskedasticity-consistent estimates of the asymptotic standard errors).

Years dummies are included in all models. Controls not reported: age, age squared, degree, degree field.

a1 and a2 test for first-order and second-order serial correlation, asymptotically N(0,1). They test the first-differenced residuals.

Sargan tests the overidentifying restrictions, asymptotically χ^2. This test uses the minimized value of the corresponding two-step GMM estimators. One-step and two-step GMM estimators are based on the same set of moment conditions, so that the overidentifying restrictions are the same for both estimators.

Dif-Sar is the Difference Sargan test, which is asymptotically χ^2 and tests the validity of the additional moment conditions used in the former case.

We use GMM-style instruments for lagged salary and lagged social network (i.e. deeper lagged values); IV-style instruments for the other regressors (i.e. available exogenous regressors or, as it is in our case, they instrument themselves).

GMM syst are one-step GMM system estimators; GMM2 syst are two-step GMM system estimators.

Table 22: One-step GMM system estimators for liquid and total wealth

	Liquid Wealth Executives	Total Wealth Executives	Liquid Wealth Non executives	Total Wealth Non executives
Ln salary (t-1)	0.523***	0.369***	0.331***	0.318***
	(0.122)	(0.129)	(0.065)	(0.063)
Female*ln weighted	-1.206	-1.448	0.412	0.427
links (t-1)	(0.945)	(1.012)	(0.357)	(0.345)
Male*ln weighted	0.520**	0.553*	0.249	0.050
links (t-1)	(0.242)	(0.330)	(0.194)	(0.190)
Female	5.878*	7.226*	-0.770	-1.433
	(3.469)	(3.789)	(1.813)	(1.750)
Intercept	1 693.541***	1 075.888***	1 181.028***	1 104.604***
	(87.904)	(76.740)	(67.910)	(61.075)
a1 (first order serial correlation)	-9.34***	-8.17***	-12.41***	-12.17***
a2 (second order serial correlation)	1.77*	1.22	-2.53**	-1.46
Sargan (p-values)	0.00	0.00	0.00	0.00
Instruments	all lags of salary for equation in difference			
	all lags of links for equation in difference and in levels			
N	1 768	1 768	2 483	2 483

Significance levels: $*$: 10% $**$: 5% $***$: 1%

Asymptotic standard errors are in parentheses (heteroskedasticity-consistent estimates of the asymptotic standard errors).

Years dummies are included in all models. Controls not reported: age, age squared, degree, degree field.

a1 and a2 test for first-order and second-order serial correlation, asymptotically N(0,1). They test the first-differenced residuals.

Sargan tests the overidentifying restrictions, asymptotically χ^2. This test uses the minimized value of the corresponding two-step GMM estimators. One-step and two-step GMM estimators are based on the same set of moment conditions, so that the overidentifying restrictions are the same for both estimators.

Dif-Sar is the Difference Sargan test, which is asymptotically χ^2 and tests the validity of the additional moment conditions used in the former case.

We use GMM-style instruments for lagged salary and lagged social network (i.e. deeper lagged values); IV-style instruments for the other regressors (i.e. available exogenous regressors or, as it is in our case, they instrument themselves).

GMM syst are one-step GMM system estimators; GMM2 syst are two-step GMM system estimators.

Table 23: Network characteristics by gender for 2008

Variables	**Women**			**Men**		
	Mean	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**
Links - Employment	281.91	289.17	1432	231.23	269.76	14772
Mean overlap - Employment	4.31	1.74	1432	4.51	1.95	14772
Mean oldness - Employment	5.23	4.04	1432	5.76	4.67	14772
Weighted mean overlap - Employment	2.29	1.48	1432	2.40	1.69	14772
Weighted links - Employment	125.22	129.95	1432	96.96	109.61	14772
Sex ratio - Employment	0.14	0.07	1431	0.11	0.07	14770
Executive ratio - Employment	0.81	0.10	1432	0.79	0.12	14772
Board ratio - Employment	0.40	0.16	1432	0.44	0.18	14772
Number of colleagues - Employment	99.40	114.05	1432	76.83	97.04	14772
Links - Education	61.59	64.89	1010	51.98	55.68	8796
Number of classmates - Education	4.69	6.21	1010	4.21	5.95	8796

