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Abstract: Connections appear to be helpful in many contexts such as obtaining a job, a promotion, a grant, a loan or publishing a paper. This may be due to favoritism or to information conveyed by connections. Attempts at identifying both effects have relied on measures of true quality, generally built from data collected long after promotion. This empirical strategy faces important limitations. Building on earlier work on discrimination, we propose a new method to identify favors and information from classical data collected at time of promotion. Under natural assumptions, we show that promotion decisions look more random for connected candidates, due to the information channel. We obtain new identification results and show how probit models with heteroscedasticity can be used to estimate the strength of the two effects. We apply our method to the data on academic promotions in Spain studied in Zinovyeva & Bagues (2015). We find evidence of both favors and information effects at work. Empirical results are consistent with evidence obtained from quality measures collected five years after promotion.

Keywords: Promotion, Connections, Social Networks, Favoritism, Information.
JEL classification: C3, I23, M51.

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I Introduction

Connections appear to be helpful in many contexts such as obtaining a job, a promotion, a grant, a loan or publishing a paper.[1] Two main reasons help explain these wide-ranging effects. On one hand, connections may convey information on candidates, projects and papers. Connections then help recruiters, juries and editors make better decisions. On the other hand, decision-makers may unduly favor connected candidates, leading to worse decisions.[2] These two reasons have opposite welfare implications and empirical researchers have been trying to tease out the different forces behind connections' impacts. Almost all existing studies do so by building measures of candidates' "true" quality. Researchers then compare the quality of connected and unconnected promoted candidates. Information effects likely dominate if connected promoted candidates have higher quality; favors likely dominate if connected promoted candidates have lower quality. For instance, articles published in top economics and finance journals by authors connected to editors tend to receive more citations, a sign that editors use their connections to identify better papers Brogaard, Engelberg & Parsons (2014). By contrast, Full Professors in Spain who were connected to members of their promotion jury publish less after promotion Zinovyvea & Bagues (2015), consistent with favoritism.

This empirical strategy, while widely used, faces three important limitations. First, building a measure of true quality may not be easy or feasible. Looking at researchers' publications or articles' citations requires a long enough time lag following promotion or publication. And such measures are in any case imperfect proxies of quality. Second, identification is only valid if the impact of promotion on measured quality is the same for connected and unconnected promoted candidates, see e.g. Zinovyeva & Bagues (2015, p.283). This assumption is critical but not necessarily plausible, and can generally not be tested. Third, connections may convey both information and favors. This empirical

[1] The literature on jobs and connections is large and expanding. Recent references include Beaman & Magruder (2012), Brown, Setren & Topa (2016), Hensvik & Skans (2016), Pallais & Sands (2016). On promotions, see Combes, Linnemer & Visser (2008), Zinovyeva & Bagues (2015). On grants, see Li (2017). On loans, see Engelberg, Gao & Parsons (2012). On publications, see Brogaard, Engelberg & Parsons (2014), Colussi (2017), Laband & Piette (1994).

[2] Favor exchange within a group might increase the group's welfare at the detriment of society, see Bramoullé & Goyal (2016). In this paper, we focus on the immediate negative implications of favoritism.

strategy may allow researchers to identify which effect dominates; it does not allow them to estimate their relative strengths.[3]

We develop a new method to identify why connections matter, building on earlier work on discrimination. Our method addresses these limitations. It does not rely on measures of true quality. Rather, it exploits classical data collected at time of promotion: information on candidates and whether they were promoted. It allows researchers to estimate the magnitudes of the two effects. The method does require exogenous shocks on connections. This is, in any case, a precondition of any study of the reasons behind the effect of connections.

The method is indirect and looks for revealing signs of information and favors on the relation between candidates' observables and promotion. Consider candidates applying for promotion. They are evaluated by a jury and some candidates are connected to jury members. When connections convey information, the jury has an extra signal on connected candidates' ability. This signal is unobserved by the econometrician and could be positive or negative. To the econometrician, then, the promotion decision looks more random for connected candidates.[4] We show how the strength of the information channel can be recovered, under appropriate assumptions, from this *excess variance* in the latent error of connected candidates. To recover favors, then, we estimate and compare the *promotion thresholds* faced by connected and unconnected candidates. Favors lead to systematic biases in evaluation and the difference between promotion thresholds measures the magnitude of the underlying favors.

Our econometric framework is based on normality assumptions. We make use of probit models with heteroscedasticity to detect and estimate excess variance. We clarify the conditions under which favors and information are identified. Identification fails to hold if the effects depend in an arbitrary way on candidates' observables (Proposition 1). Identification holds, however, under slight restrictions on this dependence, for instance in the presence of an exclusion restriction or under linearity assumptions (Theorem 1).

We then bring our method to data. We reanalyze the data on academic promotions in

[3]In a context of grant applications, Li (2016) develops a new method to recover the respective strengths of favors and information. Her method relies on measures of true quality and on jury evaluations.

[4]A similar idea underlies Theorem 4 in Lu (2016); we discuss this relation in more detail below.

Spain assembled by Manuel Bagues and Natalya Zinovyeva, Zinoveyva & Bagues (2015). This data contain information on all candidates to promotion to Associate and Full Professor in the Spanish academic system between 2002 and 2006. To be promoted, candidates had to pass a highly competitive exam at the national level. They were evaluated by a jury whose members were picked at random in a pool of eligible evaluators, providing exogenous shocks on connections. The data contain information on six types of connections between candidates and evaluators, classified in weak and strong. From data at time of promotion, Zinovyeva & Bagues (2015) estimate the causal impacts of connections. They find positive and significant impacts of both weak and strong ties on promotion for candidates at both the Associate and Full Professor level.

We investigate the reasons behind these impacts on the same data. We estimate different versions of our model. Empirical results depict a coherent, and intuitive, picture. We find strong evidence of information effects associated with both weak and strong ties at the Associate Professor level, when the uncertainty on candidates' academic ability is still strong. We do not detect favors associated with weak ties at that level. By contrast, we find that strong ties also generate favors and that these dominate information effects quantitatively. We do not detect information effect at the Full Professor level, when uncertainty on candidates is low. We detect strong favors associated with both weak and strong ties at that level, consistent with generalized favor exchange in the Spanish academic system at the time. These results, obtained through our method from data at time of promotion, are consistent with results obtained through quality measures collected five years after promotion, see Section VI.

Our analysis contributes to a growing empirical literature on the effects of connections. We develop the first empirical method able to identify favors and information from classical data collected at time of promotion and apply it to analyze academic promotions in Spain. This method could be applied in many other contexts, and could be used to cross-validate results obtained from quality measures.

Our analysis builds on, and advances, ideas first identified in the literature on discrimination. Heckman & Siegelman (1993) and Heckman (1998) clarify key implications of differences in unobservable' variances across groups. They show that differences in variances invalidate the use of standard models of binary outcomes to detect discrimination. Their critique apply to major empirical studies on discrimination, such as Bertrand & Mullainathan (2004). Neumark (2012) shows how probit models with heteroscedasticity can help address this issue. He reanalyzes the data from Bertrand & Mullainathan (2004) and finds stronger evidence for race discrimination than in the original study, once difference in variances across racial groups are accounted for. We adapt and extend these ideas to the study of connections. We show that differences in variances help identify the informational content of connections, an idea consistent with Theorem 4 in Lu (2016). Lu (2016) provides a theoretical analysis of random choice under private information. He shows that better private information generates choices that look more dispersed from the point of view of the econometrician. We provide, to our knowledge, the first applied implementation of this insight. We obtain novel identification results. The first part of Theorem 1, on exclusion restrictions, formalizes and extends the identification argument of Neumark (2012). The second part of Theorem 2, on linearity, is new and shows that identification may hold even without exclusion restrictions. We provide the first empirical application of these ideas to the study of the impact of connections.

The paper proceeds as follows. The next section illustrates the identification strategy with the help of a simple model. Section III introduces the general model and establishes formal identification results. Section IV presents the data. Section V discusses key features of the empirical implementation. Section VI presents empirical results. Section VII concludes.

II A simple model

In this Section, we introduce a simple model to explain and illustrate our identification strategy.[5] We develop our general model and derive formal identification results in Section III.

[5]This model is similar to models analyzed in Heckman & Siegelman (1993, Appendix 5.D), Neumark (2012) and Zinovyeva & Bagues (2015, Section I).

Candidates apply for promotion. A jury evaluates candidates and makes promotion decisions. We assume that the jury grades candidates and that candidates with higher grades are promoted.[6] These grades may be affected by connections to jury members, as described below. Let a_e be the exam-specific promotion threshold: a candidate is promoted iff her grade is higher than or equal to a_e. This threshold may notably depend on the number of candidates applying for promotion in that wave and discipline.

We assume that candidate i's true ability a_i can be decomposed in three parts:

$$a_i = \mathbf{x}_i\beta + u_i + v_i \tag{1}$$

where $\mathbf{x}_i \in \mathbb{R}^m$ denotes a vector of m characteristics observed by the econometrician and the jury, u_i is unobserved by both the econometrician and the jury, and v_i is observed by the jury but not the econometrician. In our empirical application, $\mathbf{x}_i$ includes number of publications, age and gender; u_i could capture creativity and v_i the performance at the exam. Without loss of generality, we assume that $E(u_i|\mathbf{x}_i) = E(v_i|\mathbf{x}_i) = 0$.[7] Thus, u_i and v_i represent parts of unobserved characteristics that cannot be explained by observables. Assume further that $E(u_i|v_i) = 0$ and that unobservables are normally distributed: $u_i \sim N(0, \sigma_u^2)$ and $v_i \sim N(0, \sigma_v)$. Denote by Φ the cumulative density function of a normal variable with mean 0 and variance 1.

Consider an unconnected candidate first. We assume that her grade is equal to the jury's expectation of her ability $E(a_i|x_i, v_i) = \mathbf{x}_i\beta + v_i$. Thus, unconnected candidate i is promoted iff $\mathbf{x}_i\beta + v_i \geq a_e$. From the econometrician's point of view, the probability that an unconnected candidate with characteristics $\mathbf{x}_i$ is promoted is equal to:

$$p_u(y_i = 1|\mathbf{x}_i) = \Phi(\frac{\mathbf{x}_i\beta - a_e}{\sigma_v}) \tag{2}$$

where $y_i = 1$ if candidate i obtains the promotion and 0 otherwise.

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[6] We develop our approach under the assumption that the econometrician does not have data on jury evaluations.

