# Dancing with the Stars: Innovation Through Interactions

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- Especially for policy, it is important to understand where productive knowledge comes from.
- Facts in the data:
    1. individuals specialize in certain occupations,
    2. researchers accumulate knowledge through interactions,
    3. researchers work in teams.

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Q3: *How can we discipline such a framework using data?*

- Q1 and Q2 require bringing together innovation-based growth models and recently growing knowledge diffusion models.
- Q3 requires data on who interacts with whom, on productivity, innovation, and research teams.

# Ideas and Contributions: Theoretical Model

Knowledge serves to produce innovations (technology improvements) and is carried through human interactions (building on the shoulders of giants).

**Innovation-based growth**

Aggregate productivity $A(t)$ evolves through innovation:

$$A(t+dt) = (1+\lambda)A(t) = A(t) + q(t)$$

$$q(t) = \lambda A(t) = \text{innovation}$$

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**Interaction-based growth**

Innovations produced by research teams

$$q(t) = \underbrace{z(t)}^{\eta} n(t)^{1-\eta}$$

Inventors' human capital/ knowledge

$\rightarrow$ evolves through diffusion

# Empirical and Quantitative Analysis

- Bring new data to this theoretical framework.
- Patent data from the European Patent Office (EPO):
  - Recently disambiguated.
  - Better representation of many different countries.
- Allows us to measure (i) interactions, (ii) research teams, and (iii) productivity (typically very challenging).
  - Can inform key ingredients of the model.
  - Can document the importance of interactions.
  - Show the model fits the data very closely (targeted & non-targeted).
  - Can perform counterfactual policy analysis.

# Related Literature

Innovation-Based Endogenous Growth Models:

Romer (1990), Aghion and Howitt (1992), Grossman and Helpman (1991), Klette and Kortum (2004), Aghion, Akcigit and Howitt (2014), Acemoglu, Akcigit, Alp, Bloom, and Kerr (2017), Akcigit and Kerr (2017).

Diffusion Models:

Kortum (1997), Lucas (2009), Lucas and Moll (2014), Staley (2011), Luttmer (2007, 2012, 2015), Perla and Tonetti (2014), Benhabib, Perla and Tonetti (2017), Alvarez, Buera and Lucas (2017), Buera and Oberfield (2016), König, Ludwig and Zilibotti (2016).

Life cycle and teams of inventors:

Wuchty et al. (2007), Ben Jones (2009, 2010), Jones and Weinberg (2011), Azoulay et al. (2015), Jaravel et al. (2017).

# Outline

Model

Empirical Results

Quantitative Analysis

Conclusion

Innovation based growth model

$$Y_i(t) = A_i(t)^{\alpha} L_i(t)^{1-\alpha}$$

Final goods producers

$$\bar{A}(t) = \int_i A_i(t)di$$

Aggregate productivity

Research teams

$$\frac{\partial \bar{A}(t)}{\partial t} = \int_{\bar{z}(t)}^{\infty} q(z,t) f(z,t) dz$$

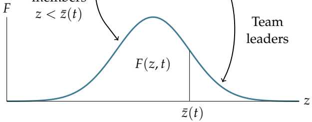
Growth in productivity through innovation/ idea qualities

$$q(z,t) = n(z,t)^{\eta} z^{1-\eta}$$

Idea qualities produced by research teams = team leaders & workers

Team members $z < \bar{z}(t)$

Team leaders




Productivity distribution

The most productive researchers choose to become team leaders.

Knowledge diffusion & human capital based model

$$F(z,t) = \int_0^{\infty} G(z,s,t) d\Omega(s)$$

age

Productivity evolves endogenously at each age ...

$$\frac{\partial \log(\tilde{G}(z,s,t))}{\partial s} = -m_D(1 - F(z,t-s+\tau)) - m_X(1 - E(z,\tau,t-s+\tau))$$

...through endogenous interactions and external learning

Interactions with others at rate $m_D$ (endogenous)

External learning at rate $m_X$ from source $E(z,s,t)$ (exogenous)

$m_D \in \arg\max V(m_D)$
$m_D$ costs $c(m_D,t)$

Agents choose endogenous interaction rate

# Final Good Sector

- Unique final good: $Y(t) = \int_0^1 y_i(t)di$
- Intermediate good producer $i$:

$$y_i(t) = A_i(t)^\alpha L_i(t)^{1-\alpha}$$

- Final good will be given by (result):

$$Y(t) = \bar{A}(t)^\alpha$$

- with aggregate productivity:

$$\bar{A}(t) = \int_0^1 A_i(t)di$$

- If research team $j$ produces innovation quality $q_j$, then regardless of market for innovation:

$$\frac{\partial \bar{A}(t)}{\partial t} = \int_i \frac{\partial A_i(t)}{\partial t} di = \int_j q_j dj$$

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# Research Teams I

- Mass 1 of skilled people (researchers); 1 unit of inelastic labor.
- Each researcher has productivity $z(t) \sim F(z,t)$ over $[0,\infty)$.
- Research teams are endogenously composed of:
  - one team leader (who hires)
  - $n(z,t)$ team members (at wage $w$).
- They produce ideas (patents) of heterogeneous qualities $q$.
- A team made of a leader with productivity $z$ and $n$ members produces idea quality

$$q = z^{1-\eta} n^{\eta}$$

$\eta \in [0,1]$ is the team leader's span of control (Lucas (1978)).

