JAQ of All Trades: Job Mismatch and Firm Productivity

Luca Coraggio[a] Marco Pagano[a] Annalisa Scognamiglio[a] Joacim Tåg[b]

[a]University of Naples Federico II and CSEF

[b]Research Institute of Industrial Economics (IFN)

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This talk

I will

- present a novel measure, based on a machine-learning (ML) algorithm, to assess how well firms' workforce is allocated to tasks
- explore how the measure is related to firm productivity and management turnover

Outline

1. Introduction
2. Data
3. ML algorithm
4. JAQ measures
5. JAQ and productivity
6. JAQ and managerial talent

Introduction

Motivation

Productivity

- Large productivity differentials across firms (Syverson 2011)
- Determinants: quality of capital and labor, innovation, competition, etc.
- Managerial practices, especially in the management of human resources, also important (Bloom and Van Reenen 2007)

Question

Does the assignment of workers to jobs also play a role?

➥ Problem: measuring workers' suitability for a job
- ➥ firms' "job assignment quality" (JAQ)

Our approach

Measure JAQ with matched employer-employee data

1. use a ML algorithm to estimate how workers' characteristics map into jobs in high-productivity firms (arguably better at allocating workers, other things equal)
2. predict worker suitability to each job, based on this algorithm
3. evaluate whether a worker's actual job coincides with the most suitable one
4. compute frequency with which this coincidence occurs in each firm (JAQ), and explore its correlation with productivity, excluding the most productive firms

Contribution

1. Novel measure of firm-level mismatch between workers and tasks, systematically correlated with productivity differentials
2. Can be built from matched employer-employee data set
   - ➥ no need for surveys (Bloom and Van Reenen 2007; Bloom, Brynjolfsson, et al. 2019)
   - ➥ no need for expert evaluations (Lise and Postel-Vinay 2020; Guvenen et al. 2020)
3. Benchmark based on ML algorithm rather than average characteristics of senior employees (Fredriksson et al. 2018)

Related to recent work applying ML to personnel economics and corporate finance (Erel et al. 2021; Li et al. 2020)

Data

Data

- Swedish matched employer-employee data (LISA) covering the whole adult population in 2001-2010
- Firms with 30+ employees that report assets and sales
- Firm observables: sales, value added, age, industry, size, assets, ownership etc.
- CVs: age, gender, location and immigrant status, education level, specialization, past work experience (labor market experience, mobility, tenure, unemployment days, experience in each industry, experience in each firm-size class, job experience)
- Jobs are 3-digit occupations

Details

ML algorithm

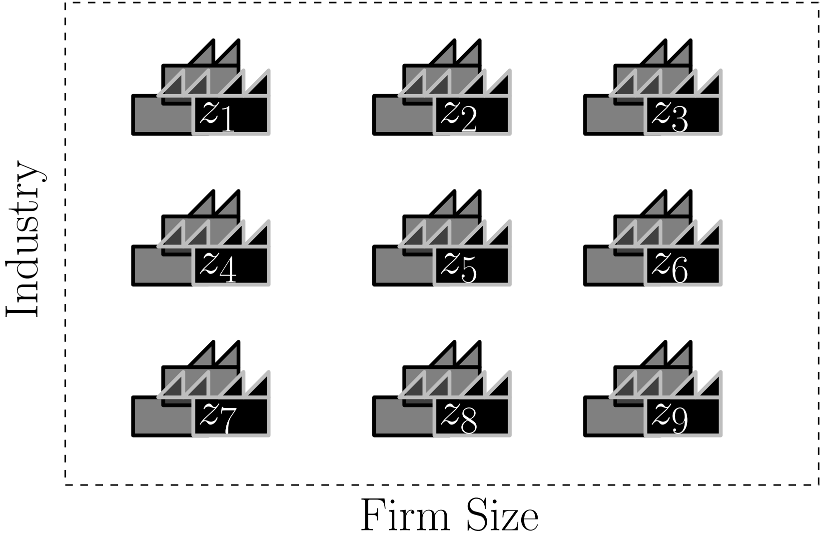
Sketch of the idea

- Map workers' and firms' observable characteristics to jobs

Worker characteristics x $\xrightarrow{\quad p_z(j|x) \quad}$ Jobs j

$p_z(j|x)$ $\uparrow$ Firm characteristics z

Firm characteristics

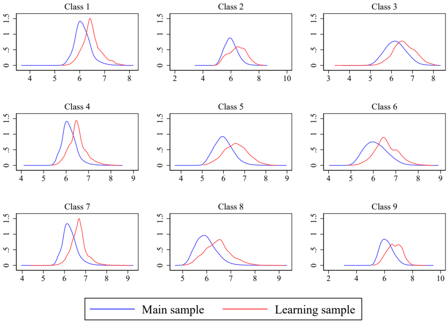


Implementation

1. Double-sorting of firms in 9 classes, by:
   - **median size:**
     - at most 50 employees;
     - between 51 and 250 employees;
     - more than 250 employees
   - **industry:**
     - manufacturing;
     - wholesale and retail;
     - real estate, renting and business activities
2. Estimate different mappings from workers' characteristics to jobs using the **top 10% of firms by (fixed effects)** value added per employee in 2010, within each class
3. Predict allocation of workers to jobs for remaining firms
4. Identify matches or mismatches relative to the predicted allocations

Common support

- Estimate wage regressions based on the main sample and including workers' characteristics used in the ML algorithm
- Using these estimates, predict wages to check whether workers' characteristics have common support in the learning and main samples:



Machine Learning algorithm

(1/2)

