Who Works Where and Why? Parental Networks and the Labor Market

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Introduction

- Motivational facts:
  - Some firms pay more to similar workers
  - Many/most jobs obtained through social contacts
  - Homophily of social networks
- Question: how parental professional networks impact early labor-market outcomes

This paper

- Build a two-sided matching model with search frictions
    - Simultaneous estimation: job assignment and wages
    - Important margin: quality of job/candidate
- Identify two mechanisms
    - Meeting rate
    - Match value

This paper

- Data: matched employer-employee data from Israel linked to the population registry
- Identifying variation: timing of active connections at a firm
- Reduced-form
  - Impact on job assignments
  - Identification strategy validation
  - Heterogeneity

This paper

- Estimation:
  - Simulation-based method
  - Novel BLP-style update mapping
- Use identifying variation to evaluate counterfactuals
  - Value of connections and meetings
  - Between-group pay gaps
- Policies
  - Subsidizing internships
  - "Rooney Rule"
  - Anti-nepotism rules

Literature and contributions

Effects of connections

Importance of social networks for finding jobs (Granovetter 1973; Bewley 1999); Networks of coworkers (Cingano and Rosolia 2012; Caldwell and Harmon 2018; Eliason et al. 2019); Impact of direct parental connections but not of indirect (Corak and Piraino 2011; Kramarz and Skans 2014; Plug et al. 2018).
Contribution: find effect for indirect parental connections

Mechanisms for the effects

Search frictions (Calvo-Armengol and Jackson 2004; Fontaine 2008); Match value: productivity (Athey et al. 2000; Bandiera et al. 2009); favoritism (Beaman and Magruder 2012; Dickinson et al. 2018), uncertainty about worker's productivity (Montgomery 1991; Dustmann et al. 2016; Bolte et al. 2020).
Contribution: separately estimate the two sets of mechanisms

Two-sided matching models

Deterministic transferable utilities (Shapley and Shubik 1971; Demange and Gale 1985); Nondeterministic utilities (Choo and Siow 2006; Galichon and Salanié 2015).
Contribution: add search frictions (more realistic + enables simulation-based estimation)

Outline

1. Data and definitions
2. Identification strategy
3. Regression results
4. Matching model
5. Estimation
6. Model results
7. Counterfactuals

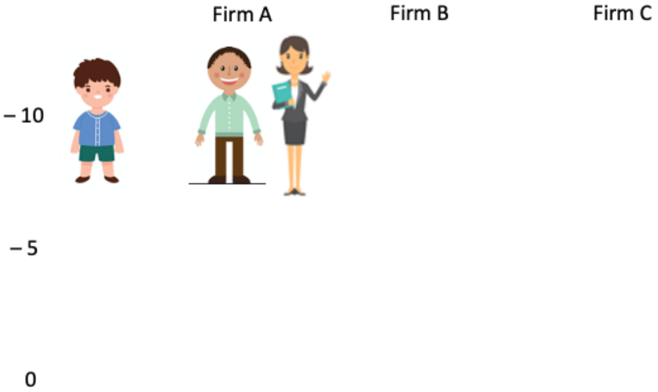
Outline

Data

- Matched employer-employee administrative records from Israel (1983-2015)
  - Person identifiers, firm identifiers, monthly indicators, yearly salary, and industry
- Israeli Population Registry
  - Date of birth, date of death, sex, ethnic group, parents identifiers, and location
- Social security records
  - Higher education (institution and years)

Types of parental connections

definitions



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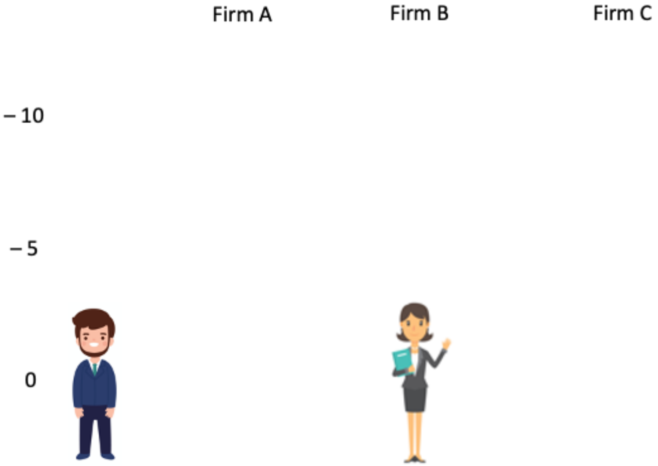

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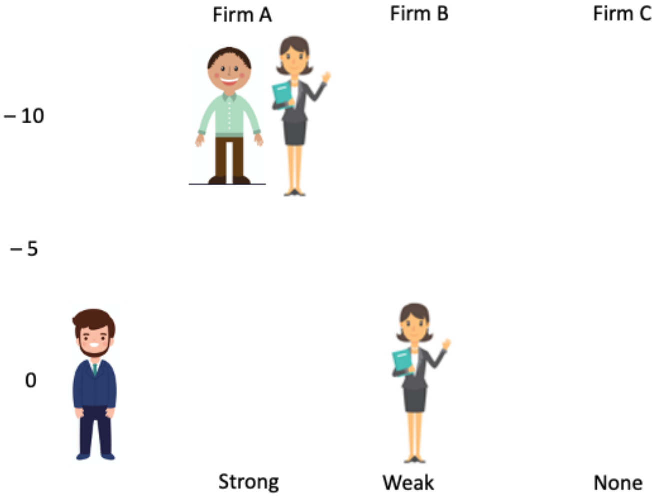


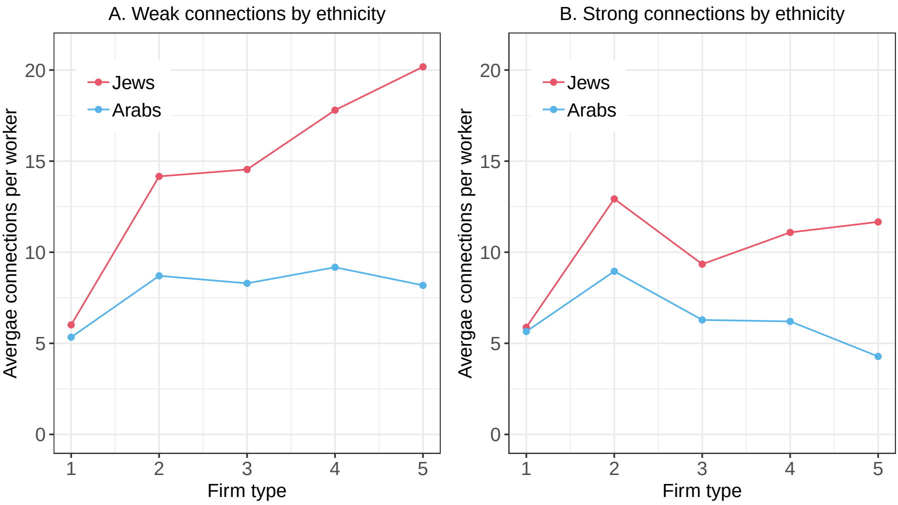
Summary statistics

Table 1: Summary statistics: new workers

	All	Ethnicity		Gender	
		Jews	Arabs	Males	Females
N.	220,806	157,023	63,783	126,233	94,573
First job					
Salary	5,839	6,053	5,312	6,223	5,325
Firm rank	0.60	0.64	0.52	0.60	0.61
Connections					
Weak	0.03	0.02	0.04	0.03	0.02
Strong	0.11	0.09	0.17	0.13	0.08
Connections quality					
Av. firm rank					
Weak	0.64	0.66	0.58	0.63	0.65
Strong	0.61	0.64	0.54	0.60	0.62

