Team production: a network study of publications in Economics

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Intro

Motivation

- Is teamwork more productive than solo-work?
- Can we empirically study properties of team production?
  - Additivity?
  - Complementarity?
- Should the planner pair workers of similar types? Or should they pair workers with very different (high/low) types?

Challenges

- We only observe team output as Y and a vector of authors as X. Note that the academic production network is different from the trade production network, because economists can usually observe the firm inputs in the the latter case. In the academic production, we don't observe labor inputs.
- Some authors don't have solo publications. How to infer their type?
- Collaboration (network) matrix is very sparse.

Literature

My dissertation is heavily motivated by Bonhomme (2021).

What's similar

- Linear fixed-effects approach
- Use of Moore-Penrose inverse (pseudo-inverse) in the least-square estimation.

What's new

- Bonhomme (2021) focuses on the methodology of estimating fixed-effects model and random-effects model. Based on his fixed-effects model, I use a LS model with stronger but simplifying assumptions. I also explore some interesting properties of team production.
- Bonhomme (2021)'s identification requires variations in the team composition. If two people always work together, their types aren't identified. My identification requires economists to have at least one solo, one 2-person, and one 3-person publications so that their types and the team-size effects can all be identified.
- Herkenhoff et al. (2018) uses wage as a proxy of human capital to study team production. My approach does not rely on wage as a proxy.

Data

My data is constructed from Microsoft Academic Graph which is a very rich and large (200GB) database including (almost) all scientific publications.

Sample selection (Metric)

- **Econometricians** - economists who have published at least 3 articles in *Journal of Econometrics*, *Journal of Business Economic Statistics*, *Journal of Applied Econometrics*, *Econometric Theory*, *Journal of Financial Econometrics*, *Journal of Time Series Econometrics*, *Journal of Time Series Analysis* and *Econometrics Journal*.
- Find all **articles** written by the econometricians defined above, **including those in non-metric journals**

Subsample selection (Metric)

From the sample of econometricians, I find those with at least one solo article, at least one two-author article and at least one three-author article.

		Sample			Subsample		
		1	2	3	1	2	3
Article Count	Number of Papers	11555.0	9616.0	3327.0	5732.0	6281.0	2561.0
	mean	6.11	5.09	1.76	8.14	8.92	3.64
	std	9.73	7.22	3.29	11.79	9.88	4.29
	min	0.0	0.0	0.0	1.0	1.0	1.0
	q10	0.0	0.0	0.0	1.0	1.0	1.0
	q30	1.0	1.0	0.0	2.0	3.0	1.0
	median	3.0	3.0	1.0	4.0	6.0	2.0
	q70	6.0	5.0	2.0	8.0	10.0	4.0
	q90	15.0	13.0	5.0	18.0	20.0	7.0
	max	145.0	130.0	48.0	145.0	130.0	48.0
Journal Quality	Number of Authors	11555.0	4808.0	1109.0	5732.0	4053.0	1087.0
	mean	3.0	2.75	2.73	2.83	2.77	2.73
	std	2.93	1.89	1.4	2.2	1.94	1.4
	min	0.11	0.5	0.51	0.38	0.51	0.51
	q10	1.16	1.37	1.39	1.18	1.37	1.37
	q30	1.82	2.1	2.1	1.85	2.1	2.1
	median	2.37	2.39	2.39	2.35	2.39	2.39
	q70	2.9	2.44	2.42	2.68	2.44	2.42
	q90	5.62	5.03	5.03	5.33	5.03	5.03
	max	53.24	53.24	15.56	53.24	53.24	15.56

Table: Descriptive statistics

Robustness Check

- I have tried other choices of dependent variables. This paper quantifies **paper quality** by journal quality which is then proxied by the (Clarivate) **impact factor**. However, I also tried other dependent variables such as *VWL Ranking Deutschland* but the results turn out to be very similar.
- In addition to econometricians, I also repeat my estimation on macro and micro theorists. Most results agree.