Unbalanced sample: jobs are not equally present in our sample

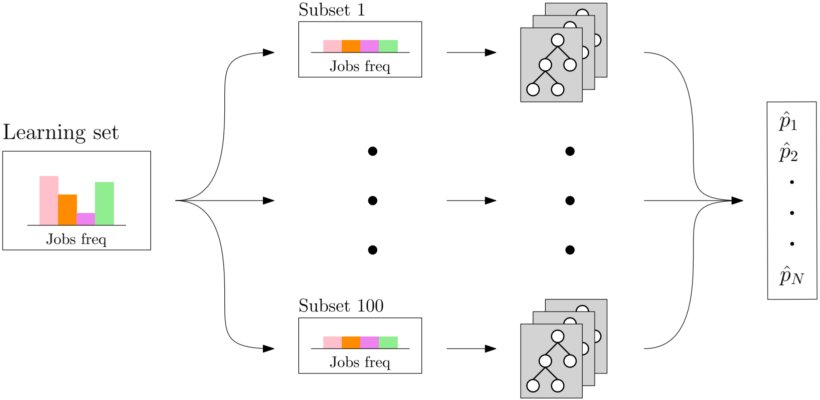
- Form balanced subsample via bootstrap (under-sampling more frequent jobs), use it to train random forest (50 decision trees, 100 times) and average results

Learning algorithm

- Random forests to estimate conditional class (job) probabilities and map employees to jobs:
  - ➥ handle mixed-type characteristics easily (continuous and categorical variable)
  - ➥ few-to-none tuning parameters $\Rightarrow$ reduced estimation time relative to other ML algorithms
  - ➥ among the best performing ML algorithms for classification

Machine Learning algorithm

(2/2)



Weighted F1-score: ML estimator's performance

	Size[a]	Manufacturing[b]	Wholesale[b]	Real estate[b]
Training sample	large	0.8013 (0.0002)	0.7254 (0.0008)	0.7194 (0.0017)
	medium	0.7699 (0.0007)	0.7054 (0.0008)	0.7537 (0.001)
	small	0.8137 (0.0005)	0.7796 (0.0007)	0.7877 (0.001)
Test sample	large	0.7683 (0.0029)	0.6678 (0.0033)	0.6096 (0.0062)
	medium	0.7245 (0.0038)	0.6253 (0.0053)	0.6597 (0.0091)
	small	0.7674 (0.0029)	0.7164 (0.004)	0.6765 (0.0093)

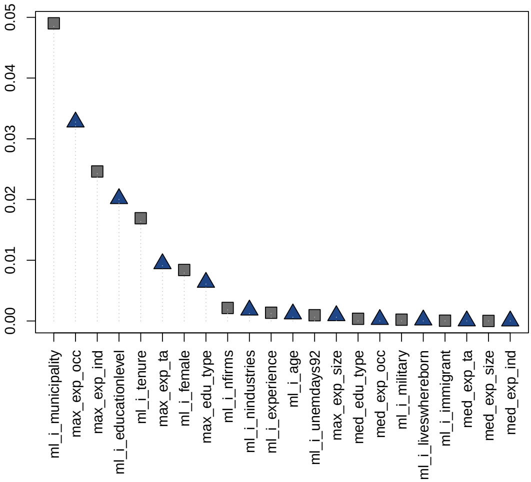
a. Industries: manufacturing; wholesale and retail; real estate, renting and business activities
b. Firm sizes: small (#employees $\leqslant$ 50); medium (#employees $\in (50, 250]$); large (#employees $>$ 250)

Ranking of workers' characteristics

(1/1)

- Preliminary ranking based on relevance of workers' characteristics in predicting jobs
- Only few characteristics significantly improve predictions
- Within these few, not all are equally relevant: e.g., experience matters more than type of education
- Among the most "useful" features:
    - ➥ location (municipality)
    - ➥ education level
    - ➥ tenure
    - ➥ gender
    - ➥ experience in some particular industries/occupations
- Ranking varies across the 9 classes

Example: ranking of worker characteristics in large manufacturing firms



More

JAQ measures

Measuring allocation quality

- Let j_i be the observed job for employee i;
- let $\hat{j}_i$ be the predicted job for employee i.

JAQ measures

- Employee-level Job Assignment Quality:

$$\text{eJAQ} = \mathbb{1}\left\{j_i = \hat{j}_i\right\}$$

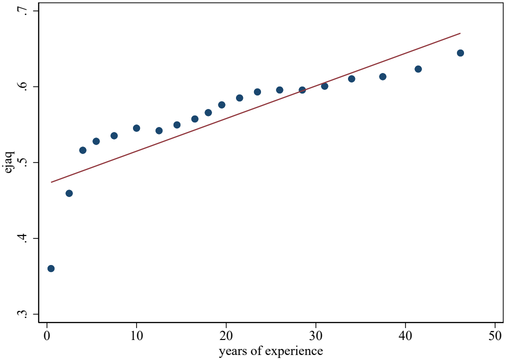
- (Firm-level) Job Assignment Quality (*JAQ*):

$$\text{JAQ} = \sum_{i \in empl.} \frac{\mathbb{1}\left\{j_i = \hat{j}_i\right\}}{\# empl.}$$

- *Suitability*: predicted probability of actual job ($\hat{p}_j$)

(Ongoing: constrain on available workers and occupations within the firm)

Job assignment quality over a worker's career



- The likelihood of being assigned correctly increases with experience
- Steepest rise in first years: combination of learning about worker type and on-the-job learning

Job assignment quality and earnings

(1/2)

To analyze the correlation between earnings and match quality, we estimate the following model:

$$\log(\text{earnings})_{it} = \alpha_j + \beta \text{eJAQ}_{it} + \gamma X_{it} + \delta Z_{f(i,t)} + \lambda_t + u_{it}$$

where

- α_j = job indicators
- eJAQ_{it} = indicator of whether worker *i* in year *t* is employed in her most suitable occupation
- X = workers' characteristics included in the ML algorithm
- $Z_{f(i,t)}$ = characteristics of the firm that employs worker *i* in year *t* (e.g., 2-digits industry dummies, firm age, indicators for family firm, listed company, presence of an HR manager, etc.)
- λ_t = year dummies