# Research Teams II

- Team leader's $z$ maximization problem:

$$\max_{n \geq 0} \{p(t)z^{1-\eta}n^{\eta} - w(t)n\}$$

where $p(t)$ is the price per unit of idea.

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$$n(z)=\left(\frac{p\eta}{w}\right)^{\frac{1}{1-\eta}}z$$

- Produces ideas of quality

$$q(z)=\left(\frac{p\eta}{w}\right)^{\frac{\eta}{1-\eta}}z.$$

- Profits are

$$\pi(z)=p^{\frac{1}{1-\eta}}\left(\frac{\eta}{w}\right)^{\frac{\eta}{1-\eta}}(1-\eta)z.$$

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Team size, quality, profits $\uparrow$ in $z$.

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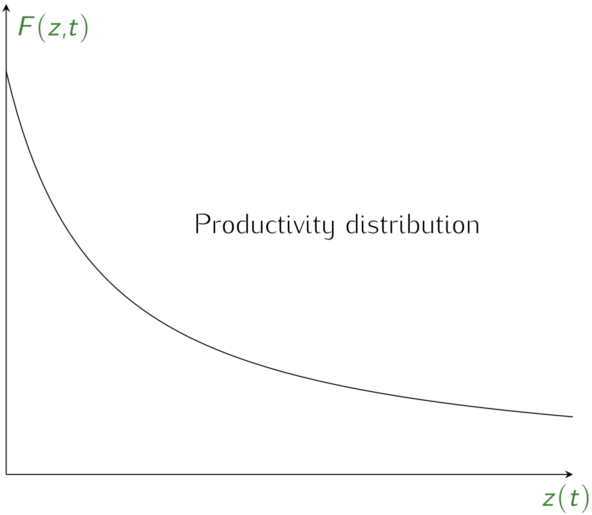
# Occupational Choice: Becoming Team Leader or Team Worker

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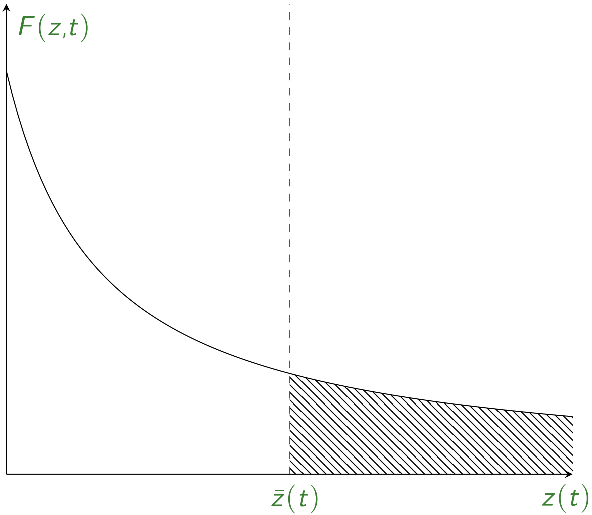


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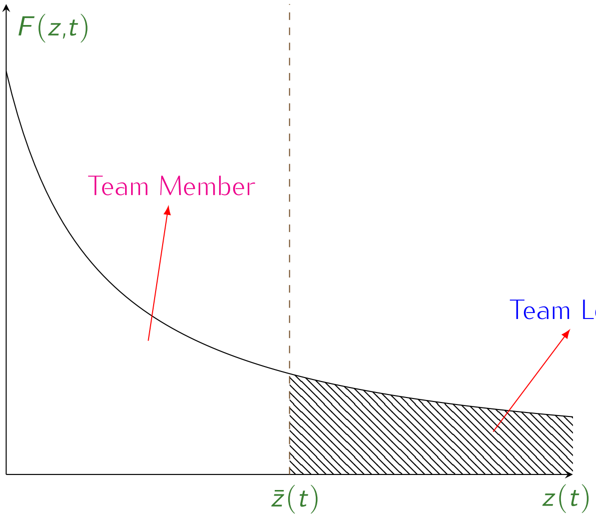


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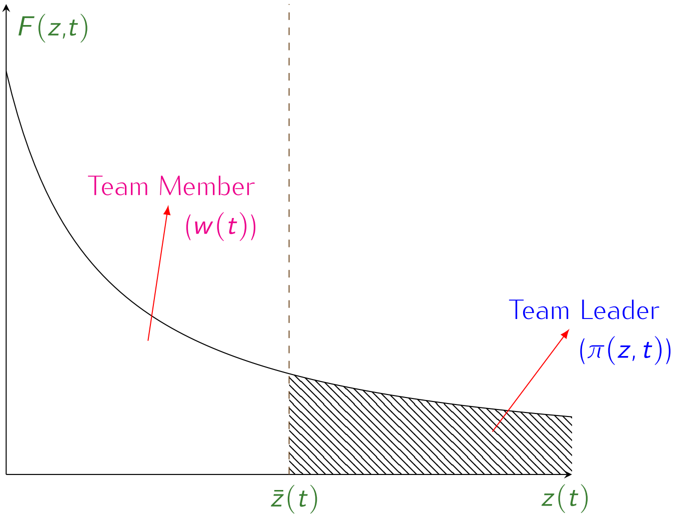


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# Learning: Two Channels

- $G(z, s, t_b)$ is the CDF of productivity of researchers of age $s$ born at time $t_b$.
- $G(z, 0, t_b)$ is the CDF at "birth."
- Learning = improving productivity.
- Throughout their life, they learn in two ways:
  - Endogenous interactions with others.
  - External (exogenous) learning channels.