sample selection AKM wage regression

Connections per worker by ethnicity

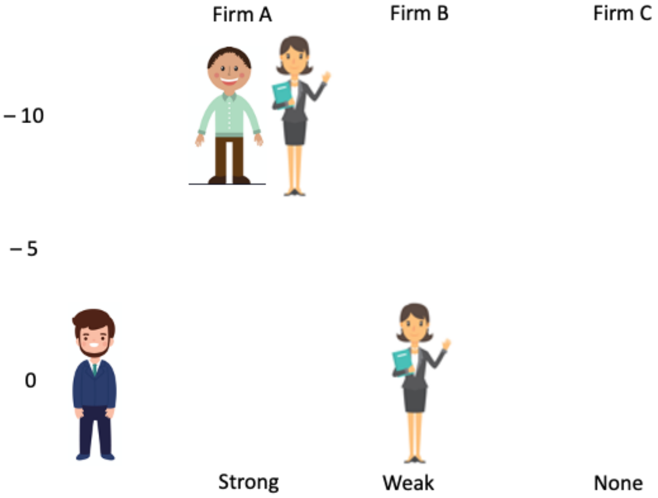


Gender

Outline

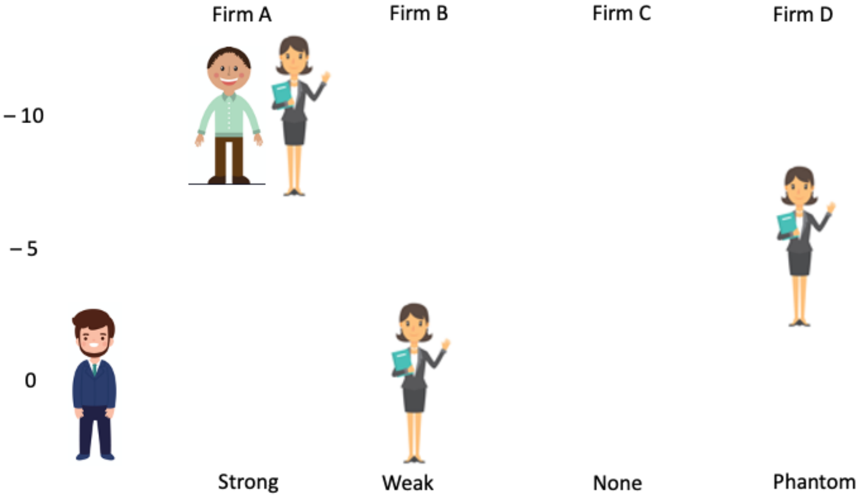
Types of parental connections

definitions

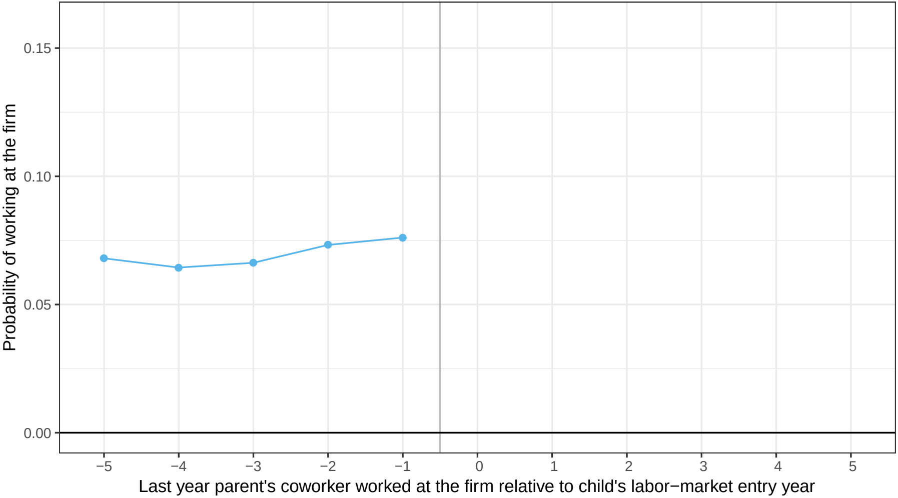


Types of parental connections

definitions balancing table



Employment probability: raw data



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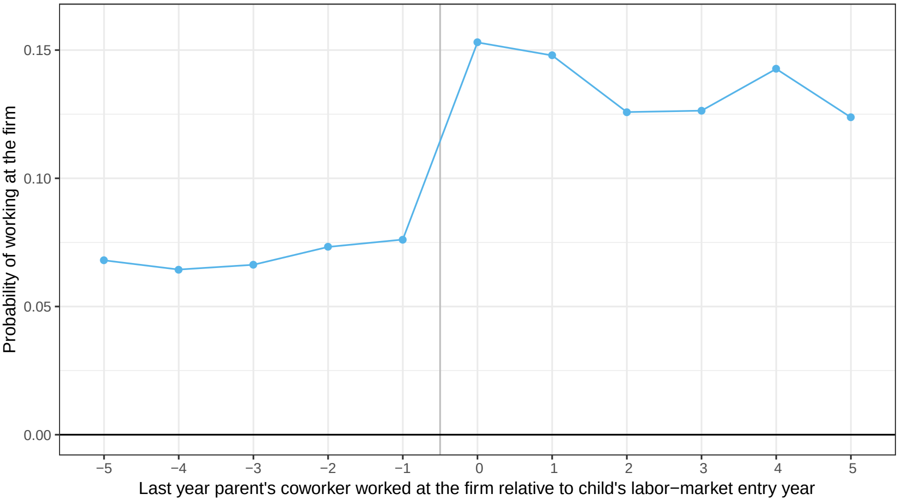


Econometric model

- Extending Kramarz and Skans (2014) fixed-effects transformation framework
- Group workers based on observables
- The probability that a worker i of a group x starts working in firm j is

$$e_{ixj} = \phi_{xj} + \sum_{c=p,w,s} \delta^c \cdot D^c_{ij} + \epsilon_{ixj}$$

with

- $e_{ixj} = 1$ if i worked at firm j
- ϕ_{xj} group-firm match specific effect
- $D^c_{ij} = 1$ if i had connections of type c at firm j

Within-group estimation in practice

- Restrict the sample to cases where there is within group-firm variation in $D_{ij} \equiv \max_c D_{ij}^c$
- For each group-firm combination, compute
  - The fraction of connected children who were hired by the firm

$$R_{xj}^{CON} = \frac{\sum_{i \in x} e_{ixj} D_{ij}}{\sum_{i \in x} D_{ij}} = \phi_{xj} + \sum_{c=1}^{C} \delta^c \cdot D_{xj}^c + \epsilon_{xj}^{CON}$$