My paper attempts to empirically examine some properties of team production

In my model of two-person team production function,

$$y_\ell^{(2)}(\alpha_1, \alpha_2) = \lambda_2(\alpha_1 + \alpha_2) + f(\alpha_1, \alpha_2) + \epsilon_\ell$$

- Linear component $\alpha_1 + \alpha_2$, scaled by team-size effects
- Non-linear component $f(\alpha_1, \alpha_2)$
  - Positive marginal effect: $\lambda_2 + \frac{\partial f}{\partial \alpha_i} > 0$
  - Strong asymmetry in individual marginal effects
  - Supermodularity: $\frac{\partial^2 f}{\partial \alpha_1 \alpha_2} > 0$

Model of fixed-effects

Additive model of fixed effects

$$\begin{cases} Y_\ell^{(1)} = \alpha_i^{(1)} + \epsilon_\ell^{(1)} \\ Y_\ell^{(2)} = \alpha_i^{(2)} + \alpha_j^{(2)} + \epsilon_\ell^{(2)} = \lambda_2(\alpha_i^{(1)} + \alpha_j^{(1)}) + \epsilon_\ell^{(2)} \\ Y_\ell^{(3)} = \alpha_i^{(3)} + \alpha_j^{(3)} + \alpha_k^{(3)} + \epsilon_\ell^{(3)} = \lambda_3(\alpha_i^{(1)} + \alpha_j^{(1)} + \alpha_k^{(1)}) + \epsilon_\ell^{(3)} \end{cases}$$

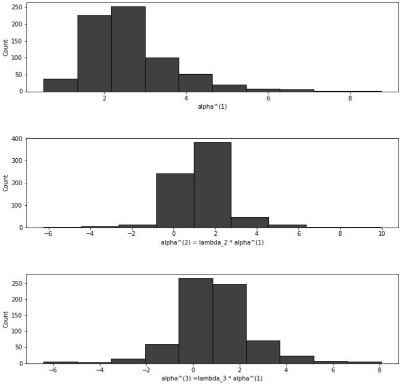
In vector notations,

$$\begin{cases} Y^{(1)} = X_1\alpha^{(1)} + \epsilon^{(1)} \\ Y^{(2)} = \lambda_2 \cdot X_2\alpha^{(1)} + \epsilon^{(2)} \\ Y^{(3)} = \lambda_3 \cdot X_3\alpha^{(1)} + \epsilon^{(3)}, \end{cases} \quad X^{(1)} = \begin{array}{cccc} & i & j & k \\ \ell_1 & 0 & 1 & 0 \\ \ell_2 & 1 & 0 & 0 \\ \ell_3 & 1 & 0 & 0 \end{array}, X^{(2)} = \begin{array}{cccc} & i & j & k \\ \ell_1 & 1 & 1 & 0 \\ \ell_2 & 1 & 0 & 1 \\ \ell_3 & 0 & 1 & 1 \\ \ell_4 & 0 & 1 & 1 \end{array}$$

Assumptions (Would be great if future theory work can relax the strong assumptions)

- Individual type α_i is fixed.
- Team-size effects λ are unobserved scalars. Normalize $\lambda_1 = 1$.
- Shocks are mutually independent
- Shocks are independent of team formation
- Shocks are independent of types
- Shocks are independent of team formation, conditional on types

Empirical distribution of fixed-effects



Some observations

- Individual types are very heterogeneous.
- Estimated distributions are roughly shape-preserving.

Team-size effect

Why care about λ?

- In two-person teams, suppose economist *i* has type α_i and coauthor *j* has type $\alpha_j = \alpha_i + \Delta$ for some $\Delta \in \mathbb{R}$.
- Solo output = α_i
- Two-person output = $\lambda_2 \left(\alpha_i + \alpha_j\right)$
- Difference in output = $\lambda_2 \left(\alpha_i + (\alpha_i + \Delta)\right) - \alpha_i = (2\lambda_2 - 1)\alpha_i + \lambda_2 \Delta$

Fixing the heterogeneity parameter Δ, the collaboration gain is $2\lambda_2 - 1$. For example, $\lambda_2 = 0.55$ implies 10% gain, if you coauthor with someone of your type instead of working alone.