# External Learning Channel

- With arrival rate $m_X$.
- Individuals draw productivity from external source $E(z, s, t)$.
- Learning by doing, experience, individual discovery, information.
- Realistic, and also key for the quantitative part.

# Endogenous Interactions Channel

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$$z_i(t + \Delta t) = \max\{z_i(t), z_j(t)\}$$

- Individual born at time $t_b$ chooses $m_D$ to maximize:

$$\max_{m_D} \int_0^\infty e^{-(r+\delta)s} \left[ \int_0^{\bar{z}(t)} w(t) dG(z,s,t) + \int_{\bar{z}(t)}^\infty \pi(z,t) dG(z,s,t) - C(m_D,t) \right] ds.$$

subject to

$$\begin{aligned} \log \frac{G(z,s,t)}{G(z,0,t-s)} = & - m_D \int_0^s (1 - F(z, t-s+\tau)) d\tau \\ & - m_X \int_0^s (1 - E(z, \tau, t-s+\tau)) d\tau. \end{aligned}$$

# Economy's Growth Rate

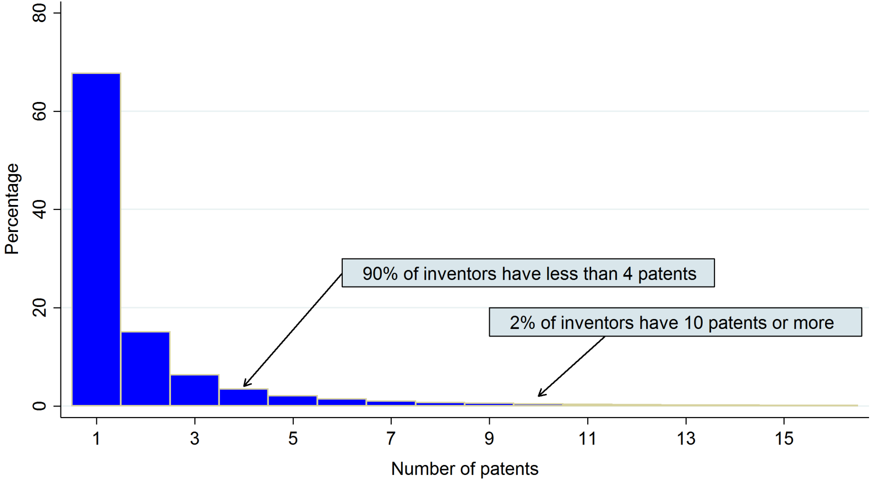
$$
\begin{aligned}
g &= \lim_{\Delta t \to 0} \frac{Z(t+\Delta t) - Z(t)}{Z(t)\,\Delta t} \\
&= \int \left[ \begin{array}{c}
m_d \times \left[ \frac{1}{Z(t)} \left[ z_i F(z_i,t) + [1 - F(z_i,t)]\, \mathbb{E}_F\left(z_i'(t) \mid z_i'(t) > z_i\right) \right] - 1 \right] \\
+ m_x \times \left[ \frac{1}{Z(t)} \left[ z_i F(z_i,t) + [1 - F(z_i,t)]\, \mathbb{E}_E\left(z_i'(t) \mid z_i'(t) > z_i\right) \right] - 1 \right] \\
+ \delta \times \left[ \frac{1}{Z(t)} \mathbb{E}_0(z_i'(t)) - 1 \right]
\end{array} \right] di
\end{aligned}
$$

where $\mathbb{E}_F$, $\mathbb{E}_E$, and $\mathbb{E}_0$ denote the expectations relative to the, respectively, cross-sectional, external, and age zero distributions.

# European Patent Office Data

- Very rich data, with myriad of information to discipline models:
  - Research teams,
  - Productivity (individual and team level),
  - Interactions (over time).
- Better representation of smaller countries as well.
- 2,955,055 patent applications.
- New disambiguation.
- 3,474,514 unique inventors.
- In 2010, $>70\%$ of patents produced by multi-inventor teams.

# Distribution of the Number of Patents per Inventor




2.2 patents per inventor on average.

# Idea Quality and Individual Productivity

- **Idea quality** of team $j$ at time $t$, $q_{j,t}$, is citations received by their patent in 3-year window (account for truncation):

$$q_{j,t} = \sum_{\tau=t}^{t+2} \text{citations}_\tau$$

- Citations to all patents in a family (better measure). Results robust to citations window used (3, 5, 8 years), self-citations.

- **Benchmark productivity measure** of inventor $i$ in year $t$ is citations-weighted patent stock produced up to time $t$:

$$P_{i,t} = \sum_{s=t_0}^{t} \sum_{j} q_{j,s}$$

- **Team leader**: most productive inventor to date in the team (also consider most senior, or first inventor listed) according to the cumulative productivity measure

# Definitions of Interactions: Strongest to Broader

- Interactions can be defined in many different ways: we explore many for robustness.
- To fit the model we define “high quality interactions” as interactions with people better than you and “low quality interactions” as interactions with people less productive than you.

