# Hiring through Networks: Favors or Information?

Yann Bramoullé and Kenan Huremović

Aix-Marseille School of Economics

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# Introduction

- Connections appear to be helpful in many contexts.
  - To get a job at a private firm, Brown, Setren & Topa (JLE 2016).
  - To publish a paper, Laband & Piette (JPE 1994), Brogaard, Engelberg & Parsons (JFE 2014).
  - To be hired or promoted in academia, Combes, Linnemer & Visser (LE 2008), Zinovyeva & Bagues (AEJ App 2015)
- Two main reasons with very different implications: better information or favors.
  - Favors could be due to altruism or repeated interactions, Bramoullé & Goyal (JDE 2016)

# Introduction

- How to identify favors from information? Existing studies rely on measures of "objective" quality.
  - If the hired connected are better than the hired unconnected, info effects dominate. If the hired connected are worse than the hired unconnected, favors dominate.
  - Papers published by connected authors are more cited (Laband & Piette, Brogaard, Engelberg & Parsons)
  - In Spain, connected candidates who obtain the promotion publish less in the following 5 years (Zinovyeva & Bagues).

# Introduction

- Two key limitations of existing studies:
  - (1) Needs a large enough time lag to build quality measures.
  - (2) Does not recover the respective sizes of the info and favor effects.
- In a recent wp, Li (2015) studies NIH grants and shows how quality measure can be used to identify both effects.
- Current view: proxy of true quality needed to identify why connections matter.

# Our approach

- We develop a new framework to identify favors and information from data on hiring only.
- Key idea: if connections provide better information on unobservables, observables should have a lower impact on success rates.
- Information effect can be recovered from differences in the effects of observables between connected and unconnected.
- Favors can then be recovered from differences in baseline success rates.

# Our approach

- We apply our method to the data assembled by Zinovyeva & Bagues.
  - Promotions to Associate and Full Professor in Spain between 2002 and 2006.
  - Large-scale natural experiment where juries are formed at random.
- We find no evidence of information effects and strong evidence of favors.
  - Favors stronger with strong ties than with weak ties.
  - Our results are consistent with the evidence obtained from future publications.

# Framework

- A jury considers candidates for promotion.
- Candidate $i$'s has ability

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

  - where $\mathbf{x}_i$ observed by the jury and the econometrician (publications, PhD students, age, gender).
  - $u_i$ unobserved by the jury and the econometrician
  - $v_i$ observed by the jury but not the econometrician (performance in the exam)
- With $E(u_i|\mathbf{x}_i) = E(v_i|\mathbf{x}_i) = 0$.

# Framework

- Some candidates are connected to the jury; others are not.
  - Assume that connections are random; connected and unconnected have the same distributions of $\mathbf{x}_i$, $u_i$, $v_i$.
- Consider an unconnected candidate,
  - For the jury, expected ability $E(a_i|\mathbf{x}_i, v_i) = \mathbf{x}_i\boldsymbol{\beta} + v_i$.
  - Candidate promoted if $E(a_i|\mathbf{x}_i, v_i) \geq a_e$ where $a_e$ exam-specific threshold.
  - For the econometrician, $p_u(h_i = 1|\mathbf{x}_i) = p(\mathbf{x}_i\boldsymbol{\beta} + v_i \geq a_e)$.
  - If $v_i \sim N(0,1)$, then

$$p_u(h_i = 1|\mathbf{x}_i) = \Phi(\mathbf{x}_i\boldsymbol{\beta} - a_e)$$

# Framework

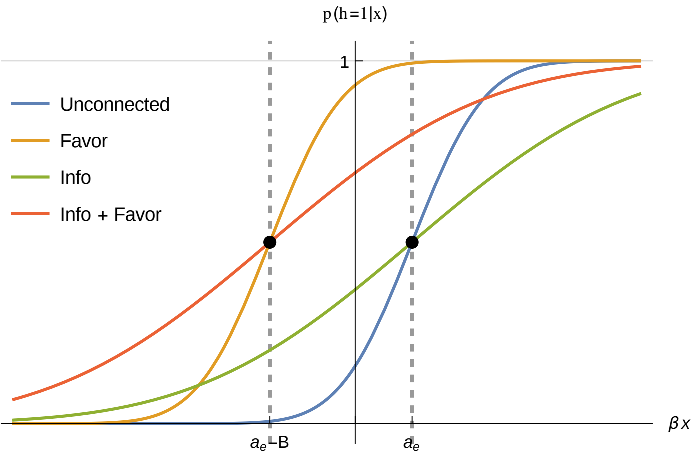
- When the candidate is connected, the jury receives a private signal $s_i$ on his ability with $s_i = u_i + \varepsilon_i$ and $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$.
  - For the jury, expected ability $E(a_i|\mathbf{x}_i, s_i, v_i) = \mathbf{x}_i\boldsymbol{\beta} + E(u_i|s_i) + v_i$ and
    $$E(u_i|s_i) = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_\varepsilon^2} s_i$$
  - Without favors, the candidate is hired if $E(a_i|\mathbf{x}_i, v_i, s_i) \geq a_e$,
    $$p_c(h_i = 1|\mathbf{x}_i) = \Phi(\frac{\mathbf{x}_i\boldsymbol{\beta} - a_e}{\sigma}) \text{ and } \sigma^2 = 1 + \frac{\sigma_u^4}{\sigma_u^2 + \sigma_\varepsilon^2} > 1$$
  - Since the jury has an additional private signal, observables are relatively less informative for the econometrician.