Two ways to estimate λ

By assumption, individuals has fixed types. We then have two moment conditions.

$$\alpha_i^{(2)} = \lambda_2 \alpha_i^{(1)}$$

$$\alpha_i^{(3)} = \lambda_3 \alpha_i^{(1)}$$

One straightforward way to estimate λ is to simply regress $\alpha_i^{(2)}$ on $\alpha_i^{(1)}$ and $\alpha_i^{(3)}$ on $\alpha_i^{(1)}$.

But we do *not* know the true $\alpha_i^{(1)}$. Instead, we have plug-in estimates $\hat{\alpha}_i^{(1)}$.

Least square regression on $\hat{\alpha}_i^{(1)}$ leads to regression attenuation because of the noisy regressors.

	Two-person team	Three-person team
Scaling factor	0.47	0.32
Collaboration gain	-5.2%	-2.8%
Number of metric-economists	704	704

Table: Attenuated Metric team-size effects

Generalized method of moments

- Because λ_2 and λ_3 are scalars, by manipulating our moment conditions, we get

$$\mathbb{E}[\alpha_i^{(2)} - \lambda_2 \alpha_i^{(1)}] = 0$$

$$\mathbb{E}[\alpha_i^{(3)} - \lambda_2 \alpha_i^{(1)}] = 0$$

- Because least-squared estimation is unbiased,

$$\mathbb{E}[\hat{\alpha}_i^{(1)}] = \alpha_i^{(1)}, \quad \mathbb{E}[\hat{\alpha}_i^{(2)}] = \alpha_i^{(2)}, \text{ and } \mathbb{E}[\hat{\alpha}_i^{(3)}] = \alpha_i^{(3)}$$

- So the sample analog is

$$\begin{cases} \frac{1}{I}\sum_i \hat{\alpha}_i^{(2)} - \lambda_2 \frac{1}{I}\sum_i \hat{\alpha}_i^{(1)} = 0 \\ \frac{1}{I}\sum_i \hat{\alpha}_i^{(3)} - \lambda_3 \frac{1}{I}\sum_i \hat{\alpha}_i^{(1)} = 0 \end{cases}$$

So,

$$\hat{\lambda}^{\text{GMM}}(\hat{\alpha}) = \begin{bmatrix} 1 \\ \frac{1}{I}\sum_i \hat{\alpha}_i^{(2)} / \frac{1}{I}\sum_i \hat{\alpha}_i^{(1)} \\ \frac{1}{I}\sum_i \hat{\alpha}_i^{(3)} / \frac{1}{I}\sum_i \hat{\alpha}_i^{(1)} \end{bmatrix}$$

GMM results

	Two-person team	Three-person team
Scaling factor	0.51	0.36
Collaboration gain	2.5%	7.8%
Number of econometricians	737	737

Table: GMM estimates of Metric team-size effects

	Two-person team	Three-person team
Scaling factor	0.52	0.37
Collaboration gain	4.8%	12.2%
Number of macro-economists	396	396

Table: GMM estimates of Macro team-size effects

	Two-person team	Three-person team
Scaling factor	0.47	0.28
Collaboration gain	-5.9%	-14.6%
Number of micro-economists	859	859

Table: GMM estimates of Micro team-size effects

Complementarity

Regressions of $Y^{(2)}$, impact factor of two-author papers

To reduce the noise in $\hat{\alpha}_i^{(1)}$, I only look at economists with more than 3 solo publications.

	(1)	(2)
Min$(\hat{\alpha}_1, \hat{\alpha}_2)$	0.677***	0.597***
	(0.066)	(0.038)
Max$(\hat{\alpha}_1, \hat{\alpha}_2)$	0.357***	0.437***
	(0.047)	(0.021)
$\hat{\sigma}(\hat{\alpha}_1, \hat{\alpha}_2)$		-0.113***
		(0.040)
Observations	1,885	1,885
R^2	0.636	0.636
Adjusted R^2	0.636	0.636
Residual Std. Error	2.234(df = 1883)	2.234(df = 1883)
Note:	*p<0.1; **p<0.05; ***p<0.01	

1. The marginal return of the lowest-type is significantly higher than that of the highest-type. Consistent with other empirical literature such as Ahmadpoora and Jones (2016).
2. Does the variance/spread of types play a role in the asymmetric marginal effects?