**Interaction Definitions:** (strongest to broadest)

1. Strongest measure of interactions: Number of past co-inventors better than you (we are sure there was an interaction).
2. Number of inventors better than you that you were ever in the same firm with.
3. Broadest measure: Number of inventors better than you that you were ever in the same region (“MSA level”) with.

# Summary Statistics

| | Mean | Standard Deviation | Min | Max |
|---|---|---|---|---|
| *Idea Quality* | | | | |
| *Conditional on patenting:* | | | | |
| 3-year citations | 1.4 | 3.09 | 0 | 401 |
| 5-year citations | 2.2 | 4.53 | 0 | 421 |
| 3-year citations (excluding self citations) | 1.2 | 2.76 | 0 | 401 |
| *Unconditional on patenting (at individual level):* | | | | |
| 3-year citations | 0.3 | 2.30 | 0 | 302 |
| *Interactions* | | | | |
| High Quality Interactions | 1.7 | 3.25 | 0 | 68 |
| Low Quality Interactions | 8.9 | 18.0 | 0 | 578 |
| Total interactions | 10.6 | 19.9 | 0 | 605 |
| High Quality Interactions in the firm | 673 | 1848 | 0 | 45443 |
| High Quality Interactions in the region | 2876 | 7581 | 0 | 184077 |
| *Team and firm characteristics* | | | | |
| Team leader age | 5.8 | 5.23 | 1 | 34 |
| Team size | 3.1 | 2.08 | 1 | 10 |
| Firm Size | 525 | 964 | 1 | 5843 |

# Effect of Interactions on Productivity

| | Benchmark | | High Tech Sector | Broader Interactions Measures | |
|---|---|---|---|---|---|
| *Dependent variable: Idea Quality* | | | | Firm | Region |
| High Quality Interactions of TL (t-1) | 0.021*** | 0.027*** | 0.035*** | 0.0000385*** | 0.0000266*** |
| | (0.001) | (0.001) | (0.004) | (0.000001) | (0.0000008) |
| Low Quality interactions of TL (t-1) | | -0.004*** | | | |
| | | (0.000) | | | |
| Team Size | 0.028*** | 0.028*** | 0.034*** | 0.027*** | 0.034*** |
| | (0.001) | (0.001) | (0.004) | (0.001) | (0.001) |
| Log Firm Size | -0.022*** | -0.021*** | -0.045*** | | -0.028*** |
| | (0.002) | (0.002) | (0.010) | | (0.003) |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Year $\times$ Sector FE | Yes | Yes | Yes | Yes | Yes |
| Year $\times$ Region FE | Yes | Yes | Yes | Yes | Yes |
| Sector $\times$ Region FE | Yes | Yes | Yes | Yes | Yes |
| Team Leader FE | Yes | Yes | Yes | Yes | Yes |
| $N$ | 1574216 | 1574216 | 286231 | 1574216 | 1338075 |
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| | (0.001) | (0.001) | (0.004) | (0.000001) | (0.0000008) |
| Low Quality interactions of TL (t-1) | | -0.004*** | | | |
| | | (0.000) | | | |
| Team Size | 0.028*** | 0.028*** | 0.034*** | 0.027*** | 0.034*** |
| | (0.001) | (0.001) | (0.004) | (0.001) | (0.001) |
| Log Firm Size | -0.022*** | -0.021*** | -0.045*** | | -0.028*** |
| | (0.002) | (0.002) | (0.010) | | (0.003) |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Year $\times$ Sector FE | Yes | Yes | Yes | Yes | Yes |
| Year $\times$ Region FE | Yes | Yes | Yes | Yes | Yes |
| Sector $\times$ Region FE | Yes | Yes | Yes | Yes | Yes |
| Team Leader FE | Yes | Yes | Yes | Yes | Yes |
| $N$ | 1574216 | 1574216 | 286231 | 1574216 | 1338075 |
| adj. $R^2$ | 0.187 | 0.187 | 0.133 | 0.187 | 0.158 |
| F | 88.25 | 103.9 | 16.52 | 164.6 | 177.4 |

# Economic Interpretations

- One additional high quality interaction $\uparrow$ idea quality by 0.02, $\approx$ 4% of mean conditional on patenting, 21% of mean unconditional on patenting.
- High tech sectors: 8% conditional, 39% unconditional.
- At the firm level: 10 more high quality inventors $\uparrow$ idea quality by 0.4%.
- At region level: 10 more high quality inventors $\uparrow$ productivity by 0.3%. (in top 25% regions, there are 2100 inventors, in top 5% there are 13,200!).

*Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)*

# Outline of the Quantitative Part

- Estimate the model.
- Non-targeted moments (out of sample) fit.
- **Exercise 1:** Quantify importance of interactions.
- **Exercise 2:** Reducing interaction costs (Google model).
- **Exercise 3:** Access to external ideas (downside of agglomeration and paradox of proximity).
- **Exercise 4:** Germany vs. the U.S.: research production functions and team dynamics
  - Could slice the data in many other ways, e.g.: by sector.