  - The fraction of non-connected children who were hired by firm j

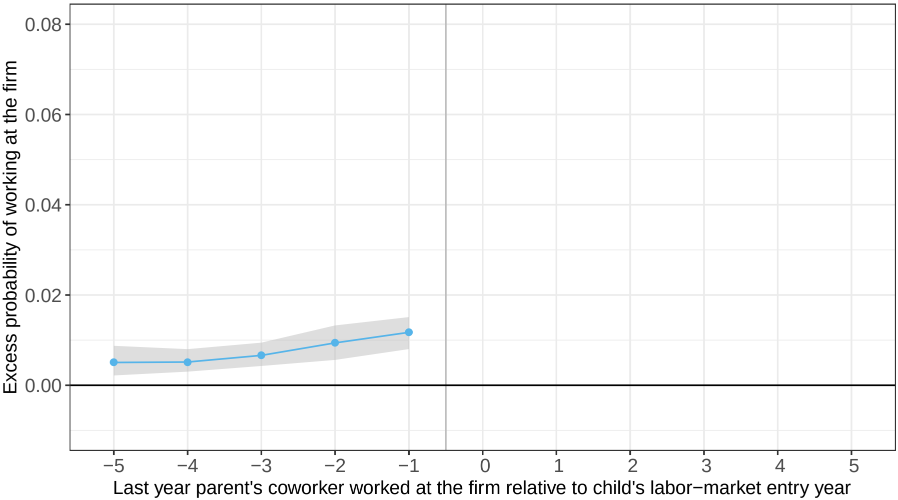
$$R_{xj}^{-CON} = \frac{\sum_{i \in x} e_{ixj}(1 - D_{ij})}{\sum_{i \in x}(1 - D_{ij})} = \phi_{xj} + \epsilon_{xj}^{-CON}$$

- Estimate

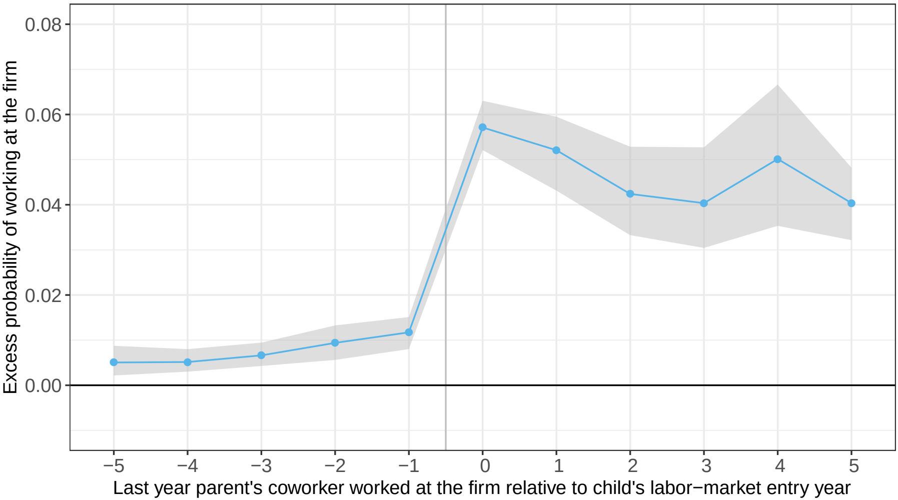
$$R_{xj} \equiv R_{xj}^{CON} - R_{xj}^{-CON} = \sum_{c=1}^{C} \delta^c \cdot D_{xj}^c + \epsilon_{xj}^{G}.$$

Outline

Effects of connections on employment: Event study



Effects of connections on employment: Event study



Effects of connections on employment: Average effects

Table 2: Effects of parental connections on firm assignment

	All (1)	Jews (2)	Arabs (3)	Males (4)	Females (5)
Phantom connections	0.010	0.006	0.030	0.011	0.008
	[0.009,0.011]	[0.005,0.007]	[0.025,0.032]	[0.010,0.013]	[0.006,0.010]
Weak connections	0.050	0.031	0.143	0.067	0.031
	[0.047,0.054]	[0.028,0.034]	[0.131,0.156]	[0.061,0.071]	[0.027,0.036]
Strong connections	0.487	0.366	0.917	0.617	0.338
	[0.472,0.501]	[0.351,0.384]	[0.878,0.956]	[0.593,0.647]	[0.320,0.354]
R0 (no connections)	0.005	0.005	0.006	0.005	0.006
	[0.005,0.005]	[0.005,0.005]	[0.006,0.006]	[0.005,0.005]	[0.005,0.006]
Ratio weak-phantom	3.666	3.259	4.177	4.409	2.731
	[3.316,4.081]	[2.841,3.681]	[3.651,4.803]	[3.912,4.959]	[2.262,3.303]
Ratio strong-phantom	32.52	33.99	25.91	38.37	25.37
	[30.02,35.53]	[30.65,37.8]	[23.52,30.03]	[34.83,43.67]	[22.41,29.39]
Observations	21,166,443	16,837,526	4,328,917	15,319,313	5,847,130
N firms	149,729	144,186	117,746	145,939	134,555
N groups	2,959	1,658	1,301	1,548	1,411
N workers	220,684	157,009	63,675	170,872	49,812
N connections	40,827,833	33,261,814	7,566,019	31,664,340	9,163,493

Exogenous separations

- Use death and retirement of contacts for exogenous separation causes

Death and retirement of contacts

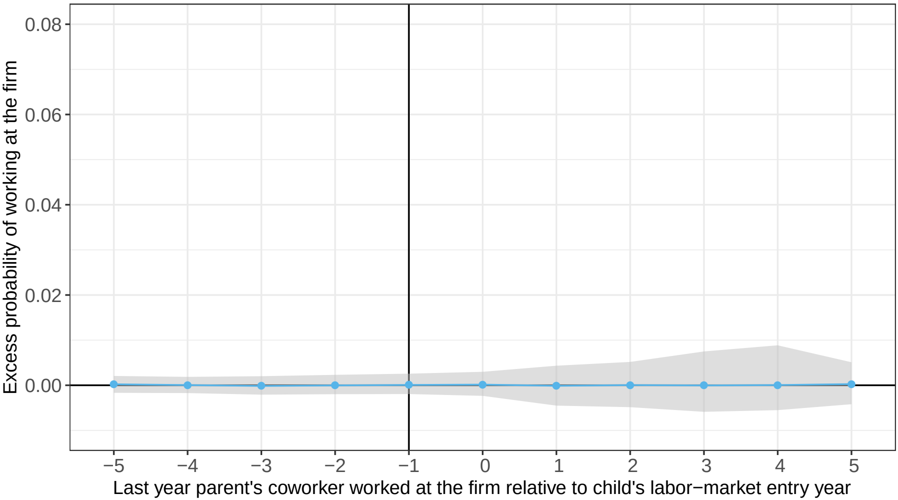
Table 3: Effects of parental connections on firm assignment: death and retirement of contacts