[7] If $E(u_i|\mathbf{x}_i) \neq 0$, define $\hat{u}_i = u_i - E(u_i|\mathbf{x}_i)$ and similarly for $\hat{v}_i$. Note that $E(\hat{u}_i|\mathbf{x}_i) = 0$ while $E(u_i|\mathbf{x}_i)$ is a function of $\mathbf{x}_i$. Under linearity, this yields $a_i = \mathbf{x}_i\hat{\beta} + \hat{u}_i + \hat{v}_i$, which is then equivalent to equation (1).

Next, consider a connected candidate. We make two simplifying assumptions in this Section. We assume, first, that being connected to the jury is random. In the empirical application, this holds conditional on the expected numbers of connections, see Section IV. This implies that connected and unconnected candidates have the same distributions of observables and unobservables. Second, we neglect issues related to the number and types of connections. These issues are accounted for in our general model, see Section III.

Being connected to the jury has two distinct impacts on grades. On the one hand, the jury has some additional information on the candidate's ability. We assume that the jury observes a noisy signal $\theta_i = u_i + \varepsilon_i$ where $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$, and updates his belief on the candidate's ability based on this additional information. On the other hand, the jury may want to favor the connected candidate. We assume that favors take the shape of a grade premium B due to connections.

A connected candidate's grade is thus equal to its expected ability $E(a_i|x_i, v_i, s_i) = \mathbf{x}_i\beta + E(u_i|\theta_i) + v_i$ plus the bias from favors B. Since $E(u_i|\theta_i) = \frac{\sigma_u^2}{\sigma_u^2+\sigma_\varepsilon^2}\theta_i$, connected candidate i is hired iff $\mathbf{x}_i\beta + \frac{\sigma_u^2}{\sigma_u^2+\sigma_\varepsilon^2}\theta_i + v_i + B \geq a_e$. From the econometrician's point of view, the signal θ_i enters in the latent error and generates extra variance on the jury's decision. Variance of the latent error is now equal to $\sigma_v^2 + \frac{\sigma_u^4}{\sigma_u^2+\sigma_\varepsilon^2}$. Let $\sigma^2 = 1 + \frac{\sigma_u^4}{\sigma_v^2(\sigma_u^2+\sigma_\varepsilon^2)} > 1$ denote the excess variance of the latent error compared to unconnected candidates. This yields:

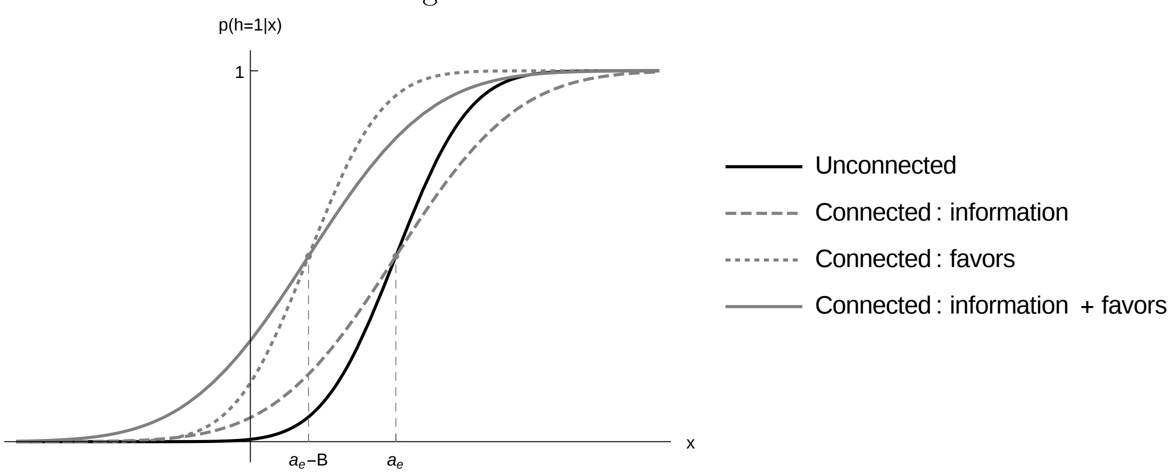
$$p_c(y_i = 1|\mathbf{x}_i) = \Phi(\frac{\mathbf{x}_i\beta + B - a_e}{\sigma\sigma_v}) \tag{3}$$

Comparing equations (2) and (3), we see that information and favors have different impacts on the probability to be promoted. When a jury has better information on connected candidates, this reduces the magnitude of the impact of observable characteristics on the likelihood to be promoted. By contrast, favors lead to a shift in the effective promotion threshold, from a_e to $a_e - B$, leaving the impact of observables unchanged.

We illustrate these effects in Figure 1. The solid black curve depicts $p_u(y_i = 1|\mathbf{x}_i)$, the probability that an unconnected candidate is promoted as function of observed ability. The dashed curve depicts the probability that a connected candidate is promoted when information effects only are present. Note that the whole curve is less steep. The observed probability to be promoted varies less with observed ability. Formally, an increase in σ leads to a second-order stochastic dominance shift of the whole curve. This also implies that the apparent impact of connections is negative for very good candidates for which $\mathbf{x}_i\beta \geq a_e$. This apparent negative impact is due to an asymmetry in the effects of good and bad news on candidates' unobservables. While good news do not improve already good chances by much, bad news significantly reduce the chances of good candidates. For the econometrician, connections then reduce the observed probability to be promoted for very good candidates.

The short-dashed curve depicts the probability that a connected candidate is promoted when only favors are present. The curve is now translated to the left, inducing a first-order stochastic dominance shift. The shape of the whole curve is preserved. The apparent impact of connections is now positive for all candidates. Finally, the grey curve depicts $p_c(y_i = 1|\mathbf{x}_i)$ when both effects are present.

Figure 1: Effects of a connection



Both effects can thus be identified from data on promotion.[8] Differences in the impacts of observables between connected and unconnected can be used to recover information effects. Differences in estimated promotion thresholds between connected and unconnected can then be used to recover favors. From an econometric point of view, the differential information that the jury has on connected candidates generates a form of *heteroscedasticity*.

[8]Formally, identification in this model holds under the standard assumption that $\sigma_v = 1$ and is a direct consequence of Theorem 1 below.

The latent error has a higher variance for connected than for unconnected. This property allows us to rely on standard techniques developed to analyze heteroscedasticity in probit estimations in our empirical analysis below.

To sum up, both information and favors can be identified from data on promotion in a simple model where the two effects are constant. We extend this model and develop our econometric framework in the next Section.

III Identification

We now develop our general framework. We maintain the assumption that connections are random and extend the simple model in three directions. We incorporate baseline heteroscedasticity, varying information and varying favors. Information and favors may notably depend on the number and types of connections of a candidate to the jury. In line with the empirical application, we consider two types here - strong and weak ties; the framework and results easily extend to a finite number of types. Denote by n_{iS} and n_{iW} the number of strong and weak ties that candidate i has to the jury.

We first assume that the variance of v_i may depend on i's observables $\boldsymbol{x}_i$. Thus, $v_i \sim N(0, \sigma_v^2(\mathbf{x}_i))$. In the empirical analysis, we adopt standard assumptions regarding heteroscedasticity in probit regressions, see Section IV. To state our identification results below, we only require that such baseline heteroscedasticity does not raise identification problems in classical probit estimations. More precisely, consider unconnected candidates. We have: $p(y_i = 1 | n_{iS} = n_{iW} = 0, \mathbf{x}_i) = \Phi[(\mathbf{x}_i\beta - a_e)/\sigma_v(\mathbf{x}_i)]$. We assume that β and $\sigma_v(.)$ are identified from the sample of unconnected candidates.[9]

Second, we assume that the private signal received by the jury on a connected candidate may depend on the candidate's number and types of connections and on his other observable characteristics. Denote by $\sigma \geq 1$ the excess variance generated by this signal. We now have $\sigma = \sigma(n_{iS}, n_{iW}, \mathbf{x}_i)$ where, by assumption, $\sigma(0, 0, \mathbf{x}_i) = 1$. Third, the bias from favors B

[9]As is well-know, a probit model with coefficients (β, a_e) and variance $\sigma_v(\mathbf{x}_i)$ cannot be distinguished from one with coefficients $(\lambda\beta, \lambda a_e)$ and variance $\lambda\sigma_v$. We therefore adopt the classical normalization assumption that $\sigma_v(\mathbf{0}) = 1$ in our econometric specifications.

may also depend on the number and types of links and on the candidate's characteristics: $B = B(n_{iS}, n_{iW}, \mathbf{x}_i)$, with $B(0, 0, \mathbf{x}_i) = 0$. While we generally expect both σ and B to be increasing in the number of connections, we do not impose it in what follows. This yields the following probability to be hired, conditional on connections and observables:

$$p(y_i = 1 | n_{iS}, n_{iW}, \mathbf{x}_i) = \Phi[\frac{\mathbf{x}_i\beta + B(n_{iS}, n_{iW}, \mathbf{x}_i) - a_e}{\sigma_v(\mathbf{x}_i)\sigma(n_{iS}, n_{iW}, \mathbf{x}_i)}] \tag{4}$$

The simple model presented in Section II is a particular case with $\sigma_v(\mathbf{x}_i) = \sigma_v$, and $B(n_{iS}, n_{iW}, \mathbf{x}_i) = B$ and $\sigma(n_{iS}, n_{iW}, \mathbf{x}_i) = \sigma$ as soon as $n_{iS} + n_{iW} \geq 1$.

Under which conditions is this general model identified? Note that our identification strategy will not work without some form of restriction on $B(.)$ and $\sigma(.)$. If the bias B varies with observable x_i^k in a direction opposite from the direct effect β_k, this leads to an apparent reduction in the impact of x_i^k on the likelihood to be promoted for connected. If this happens on all observables and without further restrictions, it prevents the identification of the information effect. We next state this negative result and derive a formal proof in the Appendix.

Proposition 1 *Consider model (4). Suppose that the precision of the signals conveyed by connections and the bias from favors depend in an arbitrary way on connections and on other observable characteristics of candidates. Then, favors and information effects cannot be identified from data on promotion only.*

We now derive our main result. We show that identification holds under mild restrictions on bias and excess variance. We consider two types of restrictions: exclusion restrictions and parametric assumptions.