# Functional Forms

| Function | Description |
|---|---|
| $q(z) = z^{1-\eta} n^{\eta}$ | Idea production function. |
| $c(m_D) = \frac{\kappa}{2} m_D^2$ | Interactions cost function. |
| $F(z,0) = \frac{1}{1+\lambda z^{-1/\theta}}$ | Initial cross-sectional productivity distribution. |
| $\Gamma(x,0) = \frac{1}{1+k_0 z^{-1/\theta}}$ | Age zero productivity distribution. |
| $\Psi(x,s) = \frac{1}{1+\rho s^{\nu} z^{-1/\theta}}$ | External (age-dependent) learning distribution. |

$\Gamma$ : Normalized $G(.)$ distribution. $\Psi$ : Normalized $E(.)$ distribution.

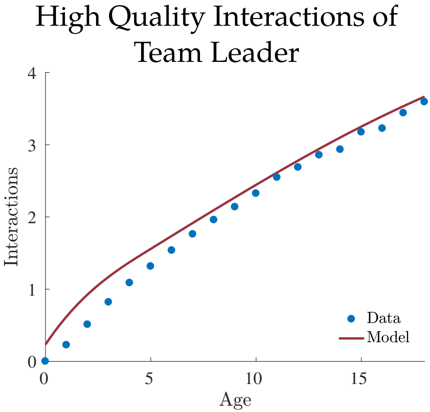
# Parameter Estimates

| **Parameter** | **Description** | **Value** |
|---|---|---|
| $\kappa$ | Cost of interactions. | 1.1906 |
| $m_X$ | External learning rate (draw from distribution $E(z,s,t)$). | 0.5281 |
| $\lambda$ | Location parameter of initial productivity distribution $F(z,0)$. | 0.5439 |
| $\theta$ | Tail of productivity distributions $F(z,t)$, $G(z,s,t)$ & $E(z,s,t)$. | 0.4503 |
| $\nu$ | Exponent on location parameter $\rho(s) = s^{\nu}$ of $E(z,s,t)$ | 0.5987 |
| $\eta$ | Team leader's span of control. | 0.2698 |
| $\delta$ | Parameter of the exponential age distribution. | 0.2171 |
| $k_0$ | Location parameter of initial distribution $\Gamma(x,0)$. | 0.0492 |
| $\alpha$ | Exponent of aggregate productivity in final good production. | 0.1220 |

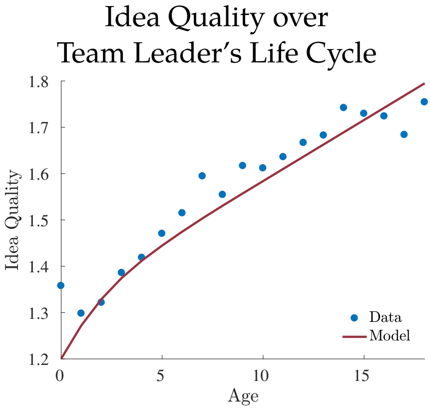
# Goodness of Fit: Moments

| Moment | Weight | Description | Model | Data |
|---|---|---|---|---|
| 1-18 | $\frac{1}{9}\frac{1}{18}$ | High-quality interactions of team leaders by age | Fig. (A) | Fig. (A) |
| 19-36 | $\frac{1}{9}\frac{1}{18}$ | Idea quality of team leaders by age | Fig. (B) | Fig. (B) |
| 37-54 | $\frac{1}{9}\frac{1}{18}$ | Productivity of all inventors by age | Fig. (C) | Fig. (C) |
| 55-74 | $\frac{1}{9}\frac{1}{20}$ | Team size distribution | Fig. (D) | Fig. (D) |
| 75-82 | $\frac{1}{9}\frac{1}{18}$ | Age distribution of team leaders | Fig. (E) | Fig. (E) |
| 83 | $\frac{1}{9}$ | Fraction of team leaders | 0.5739 | 0.5793 |
| 84 | $\frac{1}{9}$ | Regression on high-quality interactions, $\beta_2$ | 0.0561 | 0.0561 |
| 85 | $\frac{1}{9}$ | Regression coefficient on age, $\beta_3$ | 0.0389 | 0.0378 |
| 86 | $\frac{1}{9}$ | Growth rate | 0.025 | 0.025 |

# Goodness of Fit for Targeted Moments (1)



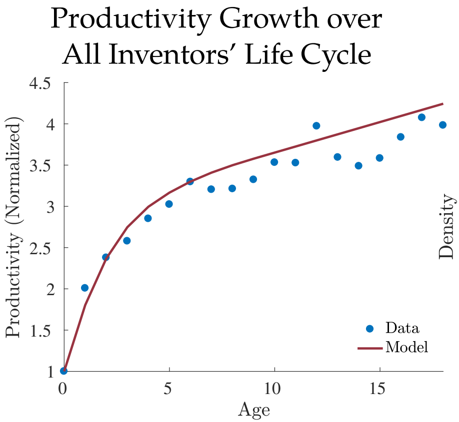

(A)