	Employment		
	(1)	(2)	(3)
Special connections:	Death	Retirement	Death or retirement
Phantom (D/R)	0.031	0.010	0.017
	[0.004,0.068]	[-0.008,0.032]	[0.001,0.034]
Phantom (Other)	0.010	0.010	0.010
	[0.009,0.011]	[0.009,0.011]	[0.009,0.011]
Weak (D/R)	0.065	0.032	0.041
	[0.010,0.126]	[0.003,0.066]	[0.017,0.071]
Weak (Other)	0.050	0.051	0.051
	[0.047,0.054]	[0.047,0.055]	[0.047,0.054]
Strong	0.487	0.487	0.487
	[0.472,0.501]	[0.472,0.501]	[0.472,0.501]
R0 (no connections)	0.005	0.005	0.005
	[0.005,0.005]	[0.005,0.005]	[0.005,0.005]
Ratio weak-phantom (D/R)	2.567	3.913	2.773
	[0.386,7.746]	[0.582,19.460]	[0.748,6.533]
Ratio weak-phantom (Other)	3.679	3.680	3.691
	[3.335,4.101]	[3.339,4.099]	[3.349,4.122]
N connections: phantom (D/R)	85,532	138,194	222,461
N connections: weak (D/R)	37,402	102,499	138,974

Placebo test

- Assigning to each worker the connections of a random worker in her group

Placebo test: event study



Placebo test: Average effects

Table 4: Effect of weak parental connections on firm assignment, placebo test

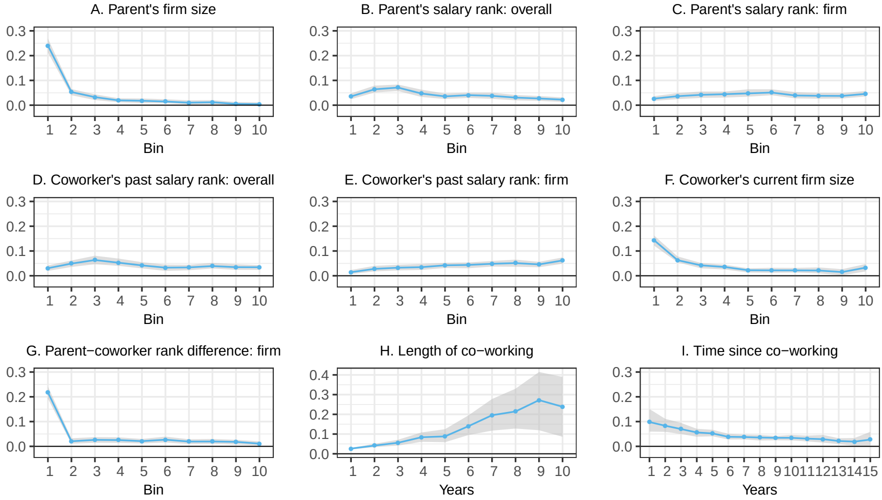
	All	Jews	Arabs	Males	Females
	(1)	(2)	(3)	(4)	(5)
Phantom connections	0.000	0.000	0.000	0.000	0.000
	[-0.001,0.001]	[-0.001,0.001]	[-0.002,0.003]	[-0.001,0.001]	[-0.001,0.001]
Weak connections	0.000	0.000	0.000	0.000	0.000
	[-0.002,0.002]	[-0.002,0.002]	[-0.006,0.006]	[-0.002,0.003]	[-0.003,0.003]
Strong connections	0.000	0.000	0.001	0.000	0.000
	[-0.006,0.007]	[-0.005,0.005]	[-0.021,0.021]	[-0.006,0.008]	[-0.008,0.010]
R0 (no connections)	0.007	0.006	0.011	0.008	0.007
	[0.007,0.008]	[0.006,0.007]	[0.011,0.012]	[0.007,0.008]	[0.007,0.007]
Ratio weak-phantom	1.010	1.000	1.053	1.011	1.017
	[0.755,1.384]	[0.727,1.330]	[0.397,1.645]	[0.660,1.334]	[0.631,1.524]
Ratio strong-phantom	1.047	1.029	1.107	1.065	1.036
	[0.206,2.019]	[0.189,1.805]	[-0.938,3.233]	[0.154,1.981]	[-0.162,2.471]
Observations	21,166,443	16,837,526	4,328,917	15,319,313	5,847,130
N firms	149,729	144,186	117,746	145,939	134,555
N groups	2,959	1,658	1,301	1,548	1,411
N workers	220,684	157,009	63,675	170,872	49,812
N connections	40,827,833	33,261,814	7,566,019	31,664,340	9,163,493

Heterogeneity of the effect

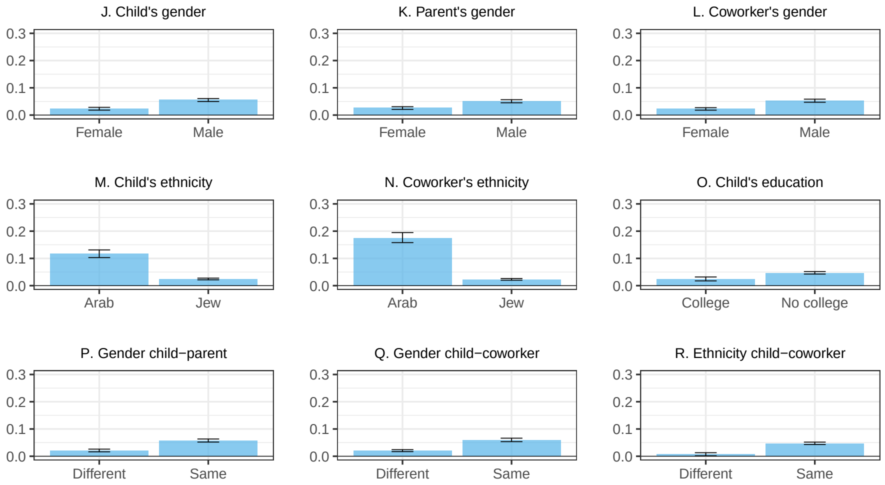
- Dividing phantom and weak connections into disjoint sets based on characteristics of the workers and the connections

$$
\begin{aligned}
e_{ixj} =& \alpha_{xj} + \sum_{c'} \left(\delta^{w,c'} \cdot D^{w,c'} + \delta^{p,c'} \cdot D^{p,c'} \right) + \\
& \delta^{s} \cdot D^{s}_{ij} + \epsilon_{ixj}
\end{aligned}
$$

Heterogeneity (1/2)



Heterogeneity (2/2)



stylized facts

Correlation with salary

- Correlation between connections at first job and salary

$$w_i = \sum_{c=p,w,s} \delta^c D^c_{i,j(i)} + \phi_{x(i)} + \psi_{j(i)} + \epsilon_i.$$

  where

  - $j(i)$ is the firm in which i works at
  - $x(i)$ is the observable group of worker i (ethnicity, education, gender, year of first job, age, district)
  - $D^c_{i,j}$ indicates connection of type c between i and j

- This analysis does not identify the causal effect: ignores selection

Salary and tenure at first job

Table 5: Correlation between parental connections at first job and salary and tenure

	Log salary	Job tenure
	(1)	(2)
Phantom connections	0.012	0.098
	(0.004)	(0.022)
Weak connections	0.026	0.187
	(0.004)	(0.025)
Strong connections	0.083	0.441
	(0.003)	(0.020)
Group FE	Yes	Yes
Firm FE	Yes	Yes
Observations	220,806	220,806
N firms	54,321	54,321
R^2 (full model)	0.624	0.414
R^2 (projected model)	0.006	0.007

$$w_i = \sum_{c=1}^{C} \delta^c D^c_{i,j(i)} + \phi_{x(i)} + \psi_{j(i)} + \epsilon_i .$$