Theorem 1 *Consider model (4).*
(Exclusion restriction). Suppose that characteristic k leaves σ and B unaffected and that $\beta_k \neq 0$. Then, the model is identified and the functions $\sigma(n_{iS}, n_{iW}, \mathbf{x}_i^{-k})$ and $B(n_{iS}, n_{iW}, \mathbf{x}_i^{-k})$ are non-parametrically identified.
(Linearity). Suppose that $\ln(\sigma(n_{iS}, n_{iW}, \mathbf{x}_i)) = \delta(n_{iS}, n_{iW})\mathbf{x}_i$ and $B(n_{iS}, n_{iW}, \mathbf{x}_i) = \gamma_0(n_{iS}, n_{iW}) + \gamma_1(n_{iS}, n_{iW})\mathbf{x}_i$, with $\gamma_0(0, 0) = 0$ and $\delta(0, 0) = \gamma_1(0, 0) = \mathbf{0}$. Then, the model is identified

and the functions $\delta(n_{iS}, n_{iW})$, $\gamma_0(n_{iS}, n_{iW})$ and $\gamma_1(n_{iS}, n_{iW})$ are non-parametrically identified.

To see why the first part of Theorem 1 holds, suppose that σ and B do not depend on x_i^k. From data on the unconnected, we can recover β_k, the direct effect of x_i^k on grade, and $\sigma_v(.)$. Focus, then on candidates with number of connections n_{iS} and n_{iW} and with other characteristics $\mathbf{x}_i^{-k}$. From data on these candidates, we can recover the heteroscedasticity-corrected impact of x_i^k on grade, equal to $\beta_k/\sigma(n_{iS}, n_{iW}, \mathbf{x}_i^{-k})$. If $\beta_k \neq 0$, we obtain $\sigma(n_{iS}, n_{iW}, \mathbf{x}_i^{-k})$. The bias $B(n_{iS}, n_{iW}, \mathbf{x}_i^{-k})$ can then be obtained as the difference in inferred promotion thresholds between unconnected candidates and candidates with ties n_{iS} and n_{iW} and characteristics $\mathbf{x}_i^{-k}$.

Therefore, our identification strategy operates as long as one exclusion restriction is present in the model. As with instrumental variables, the excluded variable should have a direct impact on the unconnected likelihood to be promoted and should not directly affect the precision of the signals conveyed by connections nor the bias from favors they may generate. In particular, a model where excess variance and bias from favors depend on connections but not on other observables is identified. We estimate several variants of such models in the empirical analysis below.

Even without exclusion restrictions, the model can still be identified thank to functional form assumptions. The second part of Theorem 1, proved in Appendix, shows that this notably holds when excess variance is log linear in observables while bias is an affine function of observables. In this case, again, dependence on connections can be arbitrary and is fully identified. To achieve non-parametric identification in practice may of course require a very large number of observations. In the empirical analysis below, we adopt standard parametric assumptions on the way $\ln(\sigma)$ and B vary with connections and observables. All models estimated in Section VI are covered by Theorem 1.

IV Data

We apply our framework to the data on academic promotions in Spain assembled and studied by Zinovyeva & Bagues (2015). We describe the main features of the data here and refer to their study for details. From 2002 to 2006, academics in Spain seeking promotion to Associate Professor (*profesor titular*) or Full Professor (*catedrático*) first had to qualify in a national exam (*habilitaćion*). All candidates in the same discipline in a given wave were evaluated by a common jury composed of 7 members. The jury had to allocate a predetermined number of positions. These exams were highly competitive and obtaining the national qualification essentially ensured promotion. A central feature of this system was that jury members were picked at random from a pool of eligible evaluators. The random draw was actually carried out by Ministry officials using urns and balls. The data contains information on all candidates to academic promotion during that period, their connections to eligible evaluators and to jury members, and their success or failure in the national exam.

Overall, there are 31,243 applications to 967 exams: 17,799 applications to 465 exams for Associate Professor (AP) positions and 13,444 to 502 exams for Full Professor (FP) positions. We have information on candidates' demographics and academic outcomes at time of application. Observable characteristics include gender, age, whether the candidate obtained his PhD in Spain, the number of publications, the number of publications weighted by journal quality, the number of PhD students supervised, the number of PhD committees of which the candidate had been a member, and the number of previous attempts at promotion. Table 1 provides descriptive statistics. Standards regarding research outputs may of course differ between disciplines. To analyze applications in a common framework, we follow Zinovyeva & Bagues (2015) and normalize research indicators to have mean 0 and variance 1 within exams.[10] The data also contain information on six types of links between candidates and evaluators. We adopt Zinovyeva & Bagues (2015)'s classification of these links in strong and weak ties.[11] A candidate is said to have strong ties to his

[10] We also normalize age and past experience to have mean 0 within exams.

[11] The data also contains information on indirect connections, for instance when a candidate and an evaluator have a common member on their PhD committees. Zinovyeva & Bagues (2015) do not find any

Table 1: Descriptive statistics: Observables

	All	AP	FP	Eng.	H&L	Sci.	Soc. Sci.
Female	0.34	0.40	0.27	0.21	0.45	0.30	0.39
	(0.47)	(0.49)	(0.44)	(0.41)	(0.50)	(0.46)	(0.49)
Age	41.21	37.49	46.14	38.74	41.86	41.97	40.39
	(7.59)	(6.41)	(6.06)	(7.07)	(7.62)	(7.55)	(7.54)
PhD in Spain	0.78	0.83	0.70	0.83	0.77	0.76	0.78
	(0.42)	(0.37)	(0.46)	(0.38)	(0.42)	(0.43)	(0.42)
Past Experience	0.81	0.73	0.91	0.85	0.63	0.89	0.88
	(1.27)	(1.27)	(1.26)	(1.36)	(0.94)	(1.40)	(1.30)
Publications	12.84	8.12	19.09	7.76	11.45	16.99	9.22
	(18.31)	(14.06)	(21.18)	(12.88)	(11.39)	(24.10)	(11.61)
AIS	0.72	0.70	0.74	0.52	-	0.80	0.62
	(0.53)	(0.57)	(0.48)	(0.37)	-	(0.51)	(0.75)
PhD Students	1.00	0.24	2.00	0.83	0.61	1.45	0.66
	(2.11)	(0.88)	(2.75)	(1.61)	(1.63)	(2.60)	(1.58)
PhD Committees	3.61	0.88	7.23	2.40	3.04	4.81	2.67
	(6.76)	(2.55)	(8.65)	(4.42)	(5.99)	(8.21)	(4.99)
Observations	31243	17799	13444	4783	9005	12858	4597

Notes: Average values of the observable characteristics at the time of exam. Standard deviation in parentheses. FP and AP stand for exams for Full Professor and Associate Professor positions respectively. Eng., H&L, Sci., and Soc. Sci. are abbreviations for Engineering, Humanities and Law, Sciences, and Social Sciences, which are 4 broad scientific areas in our sample. AIS is the sum of international publications weighted by corresponding Article Influence Scores. The table partially replicates Table 2 in Zinovyeva & Bagues (2015).

PhD advisor, to his coauthors and to his colleagues. He has weak ties with members of his PhD committee, with members of the PhD committees of his PhD students and with other members of the PhD committees of which he was a member.[12] Overall, 34.8% of candidates end up having at least one strong connection with a member of their jury and 20.6% have at least one weak connection. Table 2 provides further information on connections.

effect of indirect connections and we do not include them in our analysis.

[12]A connection which is both strong and weak is classified as strong.

Table 2: Descriptive statistics: Connections

	All	AP	FP	Eng.	H&L	Sci.	Soc. Sci.
Strong connections	31.71	29.08	35.18	37.78	27.65	31.13	34.94
Advisor	3.17	2.97	3.43	4.60	3.29	2.43	3.50
Coauthor	5.44	3.26	8.32	6.10	2.84	7.44	4.24
Colleague	29.71	27.74	32.31	36.02	26.15	28.50	33.46
Weak connections	18.79	7.33	33.97	17.06	23.63	16.43	17.71
PhD committee member	7.08	5.31	9.43	8.05	10.22	4.39	7.48
PhD committee of his PhD student	4.45	0.69	9.42	4.70	4.81	4.27	3.96
Same PhD committee member	11.65	1.82	24.66	8.84	13.90	11.59	10.31

Notes: The percentage of candidates with at least one connection to the jury. The table partially replicates Table 3 in Zinovyeva & Bagues (2015).

V Empirical Implementation

We now apply our identification strategy to the data on academic promotions in Spain. We discuss three key features of the empirical implementation: the random assignment of evaluators; the exam-specific promotion thresholds; and the specific models being estimated.

A Random assignment of jury members

Our identification result, Theorem 1, relies on the assumption that the distribution of unobservables for candidates with connections (n_{iS}, n_{iW}) does not depend (n_{iS}, n_{iW}). In the data, random assignment of jury members ensures that this holds *conditionally on the expected number of connections to the jury.* That is, candidates may vary in the extent of their connections to eligible evaluators. From the number of eligible evaluators and the numbers of weak and strong ties to eligible evaluators, we can simply compute the expected number of actual connections of the candidate to the jury. Conditional on these expected numbers, actual numbers of connections are random. We present the corresponding balance tests in Table 3.[13] Controlling for candidates' expected numbers of connections, we do not find significant correlations between observable characteristics and actual number of

[13]To be consistent with our main regressions, we run balance tests conditioning directly on the expected numbers of connections. By contrast, Zinovyeva & Bagues (2015) control for expected connections through an extensive set of dummies, see Table 4 p.278. Incorporating these dummies raise computational issues in our non-linear setup. Results from Table 1 show that even in a simple linear formulation, actual connections are uncorrelated with observable characteristics.

Table 3: Balance tests

	AIS	Publications	PhD students	PhD committees	Past experience
	Without controls for the expected number of connections				
Strong	0.009	0.010	-0.017^{***}	-0.012^{*}	0.009
	(0.007)	(0.007)	(0.006)	(0.007)	(0.008)
Weak	0.007	0.051^{***}	0.180^{***}	0.298^{***}	0.027^{***}
	(0.007)	(0.008)	(0.010)	(0.011)	(0.007)
	Including controls for the expected number of connections				
Strong	-0.001	-0.011	0.002	-0.006	-0.004
	(0.010)	(0.011)	(0.010)	(0.010)	(0.012)
Weak	-0.005	-0.008	0.013	0.010	0.003
	(0.011)	(0.013)	(0.016)	(0.016)	(0.012)
Observations	31243	31243	31243	31243	31243

Notes: Results of 10 regressions of observables (columns) on the number of strong and weak connections to the jury (rows). In regressions in the upper panel we do not control for the expected number of connections. Regressions in lower panel include controls for the expected number of strong connections to the jury and the expected number of weak connections to the jury. OLS estimates. Standard errors clustered on the exam level are in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

connections. Therefore, a conditional version of Theorem 1 holds in this context. The probability to be promoted for unconnected $p(y_i = 1 | n_{iS} = n_{iW} = 0, En_{iS}, En_{iW}, \mathbf{x}_i)$, excess variance due to better information $\sigma(n_{iS}, n_{iW}, En_{iS}, En_{iW}, \mathbf{x}_i)$ and bias from favors $B(n_{iS}, n_{iW}, En_{iS}, En_{iW}, \mathbf{x}_i)$ may depend on the expected numbers of connections to the jury. Under the assumptions underlying Theorem 1, the conditional information and favor effects are identified. Note that the expected numbers of connections represent measures of social capital, built from information available to the jury. In the empirical analysis we therefore simply include them in the set of candidates' characteristics observable to the jury.