# Framework

- A jury provides favors if its promotion threshold is lower for connected candidates.
  - Hired if $E(a_i|\mathbf{x}_i, v_i, s_i) \geq a_e - B$, hence

$$p_c(h_i = 1|\mathbf{x}_i) = \Phi(\frac{\mathbf{x}_i\boldsymbol{\beta}+B - a_e}{\sigma})$$

- To sum up,
  - Information effects reduce the impact of observables on the hiring probability.
  - Favors shift the hiring probability to the left.


p(h=1|x)
1
Unconnected
Favor
Info
Info + Favor
βx
$a_e$–B
$a_e$

# Framework: empirical implications

- If $B$ increases, FOSD increase in $p_c(h_i = 1|\mathbf{x}_i)$.
  - If $\sigma$ increases, SOSD decrease in $p_c(h_i = 1|\mathbf{x}_i)$.
- The observed effect of connections depend on observables.
  - If $\mathbf{x}_i\boldsymbol{\beta} \leq A_1$,
    $p_c(h_i = 1|\mathbf{x}_i,\text{info}) \geq p_c(h_i = 1|\mathbf{x}_i,\text{favor}) \geq p_u(h_i = 1|\mathbf{x}_i)$.
  - If $A_1 \leq \mathbf{x}_i\boldsymbol{\beta} \leq A_2$,
    $p_c(h_i = 1|\mathbf{x}_i,\text{favor}) \geq p_c(h_i = 1|\mathbf{x}_i,\text{info}) \geq p_u(h_i = 1|\mathbf{x}_i)$.
  - If $A_2 \leq \mathbf{x}_i\boldsymbol{\beta}$,
    $p_c(h_i = 1|\mathbf{x}_i,\text{favor}) \geq p_u(h_i = 1|\mathbf{x}_i) \geq p_c(h_i = 1|\mathbf{x}_i,\text{info})$.

# Framework

- Empirically, we estimate probit regressions with interaction terms. Let $c_i = 0$ if unconnected and 1 if connected.

$$\Phi^{-1}(p)(h_i = 1|\mathbf{x}_i) = \beta_0 + \alpha_0 c_i + \sum_k \beta_k x_i^k + \sum_k \alpha_k c_i x_i^k$$

- The model predicts that $\forall k, \alpha_k/\beta_k < 0$ and $\forall k, l, \alpha_k/\beta_k = \alpha_l/\beta_l$.
  - Then recover the information effect $\alpha_k/\beta_k = (1-\sigma)/\sigma$.
  - Recover the bias through $B = (\alpha_0 - \beta_0\alpha_k/\beta_k)/(1+\alpha_k/\beta_k)$ and can test for $B > 0$.
  - In the absence of info effects, $B = \alpha_0$.

# Framework

- How to account for the number and types of links?
  - Each link brings an additional signal. Then,

$$\sigma^2(n_s, n_w) = 1 + \sigma_u^2 - \frac{1}{\sigma_u^{-2} + n_s \sigma_{\varepsilon s}^{-2} + n_w \sigma_{\varepsilon w}^{-2}} > 1$$

  - Proportional reduction in observables' impacts $I(n_s, n_w) = (1 - \sigma)/\sigma$.
  - Stronger with more ties conveying better information.
  - Bias $B(n_s, n_w)$, could include non-linearities.
- Can then be estimated by maximum likelihood.

# Application

- In Spain between 2002 and 2006, individuals wanting to become Associate or Full Professors had to get *habilitación*.
  - Highly competitive exam at the national level, 1 position for 10 candidates.
  - Data on all applications (31243) and all exams (967) in all disciplines (174).
- For each exam, evaluators were picked at random in a pool of eligible evaluators.
  - Randomization actually done with urns and balls by Ministry officials.
  - Participation mandatory, less than 2% of replacements.