Outline

Set-up

- X types of workers, Y types of firms
- T markets
- In each market t, I_t workers, J_t firms (jobs), $I_t = J_t$, I_{tx} workers of type $x \in \mathcal{X}$, J_{ty} firms of type $y \in \mathcal{Y}$
- Each worker i and firm j are connected by exactly one type of connection $c = 0, 1, ..., C$
- Matching in two stages:
    - Workers and firms randomly meet
    - Given meetings: each worker chooses the best firm and vice versa; wages clear the markets

Stage 1: meeting

- The meeting probability depends on the observable characteristics of i and j

$$m_{ij} = 1\left(\rho_{ij} \leq p_{ij}\right)$$

  - m_{ij}: meeting indicator
  - ρ_{ij}: iid standard uniform
  - p_{ij}: systematic meeting probability

Stage 2: matching

- After the realization of the meetings, there is a matching process between all feasible pairs
- Transferable utilities (TU)
- The utility of a firm j which employs a worker i is:

$$V_{ij} = f_{ij} - w_{ij}$$

- The utility of the worker is:

$$U_{ij} = w_{ij}$$

Equilibrium

- An equilibrium outcome (μ, w) consist of an equilibrium matching $\mu(i,j)$ and an equilibrium wage $w(i,j)$ such that:
  1. Matching $\mu(i,j)$ is feasible:

$$\sum_j \mu(i,j) \leq 1 \quad , \quad \sum_i \mu(i,j) \leq 1 \quad , \quad \mu(i,j) = 1 \implies m(i,j) = 1$$

  2. Matching $\mu(i,j)$ is optimal for workers and firms given wages w and meetings m:

$$\mu(i,j) = 1 \implies j \in \text{argmax}_{j \in m_i} U_{ij} \quad \text{and} \quad i \in \text{argmax}_{i \in m_j} V_{ij}$$

Equilibrium characterization: matching

- Equilibrium matching is generically unique
- (Shapley and Shubik 1971): μ is an equilibrium matching if and only if it maximizes the total joint surplus $\pi_{ij} = U_{ij} + V_{ij}$

$$\mu \in \operatorname{argmax}_{\mu'} \sum_{\mu'(i,j)=1} \pi_{ij}$$
$$\text{s.t.} \quad \mu' \text{ is feasible}$$

- Equilibrium matching can be found efficiently using the auction algorithm (Bertsekas 1998) auction algorithm

Equilibrium characterization: payoffs

- Equilibrium payoffs are not unique
- If u is an equilibrium payoff schedule, so is $u + r$
- The set of (normalized) equilibrium wages is a lattice: there exist $\{\underline{u}_i, \bar{u}_i\}_{i=1}^{I}$ such that $\{u_i | \underline{u}_i \leq u_i \leq \bar{u}_i\}_{i=1}^{I}$ is the set of equilibrium payoffs (Demange and Gale 1985)
- Find the bounds using the Bellman-Ford algorithm (Bonnet et al. 2018) BF algorithm simulation
- Payoffs are $u_i = (1 - \lambda)\underline{u}_i + \lambda \bar{u}_i$ for some "bargaining power" $\lambda \in [0, 1]$

Outline

Parameterization and moments

- Parameterization
  - $p_{ij} = p_{txyc}$
  - $log(f_{ij}) = b + \beta_{txyc} + \sigma \cdot \xi_{ij}\ ,\ \xi_{ij} \sim N(0,1)$
- Parameters
  - p_{txyc}
  - β_{txyc}
  - σ
  - (b)
- Moments
  - Number of matches μ_{txyc}
  - Average wage w_{txyc}
  - Wage variance Var_w
  - (Within-group wage variance $WithinVar_w$)

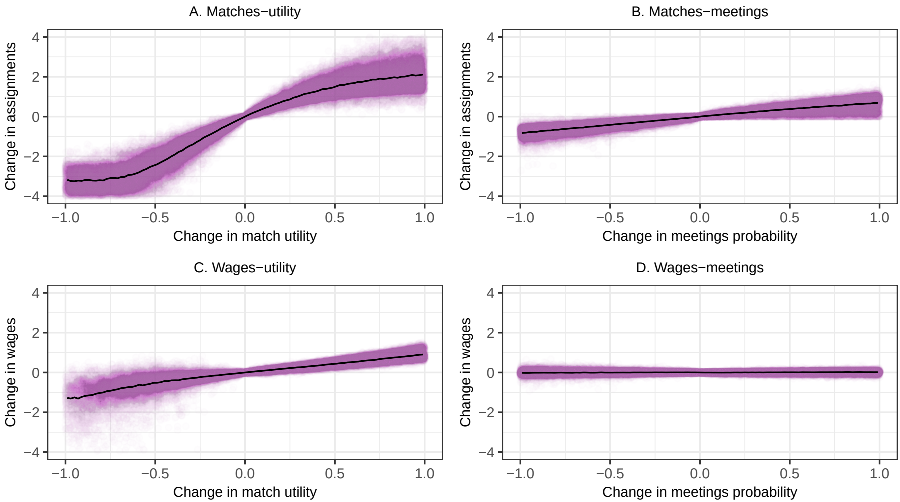
Groups and observations

- $T = 10$ (2006-2015)
- $X = 8$ (Jews/Arabs $\times$ no-college/college $\times$ males/females)
- $Y = 5$ (bins of AKM firm premiums)
- $C = 3$ (0: no connection, 1: phantom, 2: weak, 3: strong)
- $I \approx 200K$

Simulating an equilibrium outcome (inner loop)

- Given parameters and a draw of unobservables:
  1. Get the set of meetings m_{ij}
  2. Calculate the joint surplus π_{ij}
  3. Find the equilibrium matching using the auction algorithm
  4. Find the equilibrium wage using the BF algorithm
- The two-stage model offers a computational advantage over existing matching models
- Exploit the sparsity of the data using c++ implementations of the auction (Bernard et al. 2016) and BF algorithms

Identification of the model



Elasticities table

Estimation: inverting the data (outer loop)

- Use BLP-style update mapping to "invert" the data into the parameters (Berry et al. 1995)

$$
\begin{aligned}
p_n^{h+1} &= p_n^h + \eta \left[log(\mu_n) - log(\hat{\mu}_n(p^h, \beta^h, \sigma^h, b^h)) \right] \\
\beta_n^{h+1} &= \beta_n^h + \eta \left[log(\mu_n \cdot w_n) - log(\hat{\mu}_n(p^h, \beta^h, \sigma^h, b^h) \cdot \hat{w}_n(p^h, \beta^h, \sigma^h, b^h)) \right] \\
\sigma^{h+1} &= \sigma^h + \eta \left[log(WithinVar_w) - log(\widehat{WithinVar}_w(p^h, \beta^h, \sigma^h, b^h)) \right] \\
b^{h+1} &= b^h + \eta \left[log(Var_w) - log(\widehat{Var}_w(p^h, \beta^h, \sigma^h, b^h)) \right]
\end{aligned}
$$

where

- $n \equiv txyc$
- $\eta > 0$ is the update rate

Outline

Model fit

Table 6: Model's fit and precision

A. Model's fit

	Matches (μ_{txyc}) (1)	Av. wage (w_{txyc}) (2)	Overall wage variance (3)	Within-group wage variance (4)
Abs. deviation	0.013	0.008	0.0008	0.0007
	(0.0006)	(0.0006)	(0.0006)	(0.0005)
Correlation	1.000	0.998		
	(0.00002)	(0.0002)		