Table 24: Average job characteristics by gender for 2008

Variables	**Women**				**Men**			
	Median	**Mean**	**Std. Dev.**	**N**	**Median**	**Mean**	**Std. Dev.**	**N**
Total salary (in thousands USD)	88.78	167.67	192.69	1 432	146.36	240.83	277.58	14 772
Total liquid wealth (in thousands USD)	188.35	4 049.44	56 633.09	1 432	367.11	11 729.83	366 926.40	14 772
Total total wealth (in thousands USD)	405.10	5 311.09	56 992.92	1 432	689.83	13 878.66	367 718.60	14 772
Executive status (proportion)	-	0.32	-	1 432	-	0.49	-	14 772
Board status (proportion)	-	0.79	-	1 432	-	0.77	-	14 772
Years in Organization	-	9.36	6.77	1 385	-	11.76	8.74	13 728
Years in Role	-	6.73	5.35	1 385	-	6.76	6.05	13 728
Years on Board	-	8.23	6.05	1 119	-	10.10	7.84	10 849

Table 25: Job characteristics by gender for 2008 (proportions)

Variables	**Women**	**Men**
Job level: CEO	0.04	0.15
Job level: CFO	0.06	0.07
Job level: Chairman	0.01	0.08
Job level: Board Director	0.66	0.43
Job level: Director	0.05	0.07
Job level: Vice President	0.10	0.10
Job function: Board	0.68	0.51
Job function: Finance	0.08	0.11
Job function: Law	0.04	0.03
Job function: Operations	0.02	0.04
Job function: Sales	0.03	0.03

Table 26: Average firm characteristics by gender for 2008

Variables	**Women**				**Men**			
	Median	**Mean**	**Std. Dev.**	**N**	**Median**	**Mean**	**Std. Dev.**	**N**
Number of Employees	6 777.5	25 821.36	73 218.73	1 412	4 000	18 688.93	73 257.94	14 360
Market Capitalization	2 223	11 457.66	30 688.71	1 409	1 446	7 544.65	23 142.35	14 377

Table 27: Firm characteristics by gender for 2008 (proportions)

Variables	**Women**	**Men**
Sector: Finance	0.18	0.16
Sector: Manufacturing	0.27	0.26
Sector: Information	0.10	0.11
Sector: Trade	0.09	0.07
Sector: Services	0.07	0.08

Table 28: Network characteristics by executive status for 2008

Variables	**Executives**			**Non executives**		
	Mean	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**
Links - Employment	188.28	226.54	7628	277.90	300.45	8576
Mean overlap- Employment	4.59	2.09	7628	4.41	1.77	8576
Mean oldness - Employment	5.61	4.68	7628	5.80	4.56	8576
Weighted mean overlap - Employment	2.53	1.83	7628	2.25	1.51	8576
Weighted links - Employment	79.76	97.97	7628	116.98	120.19	8576
Sex ratio - Employment	0.11	0.08	7625	0.12	0.06	8576
Executive ratio - Employment	0.78	0.13	7628	0.80	0.11	8576
Board ratio - Employment	0.45	0.19	7628	0.42	0.17	8576
Number of colleagues - Employment	64.58	89.50	7628	91.49	104.91	8576
Links - Education	49.35	51.12	4033	55.50	60.27	5773
Number of classmates - Education	3.71	5.22	4033	4.63	6.43	5773

Table 29: Average job characteristics by executive status for 2008

Variables	**Executives**				**Non executives**			
	Median	**Mean**	**Std. Dev.**	**N**	**Median**	**Mean**	**Std. Dev.**	**N**
Total salary (in thousands USD)	327.92	395.57	304.18	7 628	59.19	90.98	117.29	8 576
Total liquid wealth (in thousands USD)	842.19	16 678.17	465 606.40	7 628	175.16	6 046.03	198 962.30	8 576
Total total wealth (in thousands USD)	2 469.79	20 691.50	466 718.50	7 628	268.33	6 388.33	199 079.00	8 576
Years in Organization	-	13.32	9.10	6 701	-	10.12	7.92	8 412
Years in Role	-	5.53	5.27	6 701	-	7.74	6.33	8 412
Years on Board	-	10.13	8.34	3 574	-	9.84	7.42	8 294

Table 30: Average firm characteristics by executive status for 2008

Variables	**Executives**				**Non executives**			
	Median	**Mean**	**Std. Dev.**	**N**	**Median**	**Mean**	**Std. Dev.**	**N**
Number of Employees	4 173	19 891.46	84 448.36	7 393	4 452	18 829.85	61 773.25	8 379
Market Capitalization	1 425	7 536.65	23 168.21	7 416	1 575	8 210.46	24 596.45	8 370

Table 31: Firm characteristics by executive status for 2008 (proportions)

Variables	**Executives**	**Non executives**
Sector: Finance	0.15	0.18
Sector: Manufacturing	0.27	0.26
Sector: Information	0.12	0.11

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