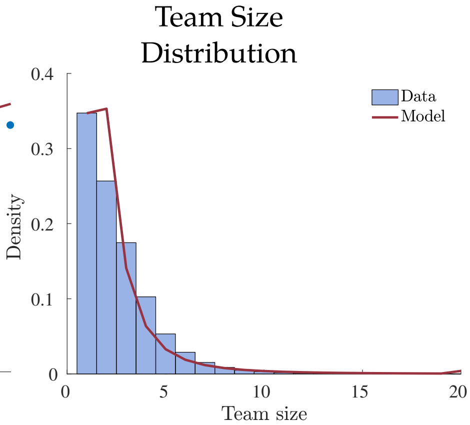

(B)

*Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)*

# Goodness of Fit for Targeted Moments (2)



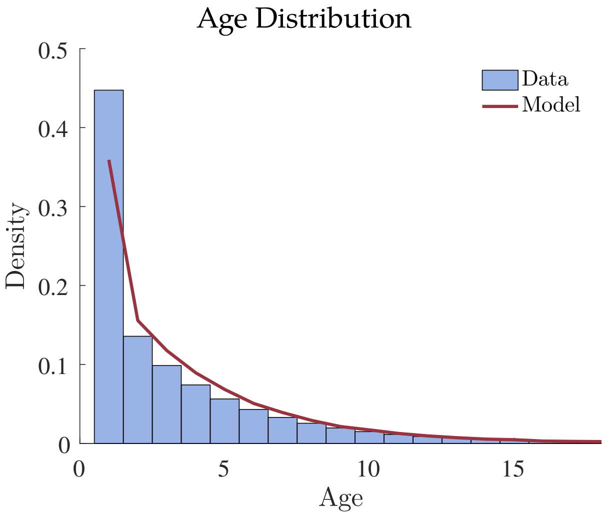

(C)




(D)

*Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)*

# Goodness of Fit for Targeted Moments (3)




(E)

# Goodness of Fit for Non-Targeted Moments I

- **Prediction 1**: Goolsbee'98: Subsidy for R&D $\uparrow$ wages of researchers.
- What is elasticity of wages to R&D subsidy in the model?

$$\ln(wage) = \beta \times \ln(subsidy)$$

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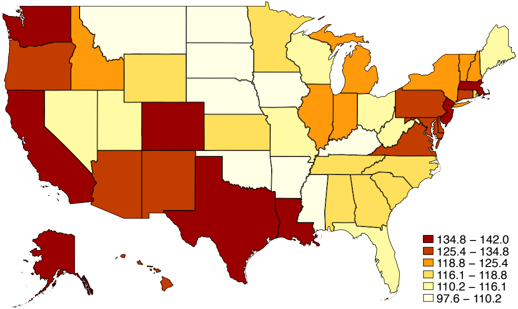
Wages of Researchers Across U.S. States




Model elasticity, $\beta_{model} = 0.0265$; Data, $\beta_{data} = 0.0227$

*Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)*

# Goodness of Fit for Non-Targeted Moments II

- **Prediction 2**: What is effect of R&D subsidy on team formation and size?

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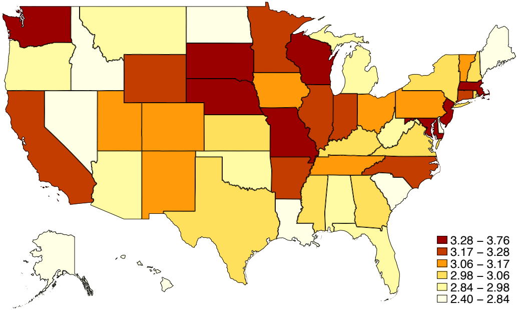
Team Sizes Across U.S. States




Model elasticity: 0.0572; Data: 0.0436

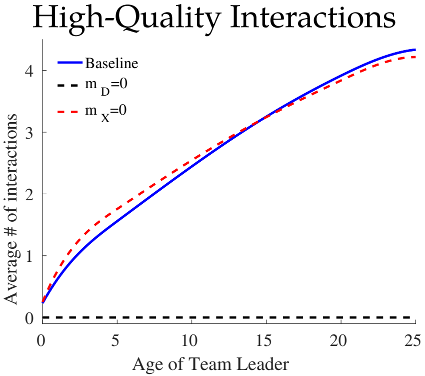
# Exercise 1:

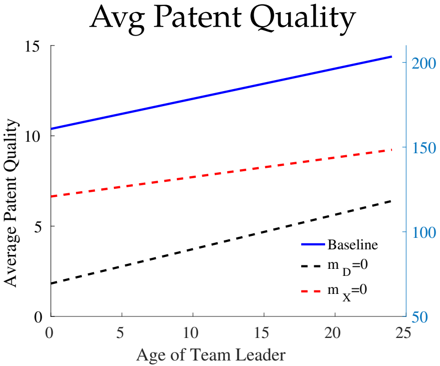
# Quantifying Different Channels

# Importance of the Two Channels

- How important are the two channels?
- Shutting down one of the two learning channels at a time:
  - $m_D = 0$
  - $m_X = 0$

# The Role of Interactions and External learning



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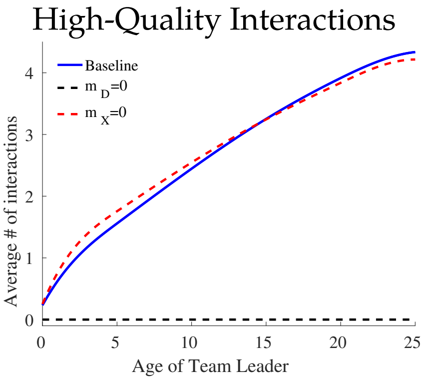


