The Composition of Knowledge and Long-Run Growth

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Motivation

- Traditional trade theory: welfare is maximized when countries specialize in sectors that they produce relatively cheaply;

- However, goods with large positive externality may be under-developed.

- **What** a country exports is important
  - Learning by doing, capabilities:
  - Product network, synergies:

- Particularly important for industry policies (e.g. “comparative advantage defying strategies” (Lin, 2009, 2010)).
However, empirical evidence is mixed:

- Difficult to establish causality using commonly adopted regression-based approaches
- Difficult to examine the GE effects of changing production structure
- Difficult to identify sectors with large externalities in the data; existing studies use outcome-based measures.
However, empirical evidence is mixed:

- Difficult to establish causality using commonly adopted regression-based approaches
- Difficult to examine the GE effects of changing production structure
- Difficult to identify sectors with large externalities in the data; existing studies use outcome-based measures.

—For example: Previous studies assume sector A and B have synergies if A and B are likely to be co-exported by the same country

![Diagram showing the relationship between sectors A and B with possible factors influencing synergies and fragmentation of production tasks.](attachment:image.png)
Motivating observation: Research spillovers across sectors are substantial but highly heterogeneous.

Figure: Intersectoral Knowledge Flow Network Corresponding to Patent Citations
This paper:

1. Incorporates this network of knowledge complementarities across sectors into a formal model of innovation, trade and growth
   - Develops a tractable framework in which a country’s composition of knowledge is endogenously determined
   - The framework is useful to analyze: (Unbiased) trade costs $\Rightarrow$ composition of knowledge accumulation $\Rightarrow$ aggregate innovation and growth

2. Empirically, 
   - Constructs a quantitative measure of “knowledge applicability” for each sector, based on patent citation network; 
   - Presents cross-country evidence that broadly supports the model implications: 
     - Geographic remoteness has a distributional effect on a country’s knowledge composition; 
     - A country’s initial knowledge applicability is positively and significantly associated with subsequent growth differences.
This paper:

1. Incorporates this network of knowledge complementarities across sectors into a formal model of innovation, trade and growth
   - Develops a tractable framework in which a country’s composition of knowledge is endogenously determined
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2 Empirically,
   - Constructs a quantitative measure of “knowledge applicability” for each sector, based on patent citation network;
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I. Model
Framework

▶ Expanding variety model
▶ Consumers maximize life-time utility and inelastically supply labor
▶ (Non-traded) final good is a CD combination of sectoral good; sectoral good \( i \) is a CES combination of differentiated (home and foreign) goods:

\[
Q_t^i = \left[ \int_0^{N_t^i + N_t^{i^*}} \left( x_{k,t}^i \right)^{\frac{\sigma}{\sigma - 1}} dk \right]^{\frac{\sigma}{\sigma - 1}}
\]

▶ Continuum of symmetric multi-sector, monopolistic competitive firms. Number of varieties per firm in sector \( i \): \( n_t^i = N_t^i / M_t \).
▶ New: Firms innovate (create new blueprints) and produce in all sectors, where the sectoral knowledge can be adapted to innovate in other sectors. Some knowledge can be easily adapted, while others cannot.
▶ Study balance growth path (BGP) equilibrium
Differentiated Goods Production

- Identical linear production technology across firms and sectors: \( y_t^i = \phi l_t^i \)

- Suppose \( \tau \) is the iceberg transportation cost,

\[
p_{ht}^i(k) = \frac{\sigma}{\sigma - 1} \frac{w_t}{\phi}, \quad p_{ft}^i(k) = \tau p_{ht}^i(k)
\]

- The firm’s (real) profit per variety in sector \( i \) is

\[
\pi_t^i = \frac{(r_{d,t}^i + r_{x,t}^i)}{\sigma w_t}
\]
Firm’s R&D Decision

> A firm’s *knowledge portfolio*: $z_t = (z_t^1, z_t^2, ..., z_t^K)$, $z_t^i$ is the number of varieties (blue prints, knowledge capital) in sector $i$
Firm’s R&D Decision

- A firm’s knowledge portfolio: \( z_t = (z_1^t, z_2^t, \ldots, z^K_t) \), \( z^i_t \) is the number of varieties (blueprints, knowledge capital) in sector \( i \).

- Sectoral knowledge accumulation:

\[
\dot{z}_t^i = z_t^i + \Delta z_t^i, \tag{1}
\]

- Firm’s R&D optimization problem:

\[
\max_{i,j \in \{1, 2, \ldots, K\}} \{ R_{ij}^t \}
\]

with constraints (1) and (2).