# Application

- Data on connections between candidates and potential evaluators:
  - Strong ties: PhD advisor, coauthor, colleague.
  - Weak ties: PhD committee member, member of a student's PhD committee, members of the same PhD committee.
- From these, compute the expected number of strong and weak connections to the jury.
- Conditional on expected connections, actual connections are random.
  - Strong ties: 32% (3%, 5%, 30%). Weak ties: 19% (7%, 4%, 12%).
  - Balance tests check out.

# Empirical analysis

- As in Zinovyeva & Bagues:
  - Observables normalized to have mean 0 and variance 1 within exams.
  - Standard errors clustered at the exam level.
  - We control for the expected number of connections to the jury.
- In addition,
  - We include exam fixed effects (as much as possible).
  - We allow for heteroskedasticity in the expected number of connections.
  - We focus on candidates with at least one link to the pool of potential evaluators.

# Empirical results

- Probit regressions with interaction terms.
- We cannot reject that $\forall k, l, \alpha_k / \beta_k = \alpha_l / \beta_l = 0$, except maybe for PhD_in_Spain.
  - The impact of observables similar for connected and unconnected.
  - No evidence of information effects.
- By contrast, strong evidence of a positive bias.

Information and Bias: Connected vs Unconnected

| | (ef: 8) | (ef: 101) | (ef: 253) | (ef: 967) |
|---|---|---|---|---|
| (Intercept) | $-0.679^{***}$ | $-1.336^{**}$ | $-0.506^{**}$ | $0.167$ |
| | $(0.117)$ | $(0.520)$ | $(0.214)$ | $(0.468)$ |
| connected | $0.382^{**}$ | $0.510^{***}$ | $0.492^{***}$ | $0.464^{**}$ |
| | $(0.162)$ | $(0.171)$ | $(0.174)$ | $(0.185)$ |
| z_phd_students | $0.071^{***}$ | $0.075^{***}$ | $0.076^{***}$ | $0.080^{***}$ |
| | $(0.017)$ | $(0.018)$ | $(0.018)$ | $(0.019)$ |
| z_phd_committees | $0.054^{***}$ | $0.053^{***}$ | $0.059^{***}$ | $0.065^{***}$ |
| | $(0.017)$ | $(0.018)$ | $(0.018)$ | $(0.019)$ |
| z_total_ais | $0.144^{***}$ | $0.151^{***}$ | $0.150^{***}$ | $0.144^{***}$ |
| | $(0.019)$ | $(0.019)$ | $(0.020)$ | $(0.020)$ |
| z_publications | $0.064^{***}$ | $0.065^{***}$ | $0.067^{***}$ | $0.065^{***}$ |
| | $(0.019)$ | $(0.020)$ | $(0.020)$ | $(0.020)$ |
| female | $-0.051$ | $-0.077^{**}$ | $-0.085^{**}$ | $-0.104^{**}$ |
| | $(0.035)$ | $(0.037)$ | $(0.037)$ | $(0.039)$ |
| age | $-0.016^{***}$ | $-0.016^{***}$ | $-0.019^{***}$ | $-0.027^{**}$ |
| | $(0.003)$ | $(0.003)$ | $(0.003)$ | $(0.003)$ |
| phd_in_spain | $-0.246^{***}$ | $-0.268^{***}$ | $-0.269^{***}$ | $-0.274^{**}$ |
| | $(0.044)$ | $(0.045)$ | $(0.045)$ | $(0.049)$ |
| con_z_phdc | $0.011$ | $0.007$ | $0.006$ | $0.013$ |
| | $(0.024)$ | $(0.025)$ | $(0.025)$ | $(0.028)$ |
| con_z_phds | $0.009$ | $0.006$ | $0.006$ | $0.015$ |
| | $(0.024)$ | $(0.025)$ | $(0.025)$ | $(0.027)$ |
| con_z_ais | $-0.027$ | $-0.029$ | $-0.025$ | $-0.034$ |
| | $(0.027)$ | $(0.028)$ | $(0.029)$ | $(0.030)$ |
| con_z_pub | $0.022$ | $0.025$ | $0.025$ | $0.034$ |
| | $(0.027)$ | $(0.028)$ | $(0.029)$ | $(0.030)$ |
| con_female | $0.012$ | $0.014$ | $0.014$ | $0.002$ |
| | $(0.048)$ | $(0.050)$ | $(0.051)$ | $(0.053)$ |
| con_age | $-0.003$ | $-0.005$ | $-0.005$ | $-0.002$ |
| | $(0.003)$ | $(0.004)$ | $(0.004)$ | $(0.004)$ |
| con_phd_in_spain | $0.146^{**}$ | $0.137^{**}$ | $0.136^{**}$ | $0.107$ |
| | $(0.062)$ | $(0.065)$ | $(0.066)$ | $(0.074)$ |
| Num. obs. | 28452 | 28452 | 28452 | 28452 |