B Exam-specific promotion thresholds

Our approach relies on exam-specific promotion thresholds. This is an important element since the bias from favors is identified from differences in promotion thresholds between connected and unconnected candidates. We consider two ways to account for exam-specific thresholds empirically: exam fixed effects a_e and exam grouped effects $a_e = \mathbf{z}_e\mathbf{a}$, where $\mathbf{z}_e$ is a vector of exam-level characteristics. A first approach is to include a full set of exam fixed effects. In practice, regressions then include 967 exam dummies. While exam fixed effects impose, in principle, less restrictions, they raise several problems in practice. They may not be identified for exams with small numbers of candidates, due to full predictability. They raise computational difficulties caused by the high dimensionality of the non-linear optimization problem to be solved in the estimations. And in circumstances where grouped effects are appropriate, estimations based on fixed effects may be inefficient.

Alternatively, we consider exam grouped effects as in Bester & Hansen (2016). We allow promotion thresholds to depend on type, area and wave fixed effects - leading to 72 dummies in total - and on the number of candidates, the number of positions, the proportion of filled positions and the proportion of unconnected candidates. This model is of course nested in the model with exam fixed effects and we can then test whether it leads to a significant loss in explanatory power.

C Econometric model

In the empirical analysis, we estimate different specifications of model (4). The general model features three key ingredients: baseline heteroscedasticity $\sigma_v(\mathbf{x}_i)$, excess variance from better information $\sigma(n_{iS}, n_{iW}, \mathbf{x}_i)$ and bias from favors $B(n_{iS}, n_{iW}, \mathbf{x}_i)$. Note that the first two elements are closely related, since $\sigma_v(\mathbf{x}_i)\sigma(n_{iS}, n_{iW}, \mathbf{x}_i)$ represents the variance of the latent errror for candidates with connections n_{iS}, n_{iW} and characteristics $\mathbf{x}_i$.

We adopt a standard formulation for baseline heteroscedasticity, see Woolridge (2010). We assume that the logarithm of the variance of v_i, the determinant of ability of unconnected candidates observed by the jury but not by the econometrician, is a linear function of observable characteristics:

$$\sigma_v(\mathbf{x}_i) = \exp(\delta \mathbf{x}_i) \tag{5}$$

and where the constant is excluded from the x_i's. To gain in statistical and computational efficiency, we do not include all characteristics in σ_v in our preferred specification. We present our estimation procedure in Appendix.

We model information effects by building on this heteroscedasticity formulation. We consider increasingly complex specifications: (1) constant information effects $\sigma(n_{iS}, n_{iW}, \mathbf{x}_i) = \exp(\delta_c)$ if $n_{iS} + n_{iW} \geq 1$; (2) information effects depending on numbers and types of links: $\sigma(n_{iS}, n_{iW}, \mathbf{x}_i) = \exp(\delta_S n_{iS} + \delta_W n_{iW})$; and (3) information effects depending on numbers and types of links as well as other observable characteristics: $\sigma(n_{iS}, n_{iW}, \mathbf{x}_i) = \exp[(\delta_S \mathbf{x}_i) n_{iS} + (\delta_W \mathbf{x}_i) n_{iW}]$. Thus, each new strong tie with the jury increases latent error variance by $\exp(\delta_S)$ in formulation (2) and by $\exp(\delta_S \mathbf{x}_i)$ in formulation (3). These assumptions allow us to study the determinants of the variance of the latent error in a common, coherent framework. In addition, observe that formulation (3) can be obtained as the first element of the Taylor approximation of $\ln(\sigma(n_{iS}, n_{iW}, \mathbf{x}_i)/\sigma_v(\mathbf{x}_i))$ with respect to n_{iS}, n_{iW} and $\mathbf{x}_i$, for any function σ.

We also model increasingly complex specifications of the bias from favors: (1) constant bias: $B(n_{iS}, n_{iW}, \mathbf{x}_i) = B$ if $n_{iS} + n_{iW} \geq 1$; (2) bias depending on the numbers and types of links, linearly: $B(n_{iS}, n_{iW}, \mathbf{x}_i) = \gamma_S n_{iS} + \gamma_W n_{iW}$, or in a quadratic way: $B(n_{iS}, n_{iW}, \mathbf{x}_i) = \gamma_{1S} n_{iS} + \gamma_{2S} n_{iS}^2 + \gamma_{1W} n_{iW} + \gamma_{2W} n_{iW}^2 + \gamma_{SW} n_{iS} n_{iW}$; and (3) bias depending on connections and other observables: $B(n_{iS}, n_{iW}, \mathbf{x}_i) = (\gamma_{0S} + \gamma_S \mathbf{x}_i) n_{iS} + (\gamma_{0W} + \gamma_W \mathbf{x}_i) n_{iW} + \gamma_{2S} n_{iS}^2 + \gamma_{2W} n_{iW}^2 + \gamma_{SW} n_{iS} n_{iW}$. Quadratic terms help capture decreasing marginal impacts of additional links. For instance in the quadratic variant of formulation (2), a new strong tie with the jury increases bias by $\gamma_{1S} + \gamma_{2S}$ for an unconnected candidate and by $\gamma_{1S} + 3\gamma_{2S}$ for a candidate who already had one strong tie.

VI Empirical Analysis

A Main results

We develop our empirical analysis in three stages. We first estimate a version of the simple model discussed in Section II, where the extent of information and favors are constant. We then account for the number and types of links, holding both effects independent of observables. Finally, we estimate a model with full dependence on links and observables.

We first examine the impact of having at least one connection of any kind to the jury. We estimate constant favors and information effects, accounting for baseline heteroscedasticity.

Denote by c_i the connection dummy: $c_i = 1$ if $n_{iS} + n_{iW} \geq 1$ and 0 otherwise. We thus estimate the following model.

$$p(y_i = 1|\mathbf{x}_i, c_i) = \Phi[(\mathbf{x}_i\beta + Bc_i - a_e)\exp[-(\delta\mathbf{x}_i + \delta_c c_i)]] \tag{6}$$

We consider grouped exam effects in our main regressions, and justify this choice in Section VI.B. Results of the estimation of Model (6) are reported in Table 4.

Table 4: Binary connections: Model (6)

	(All)	(AP)	(FP)
Bias (connected)	0.179***	0.208**	0.227**
	(0.055)	(0.084)	(0.091)
Information (connected)	0.174***	0.245***	0.072
	(0.055)	(0.069)	(0.090)
Observations	31243	17799	13444

Notes: All specifications include controls for the full set of observable characteristics, expected number of connections of each type, and the baseline heteroskedasticity. Heteroskedastic probit estimates. Exam grouped effects. Standard errors clustered on the exam level are in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

On the whole sample, both the estimated bias from favors B and the estimated information effect δ_c are positive and statistically significant. They are also both positive and significant when estimated on promotions to Associate Professor. By contrast, we detect favors but no information effect on promotions to Full Professor. Thus, connected candidates appear to face lower promotion thresholds at both levels and connected candidates to Associate Professor have excess variance in their latent errors. In other words, observable characteristics have lower power to explain promotion decisions in their case.[14]

Are these effects quantitatively significant? How much do connections help? And how much each motive contributes to the overall impact? To answer these questions, we compute for each candidate the predicted impact of a change in his connection status. We focus, for clarity, on unconnected candidates with at least one link to potential evaluators. These computations could easily be replicated on other subsamples. Consider, then, un-

[14]For clarity, we do not report estimates of the impact of candidates' and exams' characteristics on promotion (β) and on baseline variance (δ) in the Tables.

connected candidate i. Model (6) can be used to predict how much i's probability to be promoted would change if i became connected. Denote estimated coefficients with hats. The difference in predicted promotion probabilities is equal to:

$$
\begin{aligned}
\Delta p_i/\Delta c_i &= p(y_i=1|\mathbf{x}_i, c_i=1) - p(y_i=1|\mathbf{x}_i, c_i=0) \\
\Delta p_i/\Delta c_i &= \Phi[(\mathbf{x}_i\hat{\beta} + \hat{B} - \hat{a}_e)\exp[-(\hat{\delta}\mathbf{x}_i + \hat{\delta}_c)]] - \Phi[(\mathbf{x}_i\hat{\beta} - \hat{a}_e)\exp[-(\hat{\delta}\mathbf{x}_i)]]
\end{aligned}
$$

We can further decompose the overall impact of a change in connection status in two parts: one due to favors $[\Delta p_i/\Delta c_i]^F = \Phi[(\mathbf{x}_i\hat{\beta} + \hat{B} - \hat{a}_e)\exp[-(\hat{\delta}\mathbf{x}_i)]] - \Phi[(\mathbf{x}_i\hat{\beta} - \hat{a}_e)\exp[-(\hat{\delta}\mathbf{x}_i)]]$ and another due to information $[\Delta p_i/\Delta c_i]^I = \Phi[(\mathbf{x}_i\hat{\beta} + \hat{B} - \hat{a}_e)\exp[-(\hat{\delta}\mathbf{x}_i + \hat{\delta}_c)]] - \Phi[(\mathbf{x}_i\hat{\beta} + \hat{B} - \hat{a}_e)\exp[-\hat{\delta}\mathbf{x}_i]$.[15] Thus, $\Delta p_i/\Delta c_i = [\Delta p_i/\Delta c_i]^F + [\Delta p_i/\Delta c_i]^I$.[16] Finally, we compute the averages of these values over all individuals in the sample.