B. Model's precision and Monte Carlo simulation

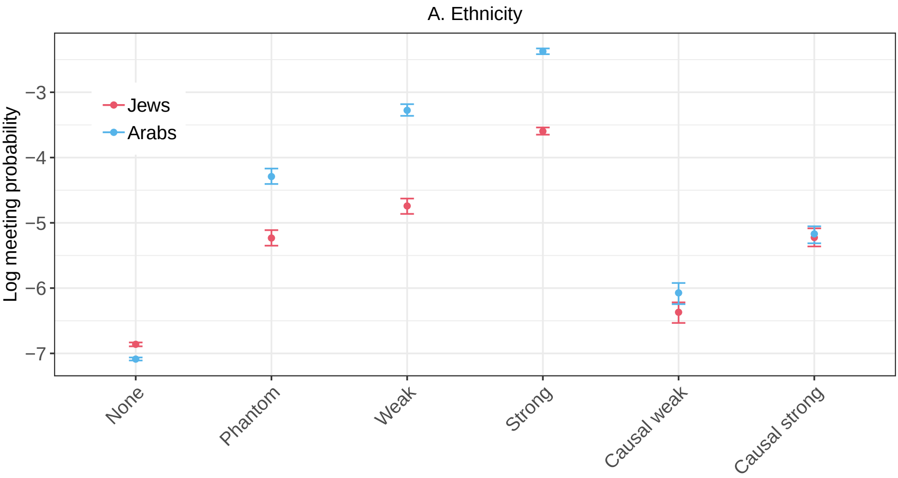
	Utility (β_{txyc}) (1)	Meetings (p_{txyc}) (2)	Unobserved heterogeneity ($log(\sigma)$) (3)	Utility scale (b) (4)
Estimates				
Correlation	0.980	0.988		
	(0.001)	(0.0006)		
Value			-1.069	9.174
			(0.007)	(0.011)
Monte Carlo				
Correlation	0.972	0.985		
	(0.003)	(0.0006)		

Model estimates

Table 7: Projection of the model estimates on workers', firms', and connections' characteristics

	Firm's utility (β_{txyc})	Meeting probability ($Log(p_{txyc})$)
	(1)	(2)
Constant	8.809	-6.900
	(0.011)	(0.015)
Phantom connections	0.012	1.964
	(0.007)	(0.039)
Weak connections	0.041	2.728
	(0.008)	(0.038)
Strong connections	0.158	3.742
	(0.004)	(0.019)
Arab	-0.011	0.051
	(0.002)	(0.010)
Female	-0.070	-0.009
	(0.002)	(0.010)
College	0.077	-0.066
	(0.002)	(0.011)
Job type: 2	0.120	-0.067
	(0.005)	(0.012)
Job type: 3	0.268	-0.028
	(0.005)	(0.012)
Job type: 4	0.459	-0.002
	(0.006)	(0.013)
Job type: 5	0.967	-0.093
	(0.007)	(0.021)
Weak - phantom	0.028	0.764
	(0.010)	(0.054)
Strong - phantom	0.146	1.779
	(0.008)	(0.042)
R^2	0.907	0.831
	(0.003)	(0.005)

Meeting probability by ethnicity and connections type



Gender by bargaining power

Outline

Value of a meeting

Table 8: Value of meetings and connections

	Total expected gains	Salary change with a job change			Salary change without a job change		
		Probability	Gains	Expected gains	Probability	Gains	Expected gains
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
New meeting, without utility effect	2.2	0.040	41.4	1.7	0.064	7.9	0.5
	(0.417)	(0.007)	(6.543)	(0.394)	(0.008)	(1.809)	(0.135)
Existing meeting, with utility effect	1.5	0.040	20.3	0.8	0.101	6.4	0.7
	(0.467)	(0.007)	(8.151)	(0.373)	(0.010)	(2.974)	(0.311)
New meeting, with utility effect	3.7	0.055	57.0	3.1	0.066	9.0	0.6
	(0.819)	(0.009)	(9.323)	(0.778)	(0.008)	(2.248)	(0.153)

by job type

Between-group pay gaps

Table 9: Counterfactual impacts of connections on between-group pay gaps

A. Equalizing number of connections per worker

	Gap	Without identification strategy			With identification strategy		
	(% Average)	Meetings effect	Utility effect	Both effects	Meetings effect	Utility effect	Both effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ethicity gap	-8.4	-59.5	-0.4	-67.6	-5.1	-1.1	-11.7
	(0.351)	(4.866)	(0.168)	(3.031)	(0.679)	(0.297)	(1.638)
Gender gap	-18.0	1.2	0.0	2.3	0.1	0.0	0.1
	(0.290)	(0.180)	(0.034)	(0.197)	(0.066)	(0.045)	(0.093)

B. Prohibiting hiring of connected workers

	Baseline	Weak	Strong	Weak + strong
	(% Average)			
	(1)	(2)	(3)	(4)
Ethnicity gap	-8.4	8.9	44.3	56.4
	(0.351)	(0.982)	(2.820)	(3.347)
Gender gap	-18.0	-4.0	-20.3	-25.3
	(0.290)	(0.320)	(0.780)	(0.798)

pay-premium utility efficiency

Thank you!

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Sample selection

- **Full sample**: panel dataset at the annual frequency
  - Ages 22-80
  - Assigning the firm with the maximal salary in February
  - Excluding worker-year observations $<$ 25% the national average monthly wage
- **5-500 sample**: firms with 5-500 workers
- **New workers sample**: the first real job of workers
  - Natives, ages 22-27 at 2006-2015
  - First job after graduation, 5-500 firm, $\geq$ 4 months, annual earnings $\geq$ 150% the national average monthly wage (Kramarz and Skans 2014)
  - Graduation year $=$ 21 for workers with no college

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Parental connections

- Three types of connections between a new worker i and firm j
  - Weak connections
    - i's parent and k worked simultaneously at $j' \neq j$ when i was 12-21 years old
    - k worked at j at time 0 (= the year i entered the labor market)
  - Phantom connections
    - i's parent and k worked simultaneously at $j' \neq j$ when i was 12-21 years old
    - k worked at j at time [-5,5] but not at time 0
  - Strong connections
    - i's parent worked at j when i was 12-21 years old, or
    - i has at least two weak or phantom contacts at j
- All firms belong to the 5-500 sample

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Firm pay premium

- Estimating AKM model (Abowd et al. 1999)

$$w_{it} = \alpha_i + \psi_{J(it)} + Z'_{it}\gamma + \varepsilon_{it}$$

with

- α_i = person FE
- $\psi_{J(it)}$ = firm FE
- Z'_{it} = year FEs, and quartic polynomials of age restricted to be flat at age 40 (Card et al. 2018)
- Firm premium at year t is calculated using the largest connected set of the full sample at years [t-4,t]
- Firms are ranked within year

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Raw ethnic and gender pay gaps