▸ Statistics Main ▸ Statistics Learning

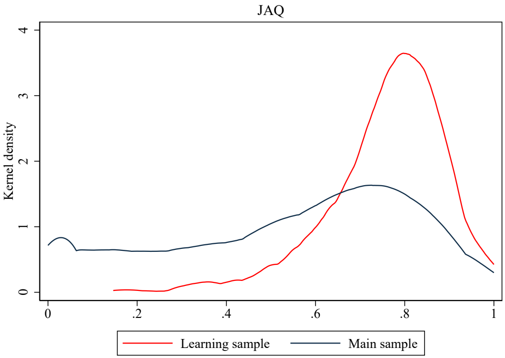
Job assignment quality and earnings (2/2)

	(1) Log(earnings)	(2) Log(earnings)	(3) Log(earnings)
Panel A:			
eJAQ	0.014***	0.007***	0.008***
	(0.000)	(0.000)	(0.000)
Panel B:			
Suitability	0.180***	0.032***	0.005***
	(0.001)	(0.001)	(0.001)
Year and job FE	✓	✓	✓
Worker controls (used in ML)	✓	✓	
Industry FE		✓	
Firm controls		✓	
Worker FE			✓
Observations	7,180,365	7,180,365	7,180,365
LHS mean	6.326	Mean earnings	330.05
LHS SD	0.658	SD earnings	206.03

- Well-matched workers earn a wage premium of 1.4% relative to mismatched workers in the same job
- Result robust to the inclusion of worker fixed effect

JAQ and productivity

Distribution of JAQ across firms



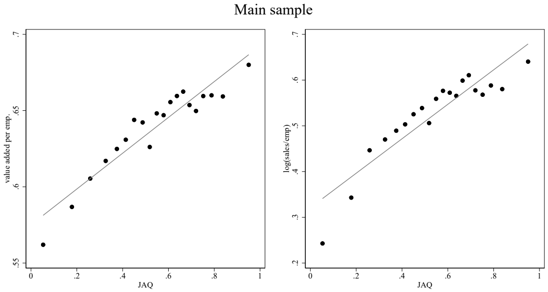
- In the main sample, JAQ is on average lower than in the learning sample: the means are 0.54 and 0.76 respectively, with standard deviations of 0.27 and 0.13

Statistics

Validating JAQ

Aim: show that JAQ is capturing meaningful variation across firms, **not just statistical noise**

- JAQ is positively associated with productivity in the main sample (relationship robust to the inclusion of several controls)



- but not in firms in the learning sample

▸ Learning sample

Comparison with Bloom et al. (2019)

	(1) log(sales/emp)	(2) VA per employee	(3) oroa	(4) log(sales/emp)	(5) VA per employee	(6) oroa
JAQ	0.521***	0.125***	-0.003	0.159***	0.039***	0.007
	(0.030)	(0.009)	(0.006)	(0.016)	(0.007)	(0.005)
log(cap/emp)				0.400***	0.107***	-0.009***
				(0.011)	(0.005)	(0.002)
log(emp)				0.017***	0.018***	0.005***
				(0.006)	(0.003)	(0.002)
Share emp w/ college				0.194***	0.301***	-0.006
				(0.040)	(0.021)	(0.013)
Observations	50,107	50,107	50,107	50,107	50,107	50,107
No. Firms	7,232	7,232	7,232	7,232	7,232	7,232
y Mean	0.525	0.639	0.067	0.525	0.639	0.067
y St. Dev.	0.788	0.304	0.178	0.788	0.304	0.178
Industry dummies				✓	✓	✓
Year dummies	✓	✓	✓	✓	✓	✓
Municipality dummies	✓	✓	✓	✓	✓	✓

Standard errors clustered at firm level in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Economic magnitude of coefficients

- Columns (1) and (2): a 10 percentage point increase in JAQ is associated with a 5.2% increase in sales per employee and a 1.2% increase in VA per employee
- A 1-s.d. increase in JAQ (0.27) is associated with a 15% increase in sales per employee and 3.4% increase in VA per employee
- Bloom, Brynjolfsson, et al. 2019: 1-s.d. increase in score is associated with 26.2% rise in sales per employee
- Municipality fixed effects control for firm labor market area
- No correlation between JAQ and profitability
- No robust correlation between JAQ and productivity in the learning sample

Learning sample

Productivity and JAQ

Conditioning on having similar occupational structure and observable characteristics, are firms with higher JAQ more productive?

$$y_{ft} = \theta_0 + \theta_1 \mathrm{JAQ}_{ft} + \theta_2 Z_{ft} + \theta_3 F_{jft} + \lambda_t + u_{ft}$$

where

- Z are firms' characteristics: firm age, indicators for family firm, state owned, listed, hr manager, log(employment) and log(capital)
- F_{jft} is the fraction of workers assigned to job j in firm f and year t
- y is log(sales/employees), value added per employee or operating return on assets

Conditioning on firms' occupational structure

	(1) log(sales/emp)	(2) VA per employee	(3) oroa	(4) log(sales/emp)	(5) VA per employee	(6) oroa
Panel A:						
JAQ	0.209***	0.061***	0.006	0.109***	0.028***	0.003
	(0.020)	(0.008)	(0.005)	(0.016)	(0.008)	(0.006)
Panel B:						
Suitability	0.591***	0.138***	0.011	0.339***	0.058***	0.007
	(0.042)	(0.019)	(0.012)	(0.034)	(0.017)	(0.012)
Industry dummies	✓	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓	✓
Municipality dummies	✓	✓	✓	✓	✓	✓
Occupations	✓	✓	✓	✓	✓	✓
Class FE	✓	✓	✓	✓	✓	✓
Firm controls				✓	✓	✓
Observations	50,107	50,107	50,107	50,107	50,107	50,107
No. Firms	7,232	7,232	7,232	7,232	7,232	7,232
y Mean	0.525	0.639	0.067	0.525	0.639	0.067
y St. Dev.	0.788	0.304	0.178	0.788	0.304	0.178

Standard errors clustered at firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Main sample · Learning sample

Is JAQ just capturing differences in workers' Xs?