We depict the results of these counterfactual computations in Table 5 and Figure 2. The Table reports averages of initial predicted probability (first column), the average predicted change in promotion probability due to connection (second column), the part of this change due to information (third column) and the part to due to favors (fourth column). Thus, an unconnected candidate with some link to potential evaluators only has, on average, a 0.08 chance to be promoted, reflecting the highly competitive nature of these promotions. Getting, by luck, connected to the jury leads to a relative increase in the promotion probability of 80%. This relative impact is higher for candidates at the Associate Professor level (+91%) than for candidates at the Full Professor level (+76%).[17] The larger part of this effect is due to information for AP candidates (63% of the total impact). By contrast, favors is the main determinant of this impact for FP candidates (71% of the total impact). Overall, these numbers provide a quantitative picture of the impact of connections. Getting connected to the jury almost doubles the chances to obtain the promotion. Consis-

[15] We assume that the exam's promotion threshold a_e is not affected by the change in connection status of candidate i.

[16] There are two ways to decompose the overall effect in two parts. Due to non-linearities, these two ways may not be equivalent. In practice they yield similar results, however, and we only present results from the decomposition described in the text.

[17] To compute the impact of connectedness for a subsample, we rely on estimates of Model (6) for this subsample as presented in Table 4.

Table 5: Marginal effect of connections: Model (6)

	Baseline	Marginal effect		
	Predicted	Total	Information	Bias
All	0.080	0.064	0.035	0.029
	(0.069)	(0.023)	(0.008)	(0.019)
AP	0.088	0.080	0.050	0.030
	(0.072)	(0.024)	(0.011)	(0.019)
FP	0.063	0.048	0.014	0.034
	(0.058)	(0.024)	(0.003)	(0.022)

Notes: Average marginal effect of being connected calculated for unconnected candidates with at least one connection to potential evaluators. Standard deviation of the effect is in the parenthesis.

tently with the estimation results, favors appear to dominate for FP candidates while the information effect dominates for AP candidates. Figure 2 then depicts how the change in predicted probability $\Delta p_i/\Delta c_i$, and its two components $[\Delta p_i/\Delta c_i]^F$ and $[\Delta p_i/\Delta c_i]^I$ vary with predicted probability $p_i = \Phi[(\mathbf{x}_i\hat{\beta} - \hat{a}_e)\exp[-(\hat{\delta}\mathbf{x}_i)]]$. We see that $[\Delta p_i/\Delta c_i]^I$ has an inverted U-shape, reaching a maximum for p_i close to 0.1 and becoming negative for high values of p_i. By contrast, $[\Delta p_i/\Delta c_i]^F$ is initially increasing over a larger range and only decreases - when it does - for high values of p_i. These qualitative patterns are consistent with Figure 1. In particular, and as discussed in Section III, better information on candidates appears to lower the promotion probabiltiy of candidates with very good CVs. On average for these candidates, the impact of bad news dominates the impact of good news. Overall, $\Delta p_i/\Delta c_i$ displays a clear inverted U shape for AP candidates, reaching a maximum around p_i equal to 0.2, due to the key role of the information effect. By contrast, FP candidates with better observable characteristics benefit more from being connected to the jury.

We next assume that the bias from favors and the information effect may depend on the number and types of links. We estimate a model with linear bias and log-linear variance:

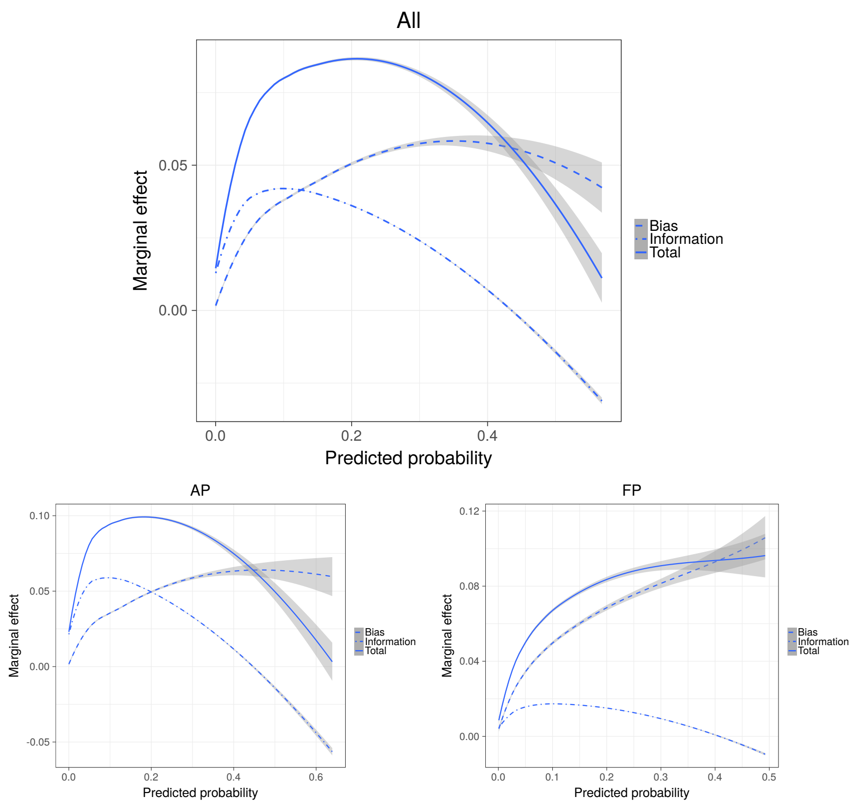
$$p(y_i = 1|\mathbf{x}_i, n_{iS}, n_{iW}) = \Phi[(\mathbf{x}_i\beta + \gamma_S n_{iS} + \gamma_W n_{iW} - a_e)\exp[-(\delta\mathbf{x}_i + \delta_S n_{iS} + \delta_W n_{iW})]] \quad (7)$$

as well as a model with quadratic bias and log-linear variance:

$$p(y_i = 1|\mathbf{x}_i, n_{iS}, n_{iW}) = \Phi[(\mathbf{x}_i\beta + \gamma_{1S}n_{iS} + \gamma_{2S}n_{iS}^2 + \gamma_{1W}n_{iW} + \gamma_{2W}n_{iW}^2 + \gamma_{SW}n_{iS}n_{iW} - a_e)\exp[-(\delta\mathbf{x}_i + \delta_S n_{iS} + \delta_W n_{iW})] \tag{8}$$

Results are reported in Table 6. In the Left panel we report estimation results from Model (7). On the whole sample, the bias and information effects from strong ties are both positive and significant; they are positive but insignificant for weak ties. For Full Professor applications, we detect favors and information effects from strong ties and, in addition, favors from weak ties. For Associate Professor applications, we do not detect favors in this specification; we do detect strongly significant and positive information effects for both strong and weak ties. Note that in general, the effects of weak ties tend to be imprecisely

Figure 2: Marginal effect of being connected: Decomposition



Notes: Nonparametric fit using LOESS method. The grey region depicts 95% confidence intervals. Plots are constructed using estimated model (6) on subsamples indicated above each plot.

estimated on the subsample of AP applications. This is due to the fact that candidates at this level have, on average, relatively few weak ties (see Table 2). In the Right panel of Table 6, we report estimation results from Model (8). Quadratic effects in bias matter and change overall estimation results. At the FP level, we now do not detect any information effect. By contrast, we still detect favors from both strong and weak ties. In addition, the marginal impact of an additional tie on the promotion threshold is decreasing in both cases. At the AP level, we now detect favors from strong ties and the bias is also increasing and concave in the number of ties. Information effects for both kinds of ties are positive and significant, and particularly so for weak ties.

Table 6: Estimation of Model (7) and Model (8)

	(All)	(AP)	(FP)	(All)	(AP)	(FP)
				Bias		
n_S	0.123***	0.071	0.120*	0.287***	0.309***	0.235***
	(0.047)	(0.070)	(0.068)	(0.047)	(0.072)	(0.061)
n_S^2				−0.051***	−0.065***	−0.036***
				(0.008)	(0.014)	(0.006)
n_W	0.038	−0.338	0.141**	0.096	−0.170	0.238***
	(0.069)	(0.230)	(0.058)	(0.073)	(0.280)	(0.067)
n_W^2				−0.026*	−0.293	−0.028***
				(0.014)	(0.240)	(0.010)
$n_S \times n_W$				0.018	0.157	−0.011
				(0.025)	(0.121)	(0.021)
				Information		
n_S	0.157***	0.240***	0.142**	0.092**	0.137***	0.095
	(0.044)	(0.055)	(0.064)	(0.040)	(0.051)	(0.061)
n_W	0.077	0.436***	−0.045	0.065	0.519***	−0.095
	(0.068)	(0.150)	(0.059)	(0.065)	(0.153)	(0.061)
Observations:	31243	17799	13444	31243	17799	13444

Notes: Estimation of Model (7) - Left panel, and Model (8) - Right panel. All specifications include controls for the full set of observable characteristics, expected number of connections of each type, and the baseline heteroskedasticity. Heteroskedastic probit estimates. Exam grouped effects. Standard errors clustered on the exam level are in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

To sum up, strong connections to the jury lower the promotion threshold effectively faced by connected candidates. This impact is increasing in the number of strong ties at a decreasing rate. For applications to Full Professor, weak connections to the jury also lower the promotion threshold in a similar way. For applications to Associate Professor, we face a problem of statistical power caused by the relatively low number of weak ties. Both kinds of ties also appear to convey better information on candidates at the AP level. By contrast, we do not detect robust information effects at FP level.

We next present the outcomes of counterfactual computations on the impact of connections in Table 7, based on Model (8). We now focus on unconnected candidates who have at least one strong tie and one weak tie to potential evaluators. For each such candidate, we compute the predicted promotion probability and the predicted increase in promotion probability caused by obtaining, by luck, one strong or weak connection to the jury. We also provide decompositions of these impacts into parts due to better information and to favors. We then average over all candidates in the subsample. We see that one strong tie increases the promotion probability by 74% for AP candidates and by 72% for FP candidates. By contrast, one weak tie increases the promotion probability by 51% for AP candidates and by 22% for FP candidates. Thus, strong ties have higher predicted impacts than weak ties. For FP candidates, favors dominate, quantitatively, for both weak and strong ties. For AP candidates, favors dominate for strong ties and information effects dominate for weak ties, consistently with the estimation results.