Table 10: Earnings gap by ethnicity and gender, new workers

	Log salary			
	(1)	(2)	(3)	(4)
Arab	-0.077	0.030	-0.062	0.030
	(0.004)	(0.003)	(0.004)	(0.003)
Female	-0.203	-0.134	-0.203	-0.134
	(0.003)	(0.002)	(0.003)	(0.002)
Weak con qualiy			0.117	-0.001
			(0.010)	(0.008)
Strong con qualiy			0.090	-0.014
			(0.007)	(0.006)
Firm FE	No	Yes	No	Yes
Observations	211,144	211,144	211,144	211,144
N firms	52,963	52,963	52,963	52,963
R^2 (full model)	0.138	0.614	0.140	0.614
R^2 (projected model)	0.080	0.047	0.083	0.047

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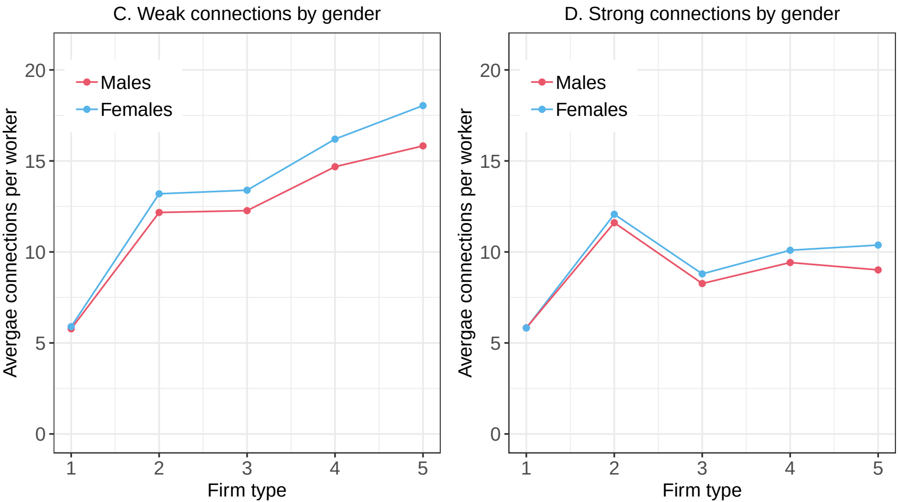
Connections per worker by gender



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Balancing test

Table 11: Balancing test: Correlation between parental connections and measures of proximity between workers and firms

	Log distance	Parent's industry
	(1)	(2)
Phantom connections	-0.369	0.077
	[-0.376,-0.362]	[0.076,0.077]
Weak connections	-0.368	0.076
	[-0.375,-0.361]	[0.075,0.076]
Strong connections	-0.926	0.281
	[-0.944,-0.909]	[0.279,0.284]
R0 (no connections)	10.102	0.033
	[10.090,10.117]	[0.032,0.033]
Ratio weak-phantom	1.000	0.989
	[1.000,1.001]	[0.984,0.995]
Ratio strong-phantom	0.943	2.871
	[0.942,0.944]	[2.850,2.887]
Observations (firms x groups)	21,166,443	21,166,443
N firms	149,729	149,729
N groups	2,959	2,959
N workers	220,684	220,684

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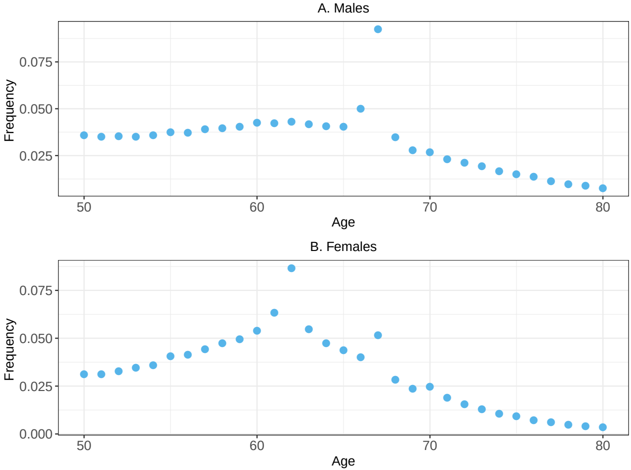
Age at retirement



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Heterogeneity: stylized facts

- Connections are stronger if generated
  - In smaller firms
  - In longer periods
  - More recently
  - Between similar individuals
- The effect is stronger for
  - Males
  - Arabs
  - No-college workers

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Auction algorithm I

1. Start with an empty assignment S, a vector of initial payoffs u_i, and some $\epsilon > 0$
2. Iterate on the two following phases:
   1. Bidding Phase
      For each unassigned firm j in the assignment S :
      1. Find a "best" worker $i_j \in m(j)$ having maximum value and the corresponding value

         $$i_j = \arg\max_{i \in m(j)} \pi_{ij} - u_i \quad , \quad v_j = \max_{i \in m(j)} \pi_{ij} - u_i$$

         and find the best value offered by workers other than i_j

         $$q_j = \max_{i \in m(j), i \neq i_j} \pi_{ij} - u_i$$

Auction algorithm II

2. Compute the "bid" of firm j given by

$$b_{ij} = u_{i_j} + v_j - q_j + \epsilon$$

2. Assignment Phase
   For each worker i, let $B(i)$ be the set of firms from which i received a bid. If $B(i)$ is non-empty, increase u_i to the highest bid

$$u_i = \max_{j \in B(i)} b_{ij}$$

   and assign i to firm the firm in $B(i)$ attaining the maximum above

3. Terminate when all workers are assigned to firms

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Bellman-Ford algorithm

- The firm-optimal equilibrium payoffs are the fixed point of the mapping

$$u_i = \max(u_i, \max_{j \in m(i)} (\pi_{ij} - v_j)) \ , \ v_j = \min(v_j, \pi_{i^*(j)j} - u_{i^*(j)}) \ , \ u_0 = 0$$

  - $i^*(j)$ denote the equilibrium match of firm j
- The fixed point can be computed by iterating on the map from the initial values $\{u_i = -\infty, u_0 = 0; v_j = \infty\}$
- The worker-optimal equilibrium payoffs can be found similarly
- The bounds are finite iff each connected set is a double connected set

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Lower and upper wage bounds

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Moments-parameters elasticities

Table 12: Moments-parameters elasticities

	Matches-utility	Matches-meetings	Wages-utility	Wages-meetings
	$dln(\mu)/d\beta$	$dln(\mu)/dln(p)$	$dln(w)/d\beta$	$dln(w)/dln(p)$
	(1)	(2)	(3)	(4)
Same workers and firms	3.511	0.777	3.427	0.015
	(0.078)	(0.017)	(0.325)	(0.009)
Same workers, different firms	-0.264	-0.033	0.001	0.014
	(0.026)	(0.003)	(0.011)	(0.001)
Different workers	-0.008	0.000	-0.032	-0.002
	(0.002)	(0.000)	(0.005)	(0.000)