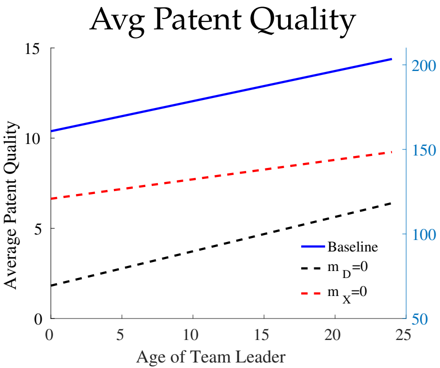


| | Interactions + External Learning | No interactions: $m_D = 0$ | No external learning: $m_X = 0$ |
|---|---|---|---|
| Growth | 2.5% | 0.1% | 0.62% |

*Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)*

# Exercise 2:

# Reducing Interaction Cost

# (Google Model)

# Cost of Interaction

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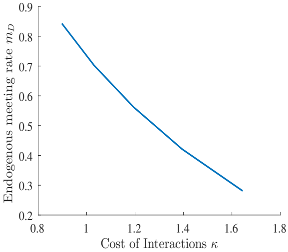
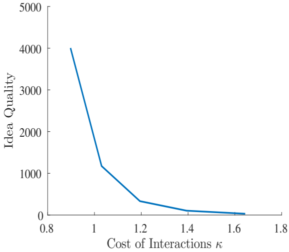
- $\kappa \downarrow$: 1) people become more productive, $\implies$ more people above the old cut-off: positive composition effect. **Net effect: ambiguous.**

# The Effect of Interaction Costs $\kappa$

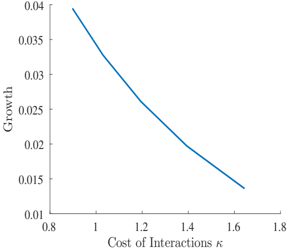
### Endogenous meeting rate $m_D$



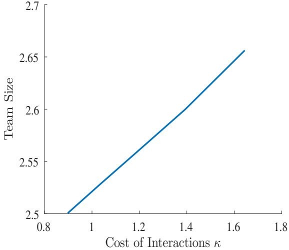

### Idea Quality




### Growth Rate




### Team Size




*Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)*

# Exercise 3:

# Access to External Ideas

# (Paradox of Proximity)

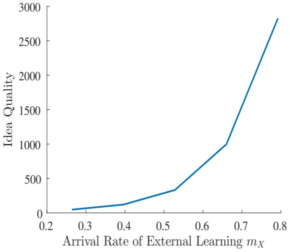
# Access to External Knowledge

- What happens if access to external learning sources is reduced?
- There are many concrete situations in which individuals become less exposed to external sources of knowledge.
- Strong agglomeration and geographical concentration of talent in some areas, which, paradoxically, may lead to a great deal of interactions with similarly-minded people.
- Proximity paradox: too much cognitive or geographical proximity with the same group of people - importantly, without additional external inflow of new knowledge - can hinder innovation.

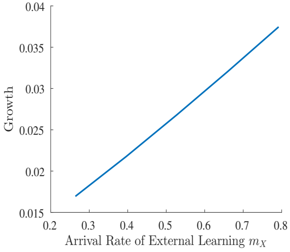
*Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)*