Table 7: Marginal effect of connections: Model (8)

	Baseline	Marginal effect					
	Predicted	Total		Information		Bias	
		Strong	Weak	Strong	Weak	Strong	Weak
All	0.082	0.060	0.023	0.019	0.012	0.041	0.011
	(0.068)	(0.026)	(0.009)	(0.004)	(0.003)	(0.024)	(0.007)
AP	0.091	0.067	0.046	0.028	0.092	0.039	-0.046
	(0.072)	(0.025)	(0.023)	(0.006)	(0.026)	(0.023)	(0.031)
FP	0.068	0.049	0.015	0.019	-0.017	0.030	0.033
	(0.058)	(0.021)	(0.017)	(0.004)	(0.005)	(0.018)	(0.020)

Notes: Average marginal effects of strong and weak connections calculated for unconnected candidates with at least one strong connection and one weak connection to potential evaluators. Standard deviation of the effect is in the parenthesis.

These results essentially conform to intuition. We would a priori expect strong ties to induce favors. We would also expect uncertainty on candidates' true ability to be stronger at the Associate Professor level, consistently with the stronger information effects detected at that level. The fact that weak ties generate stronger information effects is also consistent with the classical view of the role played by weak ties in information transmission Granovetter (1973). One finding that is, perhaps, surprising is the fact that weak ties appear to generate favors at the Full Professor level. Note that candidates at that level have been in the academic system for a relatively long time. They have likely had more opportunities to initiate favor exchange. Overall, these findings indicate that the Spanish academic system was likely subject to generalized favoritism.

These results are also consisent with - and help sharpen - the findings of Zinovyeva & Bagues (2015, Section IV.D.) derived from data collected 5 years after promotion. They find that research outcomes after promotion are lower for promoted candidates with strong ties than for promoted candidates without, considering the whole sample and controlling for observables at time of promotion. Promoted candidates with strong ties publish less, in lower quality journals, supervise less PhD students and participate in less PhD committees. Authors state: "Our preferred interpretation of the empirical evidence is that candidates with a strong connection may have enjoyed preferential treatment, which overshadows the potential informational advantages of strong links." By contrast, weak ties to the jury do not yield detectable differences in research outcomes of promoted candidates. For AP candidates, promoted candidates with weak ties are more likely to eventually be promoted to full professor than promoted candidates without weak ties.

Our empirical results, obtained from promotion data only, are consistent with these findings. On the whole sample, we clearly detect favors from strong ties. For AP candidates, we also detect information effects from weak ties. In addition, our method allow us to deepen the empirical analysis. We can detect both effects and precisely quantify their respective roles. We find, in particular, evidence of information effects from strong ties on the whole sample and no evidence of favors associated with weak ties for AP candidates.

Finally, we assume that the bias from favors and the excess variance due to better information may depend on observables. We estimate the following model:

$$p(y_i = 1|\mathbf{x}_i, n_{iS}, n_{iW}) = \Phi[(\mathbf{x}_i\beta + (\gamma_{0S} + \gamma_S\mathbf{x}_i)n_{iS} + (\gamma_{0W} + \gamma_W\mathbf{x}_i)n_{iW} + \gamma_{2S}n_{iS}^2 + \gamma_{2W}n_{iW}^2 + \gamma_{SW}n_{iS}n_{iW} - a_e)\exp[-(\delta\mathbf{x}_i + (\delta_S\mathbf{x}_i)n_{iS} + (\delta_W\mathbf{x}_i)n_{iW})]] \tag{9}$$

We present estimation results in the Appendix, see Table A1 for AP candidates and Table A2 for FP candidates. A positive coefficient of the impact of some characteristic on bias means that favors due to connections tend to be stronger for candidates with higher values of this characteristic. Similarly, a positive coefficient on the information effect means that excess variance, and hence the quality of the extra information brought about by an additional connection, is higher for these candidates. Results are rich and complex and confirm that we can detect variations in the effects of connections. For instance, AP candidates having obtained their PhD in Spain appear to have higher information effects from both weak and strong ties and lower bias from weak ties. Results on information are consistent with the idea that having obtained a PhD abroad provides an informative signal on a candidate's ability. We present counterfactual computations obtained from Model (9) in Table 8. Comparing with Table 7, we see that predicted probabilities are quantitatively similar.

Table 8: Marginal effect of connections: Model (9)

	Baseline	Marginal effect					
	Predicted	Total		Information		Bias	
		Strong	Weak	Strong	Weak	Strong	Weak
AP	0.090	0.078	0.055	0.032	0.066	0.047	-0.012
	(0.067)	(0.037)	(0.052)	(0.021)	(0.067)	(0.030)	(0.044)
FP	0.066	0.058	0.017	0.011	-0.003	0.047	0.020
	(0.056)	(0.036)	(0.027)	(0.025)	(0.039)	(0.028)	(0.026)

Notes: Average marginal effects of strong and weak connections calculated for unconnected candidates with at least one strong connection and one weak connection to potential evaluators. Standard deviation of the effect is in the parenthesis.

The average marginal impacts of gaining one strong or weak link to the jury for unconnected candidates appear to be slightly lower under Model (9) than under Model (8). This means that unconnected candidates have, on average, observable characteristics for which connections' impacts are slightly weaker. Strong ties still have higher predicted impacts than weak ties. And the relative quantitative importance of the two factors is robust. Favors dominate for strong and weak ties at the FP level and for strong ties at the AP level. By contrast, information effects dominates for weak ties at the AP level.

B Robustness

In this section, we explore variations in the specification of two important features of the econometric model: exam-specific promotion thresholds and baseline variance. First, we contrast estimations with exam fixed effects a_e and exam grouped effects $a_e = \mathbf{z}_e\mathbf{a}$. We compare estimation results of Model (6) under the two specifications in Table 9. The first

Table 9: Exam fixed effects vs. Exam grouped effects: Model (6)

	All		AP		FP	
	FE	GE	FE	GE	FE	GE
Bias	0.304***	0.179***	0.074	0.208**	0.356***	0.227**
	(0.088)	(0.055)	(0.078)	(0.084)	(0.097)	(0.091)
Information	0.166***	0.174***	0.375***	0.245***	0.013	0.072
	(0.053)	(0.055)	(0.064)	(0.069)	(0.065)	(0.090)
LogLik	-9766.6	-9965.2	-5773.2	-5847.3	-3931.7	-4064.9
df	989	98	486	61	523	61
LR	-	396.68	-	148.13	-	266.37
Observations	31243	31243	17799	17799	13444	13444

Notes: The row LR reports the value of LR statistics of comparison of the restricted model (GE) and the unrestricted model (FE) in the preceding column. Heteroskedastic probit estimates. Standard errors clustered on the exam level are in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

column reports results of fixed effects estimations; the second column duplicates the results from Table 4. We see that the sign and statistical significance of both effects are similar for both specifications on the whole sample and on the subsample of FP candidates. On AP candidates, the information effect also has similar sign and significance. Bias from favors is positive and significant in the restricted model but positive and insignificant in the unrestricted model. Results from likelihood ratio tests show that we cannot reject the hypothesis that the grouped effects specification describes the data as well as the one with fixed effects, on each subsample as well as on the whole sample. We therefore consider grouped effects in our main regressions.

Second, we consider different specifications of baseline variance $\sigma_v(\mathbf{x}_i)$. We contrast estimations under homoscedasticity, when all individual characteristics are included, and when a subset of characteristics are included, as described in the Appendix. Results are depicted in Table 10 for Model (6) and Table 11 in Model (7). We see that the sign and statistical significance of the main effects are essentially similar for the last two specifications on the whole sample and on each subsample. Likelihood ratio tests also show that we cannot reject the hypothesis that the parsimonious specification describes the data as well as the full-fledged specification, even on subsamples. By contrast, estimates of main effects differ under homoscedasticity and the homoscedastic specification is rejected by likelihood ratio test. This confirms the importance of properly accounting for baseline heteroscedasticity. For reasons of computational and statistical efficiency, we therefore adopt the more parsimonious heteroscedasticy specification in our main regressions.

Table 10: Robustness: Baseline heteroskedasticity: Model (6)

	All			AP			FP		
	Hom.	Preferred	Full	Hom.	Preferred	Full	Hom.	Preferred	Full
Bias	0.419***	0.179***	0.186***	0.398***	0.208**	0.173*	0.412***	0.227**	0.192***
	(0.058)	(0.055)	(0.064)	(0.076)	(0.084)	(0.095)	(0.096)	(0.091)	(0.072)
Information	−0.020	0.174***	0.177***	0.055	0.245***	0.267***	−0.052	0.072	0.060
	(0.052)	(0.055)	(0.058)	(0.066)	(0.069)	(0.077)	(0.083)	(0.090)	(0.089)
LogLik	-10052.3	-9965.2	-9958.8	-5906.0	-5847.3	-5844.4	-4089.6	-4064.9	-4059.6
df	88	98	109	52	61	69	52	61	69
LR	-	174.19***	12.72	-	117.53***	5.71	-	49.42***	10.62
Observations	31243	31243	31243	17799	17799	17799	13444	13444	13444

Notes: The row LR reports the value of LR statistics of comparison of the unrestricted model with the restricted model in the preceding column. Heteroskedastic probit estimates. Standard errors clustered on the exam level are in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table 11: Robustness: Baseline heteroskedasticity: Model (7)

	All			AP			FP		
	Hom.	Preferred	Full	Hom.	Preferred	Full	Hom.	Preferred	Full
Bias (strong)	0.221***	0.123***	0.128**	0.202***	0.071	0.055	0.236***	0.120*	0.066
	(0.037)	(0.047)	(0.051)	(0.052)	(0.070)	(0.067)	(0.051)	(0.068)	(0.061)
Bias (weak)	0.031	0.038	0.046	−0.093	−0.338	−0.369	0.085*	0.141**	0.135**
	(0.055)	(0.069)	(0.077)	(0.174)	(0.230)	(0.228)	(0.046)	(0.058)	(0.054)
Information (strong)	0.089***	0.157***	0.165***	0.124***	0.240***	0.250***	0.066	0.142**	0.182***
	(0.031)	(0.044)	(0.042)	(0.041)	(0.055)	(0.057)	(0.044)	(0.064)	(0.066)
Information (weak)	0.089**	0.077	0.074	0.280**	0.436***	0.471***	0.021	−0.045	−0.059
	(0.040)	(0.068)	(0.067)	(0.129)	(0.150)	(0.154)	(0.036)	(0.059)	(0.060)
LogLik	-10033.4	-9949.9	-9943.4	-5910.1	-5854.9	-5851.1	-4064.2	-4041.0	-4037.4
df	90	100	111	54	63	71	54	63	71
LR	-	166.91***	13.01	-	110.26***	7.70	-	46.34***	7.08
Observations	31243	31243	31243	17799	17799	17799	13444	13444	13444

Notes: The row LR reports the value of LR statistics of comparison of the unrestricted model with the restricted model in the preceding column. Heteroskedastic probit estimates. Standard errors clustered on the exam level are in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

VII Discussion and Conclusion

In this article, we propose a new method to identify favors and information in the impact of connections, building on earlier work on discrimination. Our method combines natural experiments and semi-structural modelling. It requires exogenous shocks on connections and only exploits information collected at time of promotion. We develop an econometric framework based on probit regressions with heteroscedasticity. Our method can thus be implemented using standard statistical softwares. We show that better information on connected candidates yields excess variance in latent errors. Differences in estimated variances between connected and unconnected candidates can be used to identify and quantify the information effect. Differences in estimated promotion thresholds can then be used to identify the bias due to favors. We apply our method to the data assembled and studied in Zinovyeva & Bagues (2015). Our empirical results are consistent with, and help sharpen, findings obtained from data collected five years after promotion.