Evidence of complementarity (Macro)

	(1)	(2)
Min($\hat{\alpha}_1, \hat{\alpha}_2$)	0.941***	0.749***
	(0.096)	(0.056)
Max($\hat{\alpha}_1, \hat{\alpha}_2$)	0.173**	0.365***
	(0.068)	(0.029)
$\hat{\sigma}(\hat{\alpha}_1, \hat{\alpha}_2)$		-0.272***
		(0.057)
Observations	1,043	1,043
R^2	0.610	0.610
Adjusted R^2	0.609	0.609
Residual Std. Error	2.938(df = 1041)	2.938(df = 1041)
Note:	*p$<$0.1; **p$<$0.05; ***p$<$0.01	

Evidence of complementarity (Micro)

	(1)	(2)
$\text{Min}(\hat{\alpha}_1, \hat{\alpha}_2)$	1.059***	0.813***
	(0.049)	(0.031)
$\text{Max}(\hat{\alpha}_1, \hat{\alpha}_2)$	0.074***	0.320***
	(0.025)	(0.011)
$\hat{\sigma}(\hat{\alpha}_1, \hat{\alpha}_2)$		-0.348***
		(0.025)
Observations	2,466	2,466
R^2	0.453	0.453
Adjusted R^2	0.452	0.452
Residual Std. Error	3.159(df = 2464)	3.159(df = 2464)
Note:		*p$<$0.1; **p$<$0.05; ***p$<$0.01

Supermodularity

Empirical evidence of supermodularity

Supermodularity

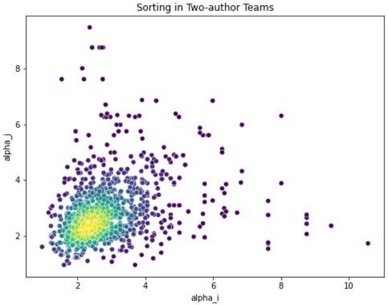
If f is twice differentiable, f is strictly supermodular is equivalent to

$$\frac{\partial f}{\partial \alpha_i \partial \alpha_j} > 0$$

I assign quartiles (Q1, Q2, Q3, Q4) to Researcher 2 based on their estimated $\hat{\alpha}_2^{(1)}$.
Then, I create three interaction terms between $\hat{\alpha}_1^{(1)}$ and the dummy variables corresponding to the quartiles.

	(1)	(2)
$\hat{\alpha}_1$	0.918***	
	(0.017)	
$\hat{\alpha}_1 \times$ Dummy for coauthor belonging to Q2		0.847***
		(0.039)
$\hat{\alpha}_1 \times$ Dummy for coauthor belonging to Q3		0.933***
		(0.038)
$\hat{\alpha}_1 \times$ Dummy for coauthor belonging to Q4		1.002***
		(0.033)
Observations	1,885	1,885
R^2	0.600	0.516
Adjusted R^2	0.600	0.515
Residual Std. Error	2.342(df = 1884)	2.578(df = 1882)
Note:		*p<0.1; **p<0.05; ***p<0.01

Positive assortive sorting and Supermodularity



Chade, Eeckhout, and Smith (2017)

Match output function is supermodular if and only if positive assortive matching (PSM) is optimal, assuming

- Transferable utility
- Frictionless searching

Put it all together

In my model of two-person team production function,

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- Linear component $\alpha_1 + \alpha_2$, scaled by team-size effects
- Non-linear component $f(\alpha_1, \alpha_2)$
  - Positive marginal effect: $\lambda_2 + \frac{\partial f}{\partial \alpha_i} > 0$
  - Strong asymmetry in individual marginal effects: Is $\frac{\partial f}{\partial \alpha_i}$ related to the cardinal value of α_i or its ordinal rank in the team? Does the size of the spread/gap between team members' types matter?
  - Supermodularity: $\frac{\partial^2 f}{\partial \alpha_1 \alpha_2} > 0$

Thank you!

Any questions?