- Augment the model with $\bar{X}^{w}_{ft}$, i.e., firm-level average employees' characteristics:

	(1) log(sales/emp)	(2) VA per employee	(3) oroa	(4) log(sales/emp)	(5) VA per employee	(6) oroa
JAQ	0.093***	0.038***	0.004	0.055***	0.025***	0.004
	(0.019)	(0.008)	(0.005)	(0.016)	(0.008)	(0.006)
Industry dummies				✓	✓	✓
Year dummies	✓	✓	✓	✓	✓	✓
Occupations	✓	✓	✓	✓	✓	✓
Workers X	✓	✓	✓	✓	✓	✓
Firm Z				✓	✓	✓
Class dummies	✓	✓	✓	✓	✓	✓
Observations	50,107	50,107	50,107	50,107	50,107	50,107
No. Firms	7,232	7,232	7,232	7,232	7,232	7,232
y Mean	0.525	0.639	0.067	0.525	0.639	0.067
y St. Dev.	0.788	0.304	0.178	0.788	0.304	0.178

Standard errors clustered at firm level in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Basing JAQ on different learning samples

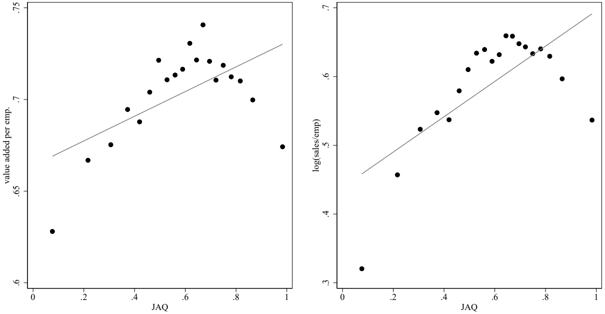
Mechanical correlation?

Could JAQ be positively correlated with productivity simply because the learning sample is formed by the most productive firms?

Checking circularity

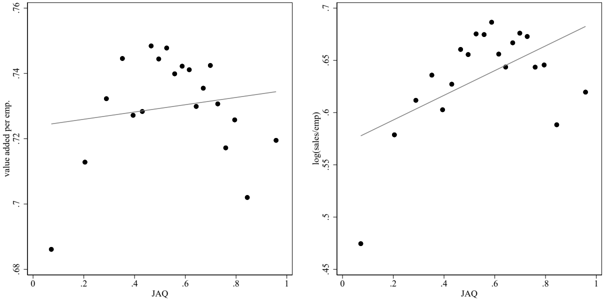
- To address this concern, we build two additional job allocation quality measures based on predictions drawn from
  - a random sample of firms → JAQ^R
  - the least productive firms → JAQ^B
- Explore the correlation between firm performance and JAQ^R and JAQ^B

JAQ^R and firm productivity



- Overall positive association between JAQ^R and productivity
- Inverse U-shape: if you mimic the average behavior very closely, you cannot excel

JAQ^B and firm productivity



Controls: year and 2digits-industry dummies

- Circularity would suggest a negative relationship between productivity and JAQ^B
- Overall positive association between JAQ^B and productivity
- Inverse U-shape: if you mimic the least productive firms very closely, you don't do well

JAQ and managerial talent

JAQ and managerial talent

- Split *JAQ* into:
  1. R&F-*JAQ*: quality of rank-and-file employees' assignment to jobs
  2. M-*JAQ*: quality of managers' allocation to their jobs
- Estimate the following model:

$$\text{R\&F-}\mathit{JAQ}_{ft} = \alpha_f + \lambda_t + \beta\text{M-}\mathit{JAQ}_{ft} + \gamma X_{ft} + \epsilon_{ft},$$

where

α_f = firm effects

λ_t = year effects

X_{ft} = firm controls (age, family firm, state-owned, listed status, dummy for the presence of a human resources manager, log number of employees and log of total assets)

JAQ and managerial talent

	(1) R&F-JAQ	(2) R&F-JAQ	(3) R&F-JAQ	(4) R&F-JAQ	(5) R&F-JAQ	(6) R&F-JAQ
M-JAQ	0.149***	0.144***	0.142***	0.077***	0.065***	0.063***
	(0.004)	(0.007)	(0.007)	(0.003)	(0.006)	(0.006)
Manager exp		0.034***	0.033***		0.019***	0.019***
		(0.002)	(0.002)		(0.002)	(0.002)
Industry FEs			✓			✓
Municipality FEs			✓			✓
Year FEs	✓	✓	✓	✓	✓	✓
Firm FEs		✓	✓		✓	✓
Firm controls			✓			✓
Observations	31,488	31,488	31,475	22,391	22,391	22,386
No. Firms		5,677	5,677		4,822	4,822

- 10 ppts increase in M-*JAQ* is associated with a 1.5 ppts increase in R&F-*JAQ* (columns 1, 2, 3)
- when M-*JAQ* refers only to top management (columns 4, 5, 6), the coefficient halves: middle management is also important for the correct allocation of workers to their jobs

JAQ and managerial turnover

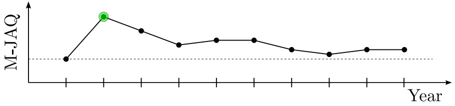
- Test if R&F-JAQ improves (worsens) upon incumbent managers being replaced with more (less) suitable ones