Our framework relies on a number of assumptions and, in particular, latent error normality, deterministic favors and jury risk-neutrality. We next discuss the robustness of our approach to relaxing these assumptions. First, we conjecture that this method can be extended to non-normal latent errors. The fact that better private information leads to excess variance is quite general, as shown by Lu (2016). It could be interesting, in future research, to try and extend this framework to logit or even non-parametric regressions. Second, suppose that favors are stochastic. Bias from favors is the sum of a deterministic part and a stochastic part. If the stochastic part is independent of connections, our analysis and results goes through without modifications. This stochastic part is simply subsumed in the latent error. Our approach must be modified, however, if the bias' stochastic part is affected by connections. Current estimates of the information effect provide a lower bound of the true effect if bias variance decreases with connections and an upper bound if it increases with connections.

Third, consider a risk-averse jury. Risk aversion might lead the jury to promote a candidate with lower expected ability if the uncertainty on her ability is lower. In other words, the grade of candidates evaluated by a risk averse jury may contain a risk penalty. This may invalidate the identification of favors. Note that it also invalidates the identification of favors in studies based on quality measures. For instance, Zinovyeva & Bagues (2015)'s finding that promoted candidates with strong ties publish less in the 5 years after promotion could also be explained by risk aversion. Interestingly, however, we suspect that the identification of the information effect might be robust to risk aversion. Developing empirical methods to identify risk aversion, favors and information effects provides an interesting challenge for future research.

To sum up, our method exploits variations in latent error variance and in promotion thresholds with connections. We clarify the conditions under which these variations yield identification of favors and information in the impact of connections. Even in circumstances when identification does not hold, however, these estimates may contain valuable information on why connections matter.

Finally, it would be interesting to combine our method with quality measures. This could, potentially, yield more precise estimates of favors and information effects and also allow researchers to test critical assumptions, such as whether promotion indeed has the same impact on quality for connected and unconnected candidates.

APPENDIX A

Proof of Proposition 1 A model with bias $B(.)$ and excess variance $\sigma(.)$ and an alternative model with bias $B'(.)$ and $\sigma'(.)$ yield the same conditional probability to be hired $p(y_i = 1|n_{iS}, n_{iW}, \mathbf{x}_i)$ if

$$\frac{\mathbf{x}_i\beta + B(n_{iS}, n_{iW}, \mathbf{x}_i) - a_e}{\sigma_v(\mathbf{x}_i)\sigma(n_{iS}, n_{iW}, \mathbf{x}_i)} = \frac{\mathbf{x}_i\beta + B'(n_{iS}, n_{iW}, \mathbf{x}_i) - a_e}{\sigma_v(\mathbf{x}_i)\sigma'(n_{iS}, n_{iW}, \mathbf{x}_i)}$$

Therefore, for any functions $B(.)$, $B'(.)$ and $\sigma(.)$, a model based on $B(.)$ and $\sigma(.)$ and one based on $B'(.)$ and

$$\sigma'(n_{iS}, n_{iW}, \mathbf{x}_i) = \frac{\mathbf{x}_i\beta + B'(n_{iS}, n_{iW}, \mathbf{x}_i) - a_e}{\mathbf{x}_i\beta + B(n_{iS}, n_{iW}, \mathbf{x}_i) - a_e}\sigma(n_{iS}, n_{iW}, \mathbf{x}_i)$$

have the same empirical implications. QED.

Proof of Theorem 1 Consider first the classical Probit model with heteroscedasticity:

$$p(y_i = 1|\mathbf{x}_i) = \Phi[(a + \mathbf{b}\mathbf{x}_i)\exp(-\mathbf{c}\mathbf{x}_i)]$$

Let us show that this model is identified if $a\mathbf{b} \neq 0$.[18] Identification holds if the mapping from parameters to the population distribution of outcomes is injective. Consider two sets of parameters $a, \mathbf{b}, \mathbf{c}$ and $a', \mathbf{b}', \mathbf{c}'$ such that $\forall \mathbf{x} \in \mathbb{R}^k$, $\Phi[(a + \mathbf{b}\mathbf{x})\exp(-\mathbf{c}\mathbf{x})] = \Phi[(a' + \mathbf{b}'\mathbf{x})\exp(-\mathbf{c}'\mathbf{x})]$. We must show that $a = a'$, $\mathbf{b} = \mathbf{b}'$ and $\mathbf{c} = \mathbf{c}'$.

Applying Φ^{-1} yields: $\forall \mathbf{x}$, $(a + \mathbf{b}\mathbf{x})\exp(-\mathbf{c}\mathbf{x}) = (a' + \mathbf{b}'\mathbf{x})\exp(-\mathbf{c}'\mathbf{x})$. At $\mathbf{x} = \mathbf{0}$, this yields: $a = a'$. Next, take the derivative with respect to x_k and apply at $\mathbf{x} = \mathbf{0}$. This yields $b_k - ac_k = b'_k - ac'_k$. Observe also that b_k and b'_k must have the same sign. Indeed if $x_l = 0$ when $l \neq k$, then $(a + \mathbf{b}\mathbf{x})\exp(-\mathbf{c}\mathbf{x}) = (a + b_k x_k)\exp(-c_k x_k)$. As x_k goes from $-\infty$ to $+\infty$, the sign of this expression can vary in one of three ways: it goes from negative to positive if $b_k > 0$; it goes from positive to negative if $b_k < 0$; or it stays constant if $b_k = 0$.

Assume first that $a \neq 0$ and $\mathbf{b} \neq \mathbf{0}$. Consider k such that $b_k \neq 0$, for instance $b_k > 0$. Set $x_l = 0$ except if $l \neq k$. For any x_k large enough, $a + \mathbf{b}\mathbf{x} = a + b_k x_k > 0$. Taking logs yields: $\ln(a + b_k x_k) - c_k x_k = \ln(a + b'_k x_k) - c'_k x_k$. Take the derivative with respect to x_k: $b_k/(a + b_k x_k) - c_k = b'_k/(a + b'_k x_k) - c'_k$. Take the derivative twice more: $b_k^2/(a + b_k x_k)^2 = b_k'^2/(a + b'_k x_k)^2$ and $-2b_k^3/(a + b_k x_k)^3 = -2b_k'^3/(a + b'_k x_k)^3$. Since this holds for any x_k large enough, this must hold for any x_k. At $x_k = 0$, this yields: $b_k^3 = b_k'^3$ and hence $b_k = b'_k$ and $c_k = c'_k$. If $b_k = 0$, then $b'_k = 0$ and $c_k = c'_k$.

Assume next that $\mathbf{b} = \mathbf{0}$. Then $\mathbf{b}' = 0$ and $\forall \mathbf{x}$, $a\exp(-\mathbf{c}\mathbf{x}) = a\exp(-\mathbf{c}'\mathbf{x})$ and hence $\mathbf{c} = \mathbf{c}'$. Finally, if $a = 0$ and $b_k > 0$, then for any $x_k > 0$, $\ln(b_k x_k) - c_k x_k = \ln(b'_k x_k) - c'_k x_k$ and hence $\ln(b_k) - c_k x_k = \ln(b'_k) - c'_k x_k$. This implies that $b_k = b'_k$ and $c_k = c'_k$. Thus, $\mathbf{b} = \mathbf{b}'$ and $\mathbf{c}\mathbf{x} = \mathbf{c}'\mathbf{x}$ for any $\mathbf{x}$ such that $\mathbf{b}\mathbf{x} \neq 0$, which implies that $\mathbf{c} = \mathbf{c}'$.

Observe that injectivity and identification also hold if $\mathbf{x}$ belongs to an open set O of $\mathbb{R}^k$. The reason is that the function $\mathbf{x} \to (a + \mathbf{b}\mathbf{x})\exp(-\mathbf{c}\mathbf{x})$ is analytic and that two analytic functions which are equal on an open set must be equal everywhere. Therefore,

[18] If $a = 0$ and $\mathbf{b} = 0$, $\forall \mathbf{x}$, $\Phi[(a + \mathbf{b}\mathbf{x})\exp(-\mathbf{c}\mathbf{x})] = 1/2$ and $\mathbf{c}$ is not identified.

$\forall \mathbf{x} \in O$, $\Phi[(a+\mathbf{bx})\exp(-\mathbf{cx})] = \Phi[(a'+\mathbf{b}'\mathbf{x})\exp(-\mathbf{c}'\mathbf{x})] \Rightarrow \forall \mathbf{x} \in \mathbb{R}^k$, $(a+\mathbf{bx})\exp(-\mathbf{cx}) = (a'+\mathbf{b}'\mathbf{x})\exp(-\mathbf{c}'\mathbf{x})$ and hence $a = a'$, $\mathbf{b} = \mathbf{b}'$ and $\mathbf{c} = \mathbf{c}'$.

Identification also holds if with some binary characteristics. Suppose that $x_i^1 \in \{0,1\}$ and denote by $\mathbf{x}_i^{-1} \in \mathbb{R}^{k-1}$, the vector of other characteristics. Then, $p(y_i = 1|x_i^1 = 0, \mathbf{x}_i^{-1}) = \Phi[(a+\mathbf{b}^{-1}\mathbf{x}_i)\exp(-\mathbf{c}^{-1}\mathbf{x}_i)]$ yielding identification of $a, \mathbf{b}^{-1}$ and $\mathbf{c}^{-1}$. Next, $p(y_i = 1|x_i^1 = 1, \mathbf{x}_i^{-1}) = \Phi[(a+b^1+\mathbf{b}^{-1}\mathbf{x}_i)\exp(-c^1-\mathbf{c}^{-1}\mathbf{x}_i)]$. Rewrite $\Phi^{-1}(p) = [e^{-c^1}(a+b^1) + e^{-c^1}\mathbf{b}^{-1}\mathbf{x}_i \exp](-\mathbf{c}^{-1}\mathbf{x}_i)$. Therefore, $e^{-c^1}\mathbf{b}^{-1}$ is identified and hence c^1 is identified. Since $e^{-c^1}(a+b^1)$ is also identified, b^1 is identified.