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

# Empirical results

- Maximum likelihood estimations incorporating the number and types of links.
  - Preliminary estimations with $I(n_s, n_w) = I_s n_s + I_w n_w$ and $B(n_s, n_w) = B_s n_s + B_w n_w$ or quadratic.
- Significant bias associated with strong ties.
  - Marginal impact of an additional strong tie decreasing.
  - Some evidence of information effects on weak ties for Associated Professors.

ML estimation: Linear Information, Linear Bias

| | All | FP | AP |
|---|---|---|---|
| Is | $-0.015$ | $0.021$ | $-0.041$ |
| | $(0.027)$ | $(0.045)$ | $(0.036)$ |
| Iw | $-0.021$ | $0.001$ | $-0.118$ |
| | $(0.055)$ | $(0.062)$ | $(0.112)$ |
| Bs | $0.310^{***}$ | $0.350^{***}$ | $0.297^{***}$ |
| | $(0.040)$ | $(0.062)$ | $(0.057)$ |
| Bw | $0.109$ | $0.104$ | $0.074$ |
| | $(0.077)$ | $(0.079)$ | $(0.174)$ |
| Num. obs. | 28452 | 12945 | 15507 |

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

ML estimation: Linear Information, Quadratic Bias

| | All | FP | AP |
|---|---|---|---|
| Is | 0.027 | 0.085 | 0.015 |
| | (0.047) | (0.074) | (0.058) |
| Iw | $-0.039$ | $-0.018$ | $-0.322^{***}$ |
| | (0.070) | (0.073) | (0.031) |
| Bs | $0.501^{***}$ | $0.550^{***}$ | $0.529^{***}$ |
| | (0.074) | (0.122) | (0.090) |
| Bss | $-0.068^{***}$ | $-0.060^{***}$ | $-0.085^{***}$ |
| | (0.013) | (0.022) | (0.019) |
| Bw | 0.142 | 0.089 | 0.447 |
| | (0.114) | (0.131) | (0.357) |
| Bww | $-0.034^{*}$ | $-0.006$ | $-0.737^{*}$ |
| | (0.019) | (0.020) | (0.374) |
| Bsw | 0.019 | 0.015 | 0.144 |
| | (0.037) | (0.043) | (0.111) |
| Num. obs. | 28452 | 12945 | 15507 |

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

# Variable bias and precision

- So far, assumption that the bias from favors and the signal's precision are constant.
  - What happens if they depend on observables?
- Suppose that $corr(\varepsilon_i, x_i^k) = \rho_k$.
  - Under normality, $var(\varepsilon_i | x_i^k) = (1 - \rho_k^2)\sigma_\varepsilon^2$. Precision increasing with $\rho_k$.
  - By the law of iterated expectations, $E(E(u_i | s_i, \mathbf{x}_i) | \mathbf{x}_i) = E(u_i | \mathbf{x}_i) = 0$.
- Even with an arbitrary correlation structure, without favors $p_c(h_i = 1 | \mathbf{x}_i) = \Phi(\frac{\mathbf{x}_i \boldsymbol{\beta} - a_e}{\sigma})$ with $\sigma > 1$.
  - Information effects induce the same relative reduction in impacts across observables.

# Variable bias and precision

- Next, assume that the bias depends on observables.
  - $B_i = B_0 + \sum_k B_k x_k^i$
- The model is then not identified.
  - If $B_k < 0$, the impact of $x_k^i$ is reduced for connected.
- However, one exclusion restriction is enough to recover identification.
  - For some $k$, $B_k = 0$.

# Variable bias and precision

- In the application, assume that there is at least one variable on which the bias does not depend.
  - Then, independent on all others except PhD_in_Spain.
- Then, stronger bias for candidates who obtained their PhD in Spain.

# Conclusion: summary

- We develop the first method to identify favors from information in the impact of connections, from data on hiring only.
- We apply it to data on academic promotions in Spain in 2002 and 2006.
- Our findings are broadly consistent with results obtained from later productivity.

# Conclusion: further work

- Maximum likelihood estimations still preliminary.
- How to combine our approach with data on later productivity?
  - To provide further tests and/or more precise estimates.
- How to identify these effects when juries are not formed at random, and connected and unconnected differ in systematic ways?