- $\Delta M\text{-}JAQ_\tau$ (due to turnover) $= M\text{-}JAQ_\tau - \frac{\sum eJAQ^r_\tau + \sum eJAQ^d_{\tau-1}}{\#\text{retained}+\#\text{dismissed}}$

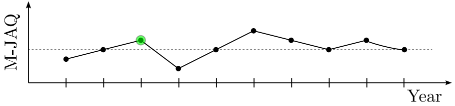
Turnover Event

Event stats

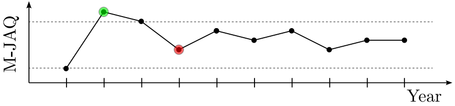
First time $\Delta M\text{-}JAQ > 0$ (<0), and rise (drop) in *M-JAQ* is not reversed



- Positive event

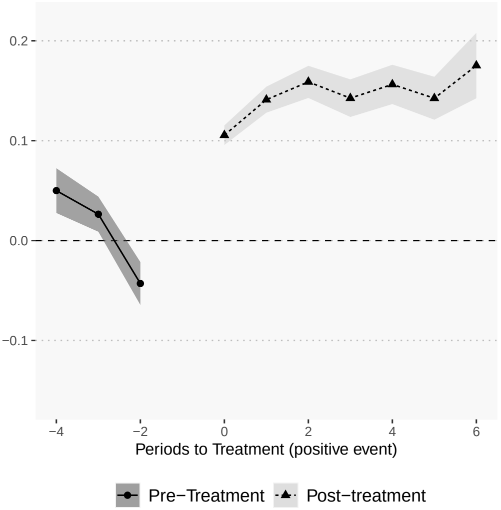


- No event (reversal)



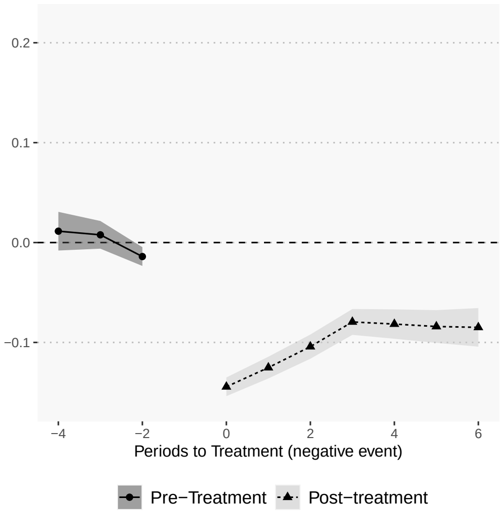
- Negative event is discarded, as it follows a positive one

JAQ and “positive” managerial turnover



Estimator: Callaway and Sant’Anna (2021)

JAQ and “negative” managerial turnover



Estimator: Callaway and Sant'Anna (2021)

Impact of turnover on retained employees

- How does managerial turnover affect changes in *R&F-JAQ* of retained employees?
  - ➥ Positive event: 14-percentage-points rise in overall R&F
  - ➥ Negative event: 13-percentage-points drop in overall R&F
  - ➥ 2/3 from the change in the allocation quality of retained workers
  - ➥ workers being reassigned to new jobs drive the effect

	$\Delta R\&F\text{-}JAQ$	$\Delta R\&F\text{-}JAQ^r$	$\Delta R\&F\text{-}JAQ^c$
Positive event	0.1443 (0.023)	0.0935 (0.019)	0.0974 (0.0765)
Negative event	−0.1317 (0.0171)	−0.0953 (0.0128)	−0.1897 (0.0519)

Conclusions

- We develop measures of job assignment quality (JAQ) using ML and matched employer-employee data
- Firm-level productivity correlates positively with JAQ
  - ➥ controlling for firms' location and occupation structure
  - ➥ controlling for employees' characteristics and work histories
- Rank and file workers' *JAQ* is positively associated with managers' *JAQ* and experience
- Rank and file workers' *JAQ*
  - ➥ increases after managers are replaced with better ones
  - ➥ decreases after managers are replaced with worse ones
- Improved ability in workforce allocation is due to better or worse ability of the management in re-allocating retained employees.

Thank you!

Appendix

Occupations

Back

1 Legislators, senior officials and managers
  - 12 Corporate managers
    - 121 Directors and chief executives
    - 122 Production and operations managers
    - 123 Other specialist managers
  - 13 Managers of small enterprises
    - 131 Managers of small enterprises

2 Professionals

3 Technicians and associate professionals

4 Clerks

5 Service workers and shop sales workers

6 Skilled agricultural and fishery workers

7 Craft and related trades workers

8 Plant and machine operators and assemblers

9 Elementary occupations

0 Armed forces

Pseudocode

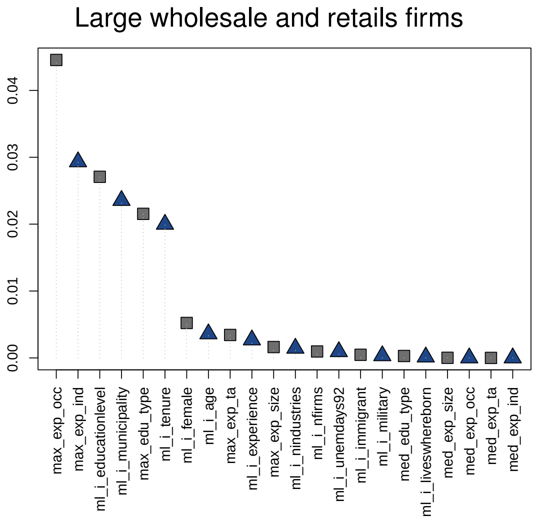
Back

```
Algorithm: Classification algorithm
input  : Data; #forests; #trees
output: RF classifier: RF(x) = y
for i = 1 : #forests do
    D = randomly extract class-balanced subset from Data
    RF_i = grow a random forest with "#trees" trees on D; begin
        for t = 1 : #trees do
            D̃ = bootstrap sample from D
            Using D̃: while tree t not fully grown do
                foreach terminal node do
                    select randomly m = √# features
                    select the best feature among m to split the node in
                      two

RF = aggregate RF_i's (average classification probabilities)
y = RF(x); y is the class with highest predicted probability.
```