Thus n becomes arbitrarily large, the econometrician can thus obtain consistent estimates of $a, \mathbf{b}$ and $\mathbf{c}$ if observables have full rank.

Consider, next, the following model

$$p(y_i = 1|n_{iS}, n_{iW}, \mathbf{x}_i) = \Phi[((\beta+\gamma_1(n_{iS}, n_{iW}))\mathbf{x}_i + \gamma_0(n_{iS}, n_{iW}) - a_e]\exp[-(\delta+\delta(n_{iS}, n_{iW}))\mathbf{x}_i]$$

We apply the identification result on the Probit model with heteroscedascticity repeatedly. On unconnected candidates, we have: $p(y_i = 1|n_{iS} = 0, n_{iW} = 0, \mathbf{x}_i) = \Phi(\beta\mathbf{x}_i - a_e)\exp(-\delta)$ and hence a_e, β, and δ are identified. Similarly for candidates with connections n_{iS} and n_{iW}, the parameters $\gamma_0(n_{iS}, n_{iW}) - a_e$, $\beta + \gamma_1(n_{iS}, n_{iW})$ and $\delta + \delta(n_{iS}, n_{iW})$ are identified. Therefore, $\gamma_0(n_{iS}, n_{iW})$, $\gamma_1(n_{iS}, n_{iW})$, and $\delta(n_{iS}, n_{iW})$ are identified. Note that to obtain consisent estimates of a_e, β, δ, $\gamma_0(n_{iS}, n_{iW})$, $\gamma_1(n_{iS}, n_{iW})$, $\delta(n_{iS}, n_{iW})$, the number of observations within exams must become arbitrarily large and observables conditional on (n_{iS}, n_{iW}) must have full rank. QED.

Preferred specification for the baseline heteroscedasticity. We first estimate model (4) on unconnected candidates, under the assumption that latent error variance is log-linear and depends on all observable characteristics. We thus estimate the following model:

$$p(y_i = 1|\mathbf{x}_i) = \Phi[(\mathbf{x}_i\beta - a_e)\exp(-\delta\mathbf{x}_i)]$$

on unconnected candidates. In our preferred specification for σ_v, we then include variables that are statistically insignificant as well expected numbers of connections En_{iS}, En_{iW}. We include these expected numbers given their critical role in ensuring the exogeneity of actual connections. We exclude other variables. Our preferred specification includes the following 10 observables: expected number of strong connections, expected number of weak connections, PhD students advised, AIS, age, gender, number of candidates at the exam, share of unconnected candidates at the exam, type of exam, and the indicator if the broad area is Humanities and Law. As discussed in Section VI.B. and following Davidson & McKinnon (1984), we also test whether this restricted model indeed explains the data as well as the non-restricted model.

Additional estimation results. Results of the estimation of Model (9) for subsamples of AP candidates and FP candidates are presented in Table A1 and Table A2 respectively.

Table A1: Estimation of Model (9): AP candidates

	Bias		Information	
	Strong	Weak	Strong	Weak
Const.	0.466**	0.587**	-	-
	(0.185)	(0.245)	-	-
Strong	−0.075***	0.020	-	-
	(0.026)	(0.128)	-	-
Weak	0.020	-0.141	-	-
	(0.128)	(0.134)	-	-
Publications	0.016	0.033	−0.061**	0.025
	(0.012)	(0.128)	(0.025)	(0.119)
PhD Committees	0.020***	-0.002	−0.017	−0.023
	(0.007)	(0.092)	(0.028)	(0.068)
AIS	−0.009	0.103	0.063**	−0.089
	(0.016)	(0.114)	(0.029)	(0.136)
PhD students	0.043**	0.086	0.078**	0.016
	(0.019)	(0.094)	(0.037)	(0.081)
Female	−0.009	0.423**	0.004	−0.452***
	(0.021)	(0.215)	(0.041)	(0.164)
PhD in Spain	−0.113	−0.650**	0.170**	0.490***
	(0.182)	(0.281)	(0.068)	(0.174)
Age	−0.004	0.001	−0.004	−0.010
	(0.002)	(0.017)	(0.004)	(0.014)
Past experience	−0.007	-0.156	0.037	0.222
	(0.024)	(0.176)	(0.025)	(0.135)
Expected strong	0.030	-0.168	−0.102***	0.060
	(0.027)	(0.189)	(0.028)	(0.150)
Expected weak	0.309	-0.415	0.180	−0.165
	(0.233)	(0.389)	(0.278)	(0.280)

Notes: Estimation of Model (9). All specifications include controls for the full set of observable characteristics, expected number of connections of each type, and the baseline heteroskedasticity. Heteroskedastic probit estimates. Exam grouped effects. Standard errors clustered on the exam level are in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Table A2: Estimation of Model (9): FP candidates

	Bias		Information	
	Strong	Weak	Strong	Weak
Const.	0.366***	0.188***	-	-
	(0.065)	(0.058)	-	-
Strong	−0.058***	−0.044	-	-
	(0.017)	(0.035)	-	-
Weak	−0.044	−0.021	-	-
	(0.035)	(0.017)	-	-
Publications	−0.054	0.037**	0.071	−0.061**
	(0.036)	(0.019)	(0.051)	(0.028)
PhD Committees	0.007	0.038*	0.085***	0.037
	(0.007)	(0.020)	(0.027)	(0.026)
AIS	0.078**	0.140***	−0.057	−0.118***
	(0.032)	(0.034)	(0.047)	(0.037)
PhD Students	−0.008	−0.061**	0.013	0.041
	(0.010)	(0.024)	(0.020)	(0.025)
Female	0.017	0.005	0.021	0.009
	(0.025)	(0.046)	(0.047)	(0.055)
PhD in Spain	−0.009	0.064	0.085**	−0.010
	(0.013)	(0.040)	(0.039)	(0.049)
Age	0.003**	0.002	−0.012***	0.002
	(0.002)	(0.004)	(0.004)	(0.005)
Past experience	−0.001	−0.041	−0.018	0.108***
	(0.006)	(0.027)	(0.025)	(0.036)
Expected strong	0.048**	0.006	−0.069***	0.002
	(0.022)	(0.035)	(0.012)	(0.067)
Expected weak	0.019	−0.005	0.021	−0.117***
	(0.054)	(0.031)	(0.071)	(0.034)

Notes: Estimation of Model (9). All specifications include controls for the full set of observable characteristics, expected number of connections of each type, and the baseline heteroskedasticity. Heteroskedastic probit estimates. Exam grouped effects. Standard errors clustered on the exam level are in the parenthesis. *p<0.1; **p<0.05; ***p<0.01.

REFERENCES

Beaman, Lori and Jeremy Magruder. 2012. "Who Gets the Job Referral? Evidence from a Social Networks Experiment." *American Economic Review*, 102(7): 3574-3593.

Bertrand, Marianne and Sendhil Mullainathan. 2004. "Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." *American Economic Review*, 94(4): 991-1013.

Bester, C. Alan and Christian B. Hansen. 2016. "Grouped Effects Estimators in Fixed Effects Models." *Journal of Econometrics,* 190: 197-208.

Bramoullé, Yann and Sanjeev Goyal. 2016. "Favoritism." *Journal of Development Economics,* 122: 16-27.

Broogard, Johnatan, Engelberg, Joseph and Christopher A. Parsons. 2014. "Networks and Productivity: Causal Evidence from Editor Rotations." *Journal of Financial Economics,* 111: 251-270.

Brown, Meta, Setren, Elizabeth and Giorgio Topa. 2016. "Do informal referrals lead to better matches? Evidence from a firms employee referral system." *Journal of Labor Economics,* 34(1): 161-209.

Colussi, Tommaso. 2017. "Social ties in Academia: A friend is a treasure." *Review of Economics and Statistics,* forthcoming.

Combes, Pierre-Phillipe, Linnemer, Laurent and Michael Visser. 2008. "Publish or Peerrish? The Role of Skills and Networks in Hiring Economic Professors." *Labour Economics,* 15: 423-441.

Davidson, Russell and James G. MacKinnon. 1984. "Convenient Specification Tests for Logit and Probit Models." *Journal of Econometrics,* 25: 241-262.

Engelberg, Joseph, Gao, Pengjie and Christopher A. Parsons. 2012. "Friends with Money." *Journal of Financial Economics,* 103: 169-188.

Granovetter, Mark. 1973. "The Strength of Weak Ties." *American Journal of Sociology,* 78(6): 1360-1380.

Heckman, James J. 1998. "Detecting Discrimination." *Journal of Economic Perspectives,* 12(2): 101-116.

Heckman, James J. and Peter Siegelman. 1993. "The Urban Institute Audit Studies: Their Methods and Findings." *Clear and Convincing Evidence: Measurement of Discrimination in America,* M. Fix and R. Struyk, eds. Urban Institute.

Hensvik, Lena and Oskar Nordstrom Skans. 2016. "Social Networks, Employee Selection, and Labor Market Outcomes " *Journal of Labor Economics,* 34(4): 825-867.

Laband, David N. and Michael J. Piette. 1994. "Favoritism vs Search for Good Papers: Empirical Evidence Regarding the Behavior of Journal Editors." *Journal of Political Economy,* 102(1): 194-203.

Li, Danielle. 2017. "Expertise vs. Bias in Evaluation: Evidence from the NIH." *American Economic Journal: Applied Economics,* 9(2): 60-92.

Lu, Jay. 2016. "Random Choice and Private Information." *Econometrica,* 84(6): 1983-2027.

Neumark, David. 2012. "Detecting Discrimination in Audit and Correspondence Studies." *Journal of Human Resources,* 47(4): 1128-1157.

Pallais, Amanda and Emily Glassberg Sands. 2016. "Why the Referential Treatment? Evidence from Field Experiments on Referalls." *Journal of Political Economy,* 124(6): 1793-1828.

Zinovyeva, Natalia and Manuel Bagues. 2015. "The Role of Connections in Academic Promotions." *American Economic Journal: Applied Economics,* 7(2): 264-292.