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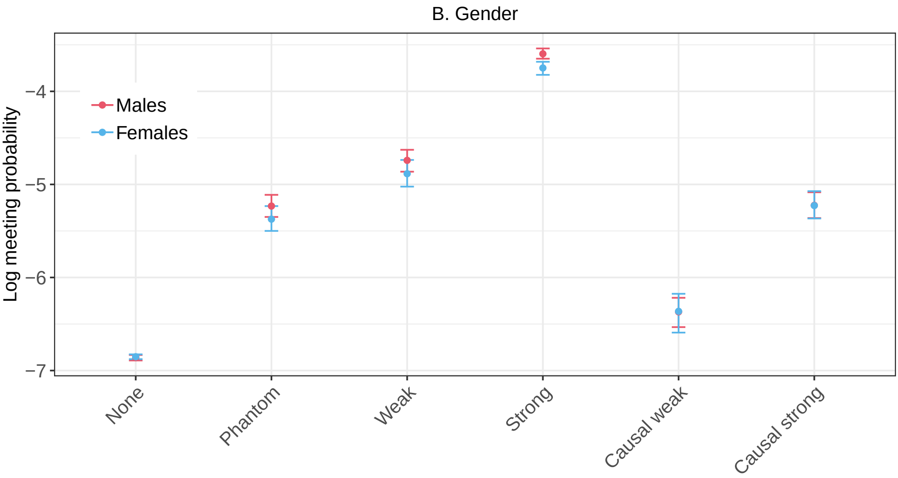
Meeting probability by gender and connections type



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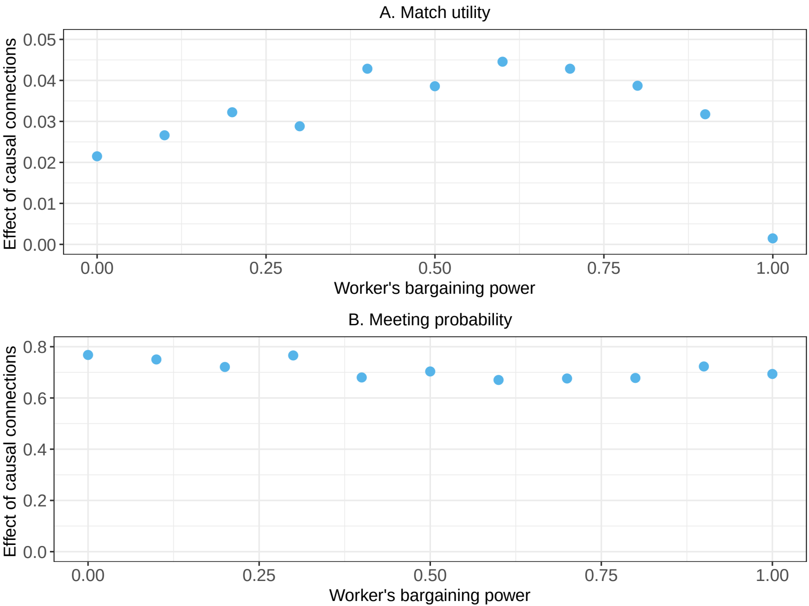
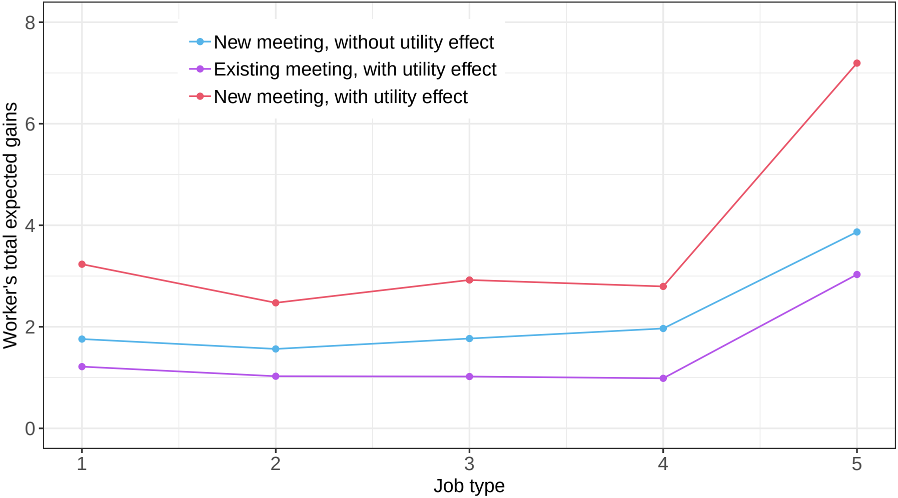
Model estimates by worker's bargaining power



Value of a meeting/connection by job type



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Between-group pay-premium gaps

Table 13: Counterfactual impacts of connections on between-group gaps in firm pay premiums

A. Equalizing number of connections per worker

	Gap (% Average)	Without identification strategy			With identification strategy		
		Meetings effect	Utility effect	Both effects	Meetings effect	Utility effect	Both effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ethicity gap	-23.1	-15.3	-0.1	-15.2	-1.4	-0.1	-2.4
	(0.299)	(1.500)	(0.180)	(0.754)	(0.326)	(0.204)	(0.502)
Gender gap	2.1	0.0	0.1	1.2	0.5	0.1	1.4
	(0.268)	(3.318)	(1.412)	(3.479)	(1.794)	(1.560)	(2.402)

B. Prohibiting hiring of connected workers

	Baseline (% Average)	Weak	Strong	Weak + strong
	(1)	(2)	(3)	(4)
Ethnicity gap	-23.1	-0.9	-1.6	-2.8
	(0.299)	(0.511)	(0.835)	(0.955)
Gender gap	2.1	8.0	36.3	46.2
	(0.268)	(4.775)	(11.271)	(11.609)

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Between-group utility gaps

Table 14: Counterfactual impacts of connections on between-group gaps in match utility

A. Equalizing number of connections per worker

	Gap	Without identification strategy			With identification strategy		
	(% Average)	Meetings effect	Utility effect	Both effects	Meetings effect	Utility effect	Both effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ethicity gap	-17.8	-20.8	-0.2	-21.6	-1.8	-0.3	-3.8
	(0.297)	(2.053)	(0.168)	(0.944)	(0.372)	(0.205)	(0.700)
Gender gap	-6.8	1.1	0.0	1.9	-0.1	0.0	-0.2
	(0.310)	(0.705)	(0.274)	(0.755)	(0.365)	(0.334)	(0.485)

B. Prohibiting hiring of connected workers

	Baseline	Weak	Strong	Weak + strong
	(% Average)			
	(1)	(2)	(3)	(4)
Ethnicity gap	-17.8	0.3	4.1	4.6
	(0.297)	(0.436)	(0.808)	(0.850)
Gender gap	-6.8	-5.1	-27.5	-33.9
	(0.310)	(1.016)	(2.102)	(2.232)

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Impacts on overall efficiency

Table 15: Counterfactual impacts of connections on efficiency

A. Equalizing number of connections per worker

	Without identification strategy			With identification strategy		
	Meetings effect	Utility effect	Both effects	Meetings effect	Utility effect	Both effects
	(1)	(2)	(3)	(4)	(5)	(6)
Equilizing connections by ethicity	0.4	0.0	0.5	0.0	0.0	0.1
	(0.032)	(0.001)	(0.015)	(0.005)	(0.003)	(0.014)
Equilizing connections by gender	0.1	0.0	0.1	0.0	0.0	0.0
	(0.005)	(0.001)	(0.005)	(0.002)	(0.001)	(0.003)

B. Prohibiting hiring of connected workers

	Weak	Strong	Weak + strong
	(1)	(2)	(3)
Prohibiting connected hiring	-0.4	-2.2	-2.6
	(0.011)	(0.026)	(0.030)

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