Ranking of workers' characteristics

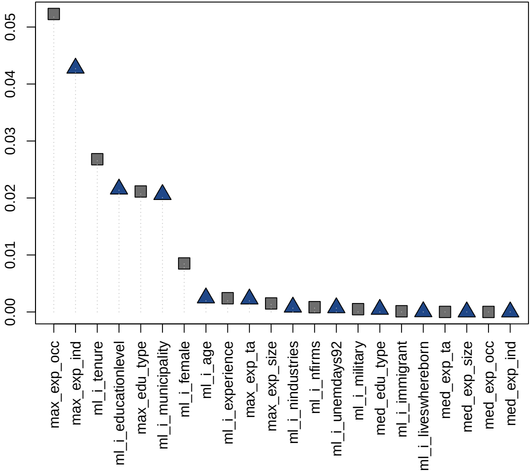
Back (1/8)



Ranking of workers' characteristics

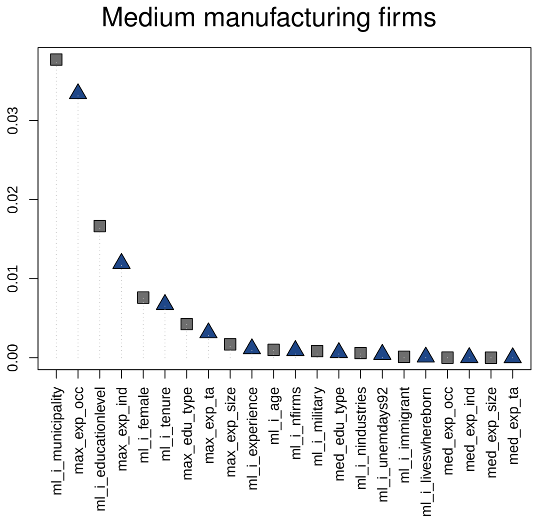
Back (2/8)

Large real estate, renting, and business activities firms



Ranking of workers' characteristics

Back (3/8)



Ranking of workers' characteristics

▸ Back

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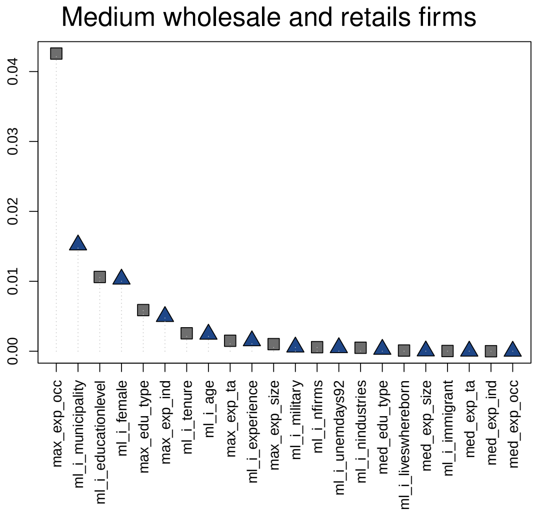
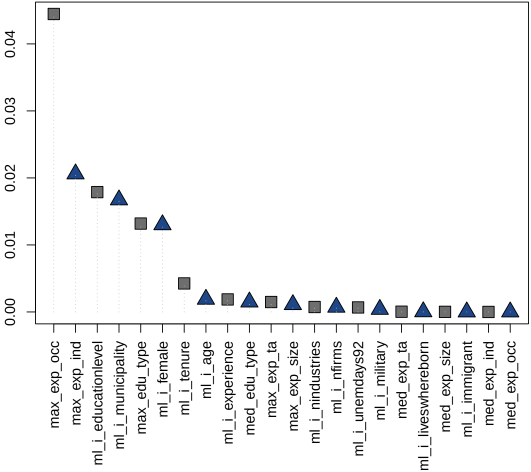


Ranking of workers' characteristics

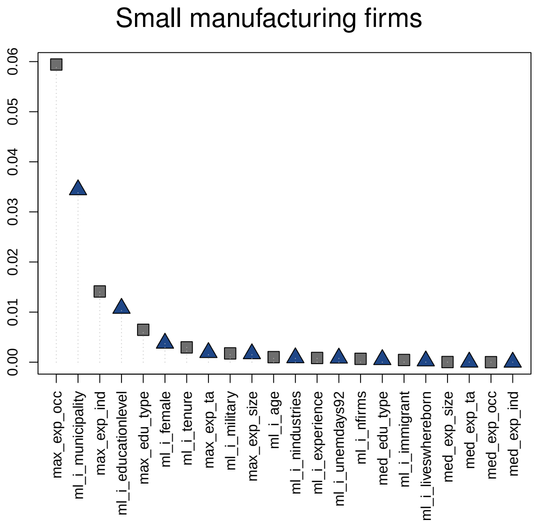
Back (5/8)