# Effect of Access to External Ideas

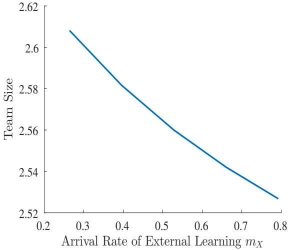
Idea Quality




Growth Rate




Team Size



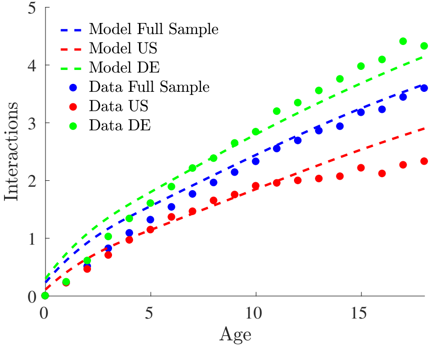

*Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)*

# Exercise 4:

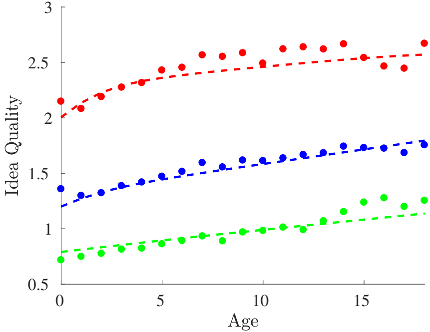
# Germany vs the United States

# Moments for the U.S. and Germany (1)

High Quality Interactions of the Team Leader

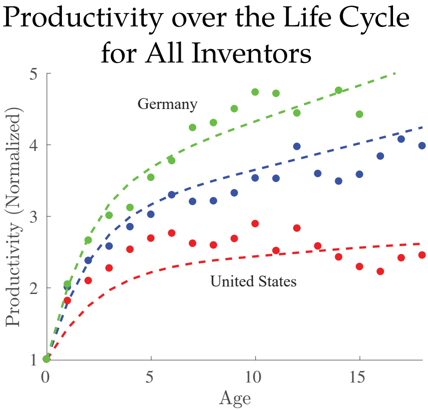


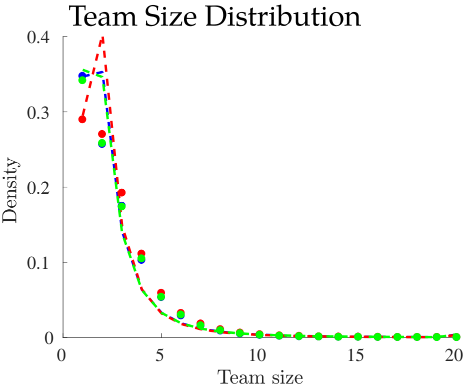

Idea Quality over Team Leader's Life Cycle




Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)

# Moments for the U.S. and Germany (2)

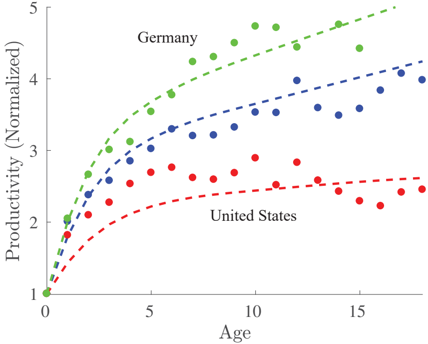


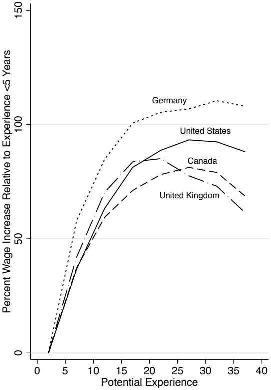

*Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)*

# Moments for the U.S. and Germany (2)

Productivity over the Life Cycle for All Inventors

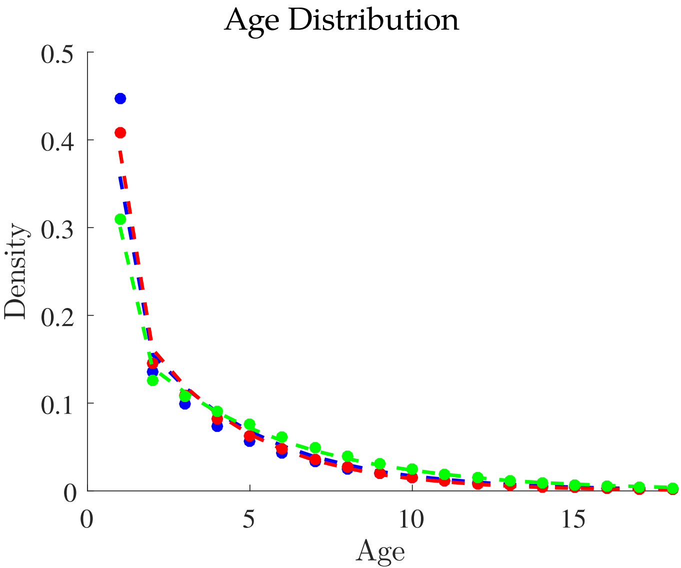



Lagakos, Moll, Porzio, Qian, Schoellman (2016)

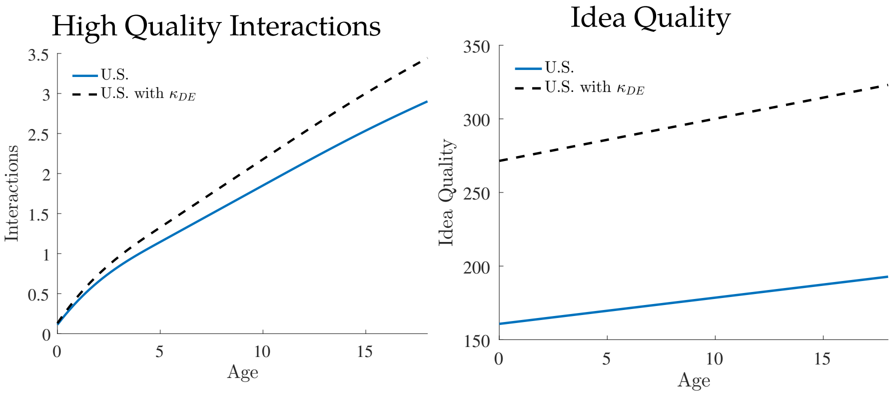



*Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)*

# Moments for the U.S. and Germany (3)



# Reducing Interaction Costs in the U.S. to the German level




Akcigit, Caicedo, Miguelez, Stantcheva, Sterzi (2018)

# Conclusion

- We bring together the diffusion and innovation-based growth.
- We bring data to a largely theoretical literature.
- Future work:
  - What are the effects of non-compete laws which prevent inventors from easily moving between companies?
  - Do labor market frictions indirectly play a role for innovation and productivity because of their impact on interactions?
  - How do immigration policies affect the inflow of new inventors and ideas?