

Employee Spinouts and Productivity Growth: Updates

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Updates - Overview

- ▶ **Data:** opportunity to RA for Teresa Fort in exchange for **access to LBD data** which is to be **linked with data on patenting activity**
 - ▶ No access to LEHD: **I need Venture Source to identify spinouts.**
- ▶ **Model:** Algorithm doesn't converge for some parameter settings, need to keep fiddling with update rules. Still optimistic since there is much I have not yet tried.
- ▶ **Next step:** Write this all up and ask for funding to use the Venture Source data.
- ▶ For this: would help to get (a) model up and running and think more carefully about how I am going to identify the mechanisms I will explore
 - ▶ Working on this now that data issue is done / end of year (no more writing / grading exams)

Data - Getting access

- ▶ Teresa Fort & colleagues are working on a project exploring connection between offshoring (and co-location more generally) and innovation
- ▶ Benefits to the Census involve understanding "whole process of innovation", not just R&D but also patenting, patent citations, etc.
- ▶ To connect my project to this benefit, argue: spinouts inherit knowledge from parents and innovate on it → understanding these relationships is vital to understanding the innovation process (which the Census is interested in)
- ▶ Also presents other interesting question, such as whether co-location affects spinout formation.

Data - Overview

- ▶ **Innovation input:** BRDIS (R&D Survey), BRDI-M (R&D survey for small firms), ACES (Annual Capital Expenditures Survey), ABS (Annual Business Survey), COS (Company Organization Survey), CWH (Census of Wholesale Trade), CMF (Census of Manufactures)
- ▶ **Innovation output:** USPTO patent data
- ▶ **Matching:** Name + address match using Statistical Establishment Listing data
- ▶ **Identifying competing spinouts:** Venture Source data then allows me to identify spinouts, industry codes (and possibly other approaches) identify extent spinout is using inherited technology / competing with parent firm (hence would be prevented in a non-compete)
- ▶ **Venture Source data** also has plentiful information on financing of startups...my project is not about this, but since financial frictions interact with the effect of non-compete agreements, it seems promising for future work, no?

Model recap

- ▶ Time t is continuous
- ▶ Agents:
 - ▶ Households
 - ▶ Intermediate goods firms
 - ▶ Final goods firm

Model recap

- ▶ Standard quality ladders model, step size $\lambda > 1$
- ▶ Continuum of intermediate goods, indexed by $j \in J = [0, 1]$
- ▶ Frontier quality of good j by q_j
- ▶ x_j is amount produced
- ▶ Each good produced with technology

$$x_j = \bar{q} l_j$$

where $\bar{q} = \int_0^1 q_j dj$ is the average quality level of the economy

- ▶ Each good j has monopolist, standard assumptions to guarantee no limit pricing
- ▶ Demand (final goods production) CES across goods j implies constant markup

Nesting

- ▶ Free entry into R&D
- ▶ Spinouts more productive – χ as they emerge, spinouts replace ordinary entrants in R&D race
- ▶ Making precise:
 - ▶ Let \bar{z} denote total innovation effort by entrants – spinouts and non-spinouts alike
 - ▶ Assume that the R&D production functions are

$$R_S(z_S; \bar{z}) = \chi_S z_S \eta(\bar{z})$$

$$R_E(z_E; \bar{z}) = \chi_E z_E \eta(\bar{z})$$

for spinouts, non-spinouts, respectively.

- ▶ Both depend on $\eta(\bar{z}) \Rightarrow$ standard model when $\chi_E \geq \chi_S$
- ▶ If instead draw from different pools of ideas (with Inada conditions) need to assume $\chi_S = 0$ to get standard model

Identification

- ▶ Specialize $\phi(z) = \eta(z) = z^{-\psi}$
- ▶ Parameters in baseline model: $\{\beta, \rho, \lambda, \chi, \psi, \nu, \xi, \theta\}$
- ▶ No closed forms so even when a certain moment “identifies” a parameter, I will have to do identification with indirect inference.
- ▶ General parameters: $\{\rho, \beta\}$
- ▶ R&D parameters: $\{\psi, \lambda, \chi\}$
- ▶ Spinout parameters: $\{\nu, \xi, \theta\}$
 - ▶ Empirical component of my paper
 - ▶ Attempt to identify using data on spinouts and creative destruction (details on next slide)

Identification: ρ, β

- ▶ Calibrating ρ :
 - ▶ Agents in model are risk-neutral \Rightarrow Interest rate = ρ
 - ▶ To get realistic interest rate, have to assume unrealistic discount factor
- ▶ Calibrating β :
 - ▶ In model, β determines elasticity of substitution across intermediate goods varieties labor share of final goods firm value-added
 - ▶ In my model, makes more sense to have realistic markups than realistic labor share of final goods production
 - ▶ Idea: follow AK 2017 in identifying based on profit / sales ratio (of, say, incumbent firms)
 - ▶ How to interpret final goods labor in this model if I think of intermediate goods as actually goods? Retail workers? Does this pose a problem given that I have required R&D workers to be indifferent?

Identification: R&D parameters ψ, λ, χ

- ▶ Difficult to disentangle using data generated from a single BGP
- ▶ Setting ψ :
 - ▶ Literature has identified using (1) elasticity of R&D spending to tax changes, (2) elasticity of patents to R&D spending
 - ▶ Both suggest $\psi \approx 2$
- ▶ Calibrating λ :
 - ▶ Literature has typically tried various values (approx 1.2) and checked robustness
 - ▶ AK 2017: identify based on patent citation distribution
- ▶ Calibrating χ :
 - ▶ Given other R&D parameters, can identify from measures of R&D intensity

Model predictions re: spinouts

- ▶ Aggregate moments
 - ▶ Fraction of firms which were spinouts vs. non-spinouts originally
- ▶ Individual moments
 - ▶ Depending on “state” of some good j , what is incumbent / spinout / non-spinout individual and aggregate R&D intensity
 - ▶ How to measure “state” m of good j ? Note that this is really a good j , not an industry.
 - ▶ How to measure R&D intensity of non-incumbents?
 - ▶ If can't measure m , can maybe measure “creative destruction” events; model has predictions for how R&D typically evolves over time after a “creative destruction” event.
- ▶ Causal relationships: more R&D leads to more spinout entrants. How to measure?!?

Bringing model to data

- ▶ Previous slide: shows that bringing this model to the data is somewhat contrived
- ▶ In the data:
 - ▶ Can't find individual good / service j
 - ▶ Individual goods are not completely overtaken by creative destruction
- ▶ Would be useful if my model had “market share” object in it, because that I can bring to the data.
- ▶ Can I do this while maintaining endogenous growth flavor?
- ▶ Idea: distribution of consumer types, every version of product is best for some consumers but not for others. Spinouts decide which consumers to go for, get incomplete overtaking. Models like this? Seem reasonable to keep thinking along these lines?

Research plan

- ▶ Empirical work: similar to Balasubramaniam & Sakakibara 2015, "Human capital of spinouts"
- ▶ **My contribution:** Link patent data (NBER patent database) and R&D data (Compustat)
- ▶ Question is roughly: does more R&D output (patents, or spending as another proxy for output) lead to more / more successful spinouts?
- ▶ Get out of R&D paradigm: does faster parent firm productivity growth lead to more spinouts? **For this, need to argue they are not demand shocks.**
- ▶ Rationalize this result taking seriously a model where R&D (broadly defined) "sows the seeds of future competing spinouts"
 - ▶ Current model: spinouts are all R&D firms, not small firms that grow large – hard to discipline with data moments on how growth patterns vary with
 - ▶
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