Medium real estate, renting, and business activities firms



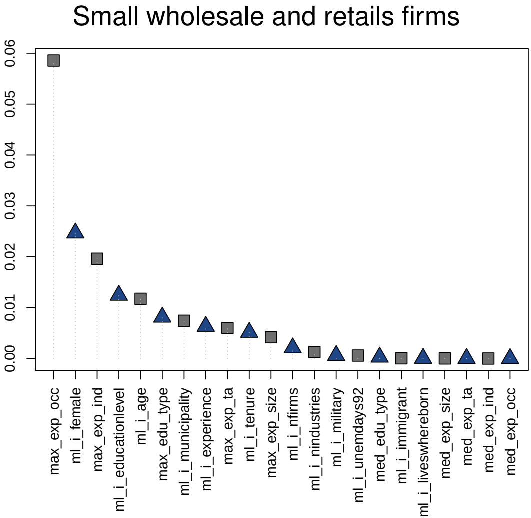
Ranking of workers' characteristics

Back



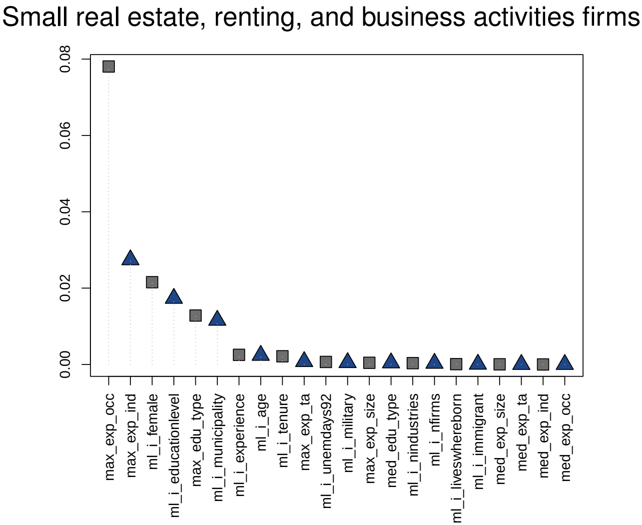
Ranking of workers' characteristics

Back (7/8)



Ranking of workers' characteristics

Back (8/8)



Summary statistics: main sample

Back

	mean	p50	p10	p25	p75	p90	sd	count
iJAQ	0.55	1.00	0.00	0.00	1.00	1.00	0.50	7,180,365
i_loglaborincome	6.33	6.42	5.58	6.15	6.66	6.95	0.66	7,180,365
maxval	0.35	0.32	0.11	0.17	0.48	0.65	0.21	7,180,365
i_laborincome	330.05	305.59	132.78	234.08	390.54	521.77	206.03	7,180,365
college	0.13	0.00	0.00	0.00	0.00	1.00	0.34	7,180,365
i_age	40.49	40.00	24.00	31.00	50.00	58.00	12.19	7,180,365
i_female	0.35	0.00	0.00	0.00	1.00	1.00	0.48	7,180,365
i_immigrant	0.14	0.00	0.00	0.00	0.00	1.00	0.34	7,180,365
i_liveswhereborn	0.64	1.00	0.00	0.00	1.00	1.00	0.48	7,180,365
i_experience	19.46	18.00	3.00	8.00	29.00	39.00	13.05	7,180,365
i_tenure	4.99	3.00	0.00	1.00	8.00	13.00	5.08	7,180,365
i_nindustries	2.30	2.00	1.00	1.00	3.00	4.00	1.27	7,180,365
i_nfirms	2.99	3.00	1.00	2.00	4.00	5.00	1.72	7,180,365
i_unemdays92	192.46	0.00	0.00	0.00	243.00	626.00	349.44	7,180,365
i_military	0.06	0.00	0.00	0.00	0.10	0.20	0.10	7,180,365

Summary statistics: learning sample

Back

	mean	p50	p10	p25	p75	p90	sd	count
iJAQ	0.77	1.00	0.00	1.00	1.00	1.00	0.42	81,390
i_loglaborincome	6.64	6.66	6.10	6.43	6.92	7.23	0.58	81,390
maxval	0.59	0.59	0.29	0.41	0.79	0.91	0.23	81,390
i_laborincome	444.78	389.02	221.95	309.10	505.68	691.86	315.90	81,390
college	0.21	0.00	0.00	0.00	0.00	1.00	0.41	81,390
i_age	42.45	42.00	27.00	34.00	51.00	58.00	11.36	81,390
i_female	0.32	0.00	0.00	0.00	1.00	1.00	0.47	81,390
i_immigrant	0.14	0.00	0.00	0.00	0.00	1.00	0.35	81,390
i_liveswhereborn	0.62	1.00	0.00	0.00	1.00	1.00	0.49	81,390
i_experience	20.55	20.00	4.00	10.00	30.00	39.00	12.62	81,390
i_tenure	6.95	5.00	0.00	2.00	11.00	19.00	6.41	81,390
i_nindustries	2.64	2.00	1.00	1.00	4.00	5.00	1.44	81,390
i_nfirms	3.42	3.00	1.00	2.00	5.00	6.00	1.96	81,390
i_unemdays92	182.10	0.00	0.00	0.00	220.00	576.00	344.07	81,390
i_military	0.07	0.00	0.00	0.00	0.10	0.20	0.13	81,390