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Firm’s R&D Decision

- A firm’s knowledge portfolio: \( z_t = (z_1^t, z_2^t, ..., z^K_t) \), \( z^i_t \) is the number of varieties (blue prints, knowledge capital) in sector \( i \)

- Sectoral knowledge accumulation:
  \[
  z^i_{t+1} = z^i_t + \Delta z^i_t,
  \]

- Innovation: a process of developing new varieties in a given sector using existing knowledge in all sectors:
  \[
  \Delta z^i_t = \sum_{j=1}^{K} A^{ij} \left( \bar{z}^i_t R_t^{ij} \right)^\alpha \left( \bar{z}^j_t \right)^{1-\alpha}
  \]
  — \( A^{ij} \): applicability of ideas from \( j \rightarrow i \)
  — \( \bar{z}^i_t \): researcher efficiency (measured by average knowledge stock in \( i \))
Firm’s R&D Decision

▶ A firm’s knowledge portfolio: \( z_t = (z^1_t, z^2_t, \ldots, z^K_t) \), \( z^i_t \) is the number of varieties (blue prints, knowledge capital) in sector \( i \)

▶ Sectoral knowledge accumulation:

\[
\hat{z}_t^{i} + 1 = \hat{z}_t^{i} + \Delta \hat{z}_t^{i}, \tag{1}
\]

▶ Innovation: a process of developing new varieties in a given sector using existing knowledge in all sectors:

\[
\Delta \hat{z}_t^{i} = \sum_{j=1}^{K} A^{ij} (\hat{z}_t^{i} R_t^{ij})^\alpha (\hat{z}_t^{j})^{1-\alpha} \tag{2}
\]

— \( A^{ij} \): applicability of ideas from \( j \rightarrow i \)
— \( \hat{z}_t^{i} \): researcher efficiency (measured by average knowledge stock in \( i \))

▶ Firm’s R&D optimization problem:

\[
\max_{\{R_t^{ij}\}_{i,j \in \{1,2,\ldots,K\}}} V(z_t) = \sum_{j=1}^{K} \pi_t^{j} z_t^{j} - \sum_{i=1}^{K} \sum_{j=1}^{K} R_t^{ij} + \frac{1}{1 + r_t} V(z_{t+1})
\]

s.t. (1) and (2)
Solution: Firm value

- Firm’s value is a linear aggregate of the value of its knowledge capital in all sectors

\[ V(z_t) = \sum_{j=1}^{K} v^j \]

- On the BGP, the market value of the firm’s knowledge capital in sector \( j \)

\[ v^j = \frac{1}{1 - \rho} \left( \pi^j + \sum_{i=1}^{K} \omega^{ij} \right) \]

\( \omega^{ij} \): application value of the firm’s knowledge in sector \( j \) to innovation in sector \( i \):

\[ \omega^{ij} = \frac{n^j}{n^i} \left( v^i A^{ij} \alpha \rho \right)^{\frac{1}{1-\alpha}} \frac{1}{1 - \alpha} \frac{1}{\alpha} \]

- \( v^i, \omega^{ij} \) and \( \pi^i \) are all time-invariant in the BGP equilibrium
Optimal R&D: The firm scales up its R&D by its market share

\[ R_{ij}^t = \frac{\alpha \omega_{ij} z_{ij}^t}{1 - \alpha n_{ij}^t} \]

Closing the model
- Labor market clearing
- Balance of trade
- Free entry
Proposition 1: At aggregate, R&D resources are allocated according to the value of firm’s sectoral knowledge

\[
\frac{R_i^i}{R_j^j} = \frac{v^i}{v^j}
\]

Proposition 2: On the BGP, the aggregate innovation rate increases with the importance of firm’s knowledge application value \((\frac{\sum_i \sum_j \omega_{ij}^i}{\sum_i v^i})\):

\[
g = \left(\beta(1 - \alpha) \frac{\sum_i v^i}{\sum_i \sum_j \omega_{ij}^i} - 1\right)^{-1}
\]
An illustrative example

Assume two types of sectors: central sectors \((c)\), peripheral sectors \((p)\)
- \(c\): 1.
- \(p\): 2, 3, ..., \(K\)

Figure: Star-shaped knowledge complementarity network

Other Parameters: \(\beta = 0.98\), \(K = 10\), \(L^* = 50L\), \(\sigma = 6\), \(\alpha = 0.4\).
Intuition

- Trade cost $\tau \uparrow \Rightarrow w \downarrow \Rightarrow \uparrow \pi$ (GE effect)
- Trade cost $\tau \uparrow \Rightarrow \downarrow \pi$
- In equilibrium $n^c > n^p$, loss of competitiveness in $c$ sector $\Rightarrow \pi^c \downarrow$, $\pi^p \uparrow$

$$v^j = \frac{1}{1-\rho} \left[ \pi^j + \kappa \sum_{i=1}^{K} \frac{n^j_i}{n^i} \left( v^i A^{i\leftarrow j} \right)^{\frac{1}{1-\alpha}} \right] \quad \text{where}$$

$A^{c\leftarrow p} = 0$, $A^{p\leftarrow c} > 0$

$$\Rightarrow \frac{n^c}{n^p}, \frac{v^c}{v^p}, \frac{R^c}{R^p} \downarrow$$

$$\Rightarrow g \downarrow$$
Results

\[ \pi^c, \pi^p \]

\[ W \]

\[ X \]

\[ R^c/R^p \]

\[ n^c/n^p \]

\[ X^c/X \]
Results

Testable predictions:

- Rising $\tau$ leads to lower $n_c/n_p$.
- Lower $n_c/n_p$ is associated with lower aggregate growth.

\begin{center}
\begin{tabular}{ccc}
5.5 & 6 & 6.5 \\
0.0295 & 0.03 & 0.0305 \\
0.031 & 0.0315 & 0.032 \\
0.0325 & 0.033 & \\
\end{tabular}
\end{center}
Results

Testable predictions:

- rising $\tau$ leads to lower $n^c/n^p$
- lower $n^c/n^p$ is associated with lower aggregate growth
I. Empirics
Measuring Technology Applicability


- Jaffe et al. (2000), Hall et al. (2001): use patent citations as an indicator of knowledge spillovers

Assume that the knowledge spillover linkages uncovered in the U.S. patent data persist across countries.

- This paper is about the fundamental relationship between technologies
  - Nelson and Winter (1977) “Innovations follow ‘natural trajectories’ that have a technological or scientific rationale rather than being fine tuned to changes in demand and cost conditions”
- 50% of patents applied in U.S. were from foreign inventors
- Due to the territorial principle in the U.S patent laws, anyone intending to claim exclusive rights for inventions is required to file U.S. patents; U.S. has been the largest technology consumption market over the past few decades.
Measuring Technology Applicability

Measure of applicability: \( \{aw^i\}_{i=1,..K} \)

Apply Kleinberg (1998) algorithm to construct, for each sector, two network-based measures— authority weight \((aw)\) and hub weight \((hw)\).

\[
aw^i = \lambda^{-1} \sum_j W^{ji} hw^j
\]

\[
hw^i = \mu^{-1} \sum_j W^{ij} aw^j
\]

where \(W^{ji}\) = Citations from sector \(j\) to sector \(i\)

Compute \(\{aw_t^i\}_i\) using cross-sector citations from \([t - 10, t]\)
Knowledge applicability across sectors is heterogeneous and highly skewed

**Observation:** A small number of sectors are responsible for fostering disproportionately many subsequent innovations
Measuring a country’s composition of knowledge

- Can only observe various economic manifestations of the country’s composition of knowledge

- Evaluate a country’s knowledge composition by its export composition. 
  - export share in each sector: $x^i_{c,t} = \frac{EX^i_{c,t}}{\sum_i EX^i_{c,t}}$

- At country level, measures of a country’s knowledge applicability:
  - Measure I: export weighted knowledge applicability
    $$TA_{c,t} = \sum_i \log(a w^i_t) x^i_{c,t}$$
  - Measure II: The fraction of exports in the most applicable third of all sectors $Perc33$.

- Data source: UN Comtrade sectoral export data, 1972-2013, UN Comtrade sectoral export data.
Determinants of a country’s export structure

\[ x_{c,t}^i = c + \beta_0 \ln(aw_{t}^i) + \beta_1 \ln(aw_{t}^i) \times \text{remoteness}_{c} + \beta_2 \ln(aw_{t}^i) \times Z_{c,t} + \beta_3 Z_{c,t} + \mu_c + \eta_i + \epsilon_{c,t} \]

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<td>(2.84)***</td>
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| Sector FEs | Yes | Yes | Yes | Yes | Yes |
| Country FEs | Yes | Yes | Yes | Yes | Yes |
| Six governance variables | No | No | No | No | Yes |
| Observations | 125,727 | 54,883 | 23,578 | 75,057 | 65,154 |
| $R^2$ | 0.45 | 0.47 | 0.47 | 0.46 | 0.49 |
Growth Regression

\[
\frac{(\log y_{c,t} - \log y_{c,0})}{t} = \beta_0 + \beta_1 \log TA_{c,0} + \beta_2 \log(y_{c,0}) + \delta X_{c,0} + \varepsilon_c
\]

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<td><strong>Knowledge applicability</strong></td>
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<td>0.52 (2.12)**</td>
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<td>Initial investment share</td>
<td>0.05 (2.22)**</td>
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<tr>
<td><strong>R^2</strong></td>
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Growth Regression

\[
\frac{\log y_{c,t} - \log y_{c,0}}{t} = \beta_0 + \beta_1 \log TA_{c,0} + \beta_2 \log (y_{c,0}) + \delta X_{c,0} + \varepsilon_c
\]

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Final Remarks

- A systematic analysis to investigate the relationship between the (endogenous) composition of knowledge and growth.

- Questions: How do countries increase the amount of applicable knowledge? Can policy changes such as trade liberalization help to improve the knowledge structure of the economy?

- Our theoretical model is well-suited to answer these questions: Lower trade barriers (besides leading to more trade) increase aggregate innovation productivity by reallocating R&D towards sectors with higher knowledge applicability—“composition effect” of trade cost.

- Further extensions:
  - Endogenous $K$ (adding sectoral entry cost)
  - Imports and cross-country knowledge spillovers (technology adoption)
  - Quantitative analysis