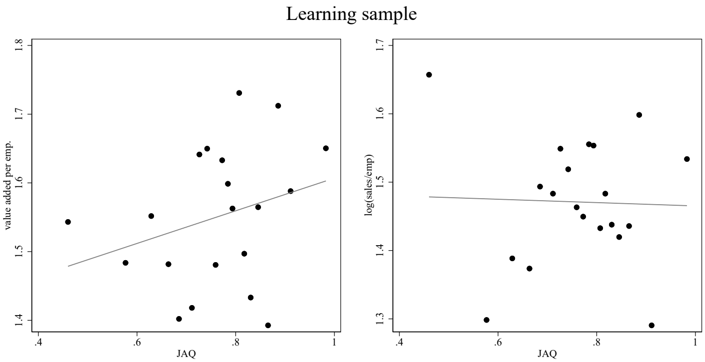
Summary Statistics

Back

	mean	p50	p10	p25	p75	p90	sd	count
JAQ	0.54	0.60	0.10	0.33	0.76	0.86	0.27	50,107
A-JAQ	0.57	0.62	0.14	0.37	0.78	0.89	0.27	50,107
VA per employee	0.64	0.59	0.35	0.46	0.76	0.96	0.30	50,107
sales	348.09	116.47	31.39	58.16	254.63	633.86	1,123.61	50,107
sales/emp	2.28	1.71	0.66	1.09	2.79	4.21	2.20	50,107
log(sales/emp)	0.53	0.53	-0.42	0.08	1.02	1.44	0.79	50,107
oroa	0.07	0.07	-0.09	0.01	0.15	0.24	0.18	50,107
total assets	340.42	58.81	13.07	27.04	149.79	457.02	2,681.51	50,107
log(capital)	4.23	4.07	2.57	3.30	5.01	6.12	1.46	50,107
employees	146.04	61.00	32.00	41.00	118.00	276.00	345.03	50,107
log(emp)	4.33	4.11	3.47	3.71	4.77	5.62	0.95	50,107
family firm	0.22	0.00	0.00	0.00	0.00	1.00	0.41	50,107
listed	0.01	0.00	0.00	0.00	0.00	0.00	0.10	50,107
state owned	0.02	0.00	0.00	0.00	0.00	0.00	0.15	50,107
hr manager	0.12	0.00	0.00	0.00	0.00	1.00	0.33	50,107
firm age	11.66	12.00	3.00	8.00	16.00	18.00	5.38	50,107

No correlation b/w *JAQ* and productivity

Back



Controls: year and 2digits-industry dummies

Learning sample

Back

	(1) log(sales/emp)	(2) VA per employee	(3) oroa	(4) log(sales/emp)	(5) VA per employee	(6) oroa
			Panel B: Learning-sample Firms			
JAQ	0.135	0.717***	-0.003	-0.067	0.218	0.142**
	(0.202)	(0.207)	(0.060)	(0.173)	(0.207)	(0.060)
log(capital/emp)				0.389***	0.190***	-0.043***
				(0.041)	(0.041)	(0.013)
log(employment)				0.018	0.016	0.012
				(0.023)	(0.034)	(0.010)
Share emp w/ college				-0.153	-0.040	-0.082*
				(0.177)	(0.181)	(0.043)
Observations	505	505	505	505	505	505
y Mean	1.471	1.550	0.155	1.471	1.550	0.155
y St. Dev.	0.618	0.630	0.163	0.618	0.630	0.163
Industry dummies				✓	✓	✓
Year dummies	✓	✓	✓	✓	✓	✓

Standard errors clustered at firm level in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

JAQ and productivity: main-sample firms

Back

	(1) log(sales/emp)	(2) VA per employee	(3) oroa	(4) log(sales/emp)	(5) VA per employee	(6) oroa
JAQ	0.211***	0.060***	0.006	0.107***	0.026***	0.002
	(0.020)	(0.009)	(0.005)	(0.016)	(0.008)	(0.005)
firm age				0.004***	0.003***	0.002***
				(0.001)	(0.000)	(0.000)
family firm				-0.074***	-0.007	0.012***
				(0.010)	(0.004)	(0.003)
state owned				0.008	0.064**	-0.033***
				(0.036)	(0.027)	(0.008)
listed				-0.412***	-0.113**	-0.049***
				(0.067)	(0.046)	(0.015)
hr manager				-0.043***	-0.019***	-0.013***
				(0.013)	(0.006)	(0.004)
log(emp)				-0.384***	-0.081***	0.010***
				(0.013)	(0.006)	(0.003)
log(capital)				0.374***	0.103***	-0.003
				(0.011)	(0.005)	(0.002)
Industry dummies	✓	✓	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓	✓	✓
Occupations	✓	✓	✓	✓	✓	✓
Group	✓	✓	✓	✓	✓	✓
Observations	50,107	50,107	50,107	50,107	50,107	50,107
No. Firms	7,232	7,232	7,232	7,232	7,232	7,232
y Mean	0.525	0.639	0.067	0.525	0.639	0.067
y St. Dev.	0.788	0.304	0.178	0.788	0.304	0.178

Standard errors clustered at firm level in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

JAQ and productivity: learning-sample firms

Back

	(1) log(sales/emp)	(2) VA per employee	(3) oroa	(4) log(sales/emp)	(5) VA per employee	(6) oroa
JAQ	-0.200	0.431*	0.083	-0.293	0.357	0.076
	(0.236)	(0.259)	(0.082)	(0.198)	(0.233)	(0.076)
firm age				-0.005	0.002	0.000
				(0.005)	(0.006)	(0.002)
family firm				-0.191***	-0.129*	-0.027
				(0.070)	(0.074)	(0.026)
state owned				0.048	0.055	-0.071**
				(0.170)	(0.229)	(0.034)
listed				-0.723***	-0.461	-0.089*
				(0.214)	(0.423)	(0.053)
hr manager				-0.050	0.118*	0.007
				(0.058)	(0.067)	(0.020)
log(emp)				-0.333***	-0.379***	0.007
				(0.054)	(0.061)	(0.022)
log(capital)				0.354***	0.217***	-0.041***
				(0.038)	(0.038)	(0.012)
Industry FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Occupations	✓	✓	✓	✓	✓	✓
Group	✓	✓	✓	✓	✓	✓
Observations	505.000	505.000	505.000	505.000	505.000	505.000
No. Firms	505.000	505.000	505.000	505.000	505.000	505.000
y Mean	1.471	1.550	0.155	1.471	1.550	0.155
y St. Dev.	0.618	0.630	0.163	0.618	0.630	0.163

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Turnover event statistics

Back

- Total number of firms: 6549
- Firms experiencing a positive event: 1,360 (20.8% of the total)
- Firms experiencing negative event: 3,124 (47.7%)
- Firms experiencing no event: 2,065 (31.5%)
- No firm experience both positive end negative events