Learning Production Process Heterogeneity Across Industries: Implications of Deep Learning for Corporate M&A Decisions

authors: **Jongsub Lee** and **Hayong Yun**

Discussant: **Nagpurnanand Prabhala**
Johns Hopkins University Carey Business School

ABFER 2023

Overview

1. Research question
2. Methods
3. Comments
4. Summary

1. Research Question

- Why do M&As happen?
  - Agency problems -- managers like big firms
  - Market timing due to mispricing
  - Market power, common ownership or not.
  - Taxes

- Synergies between acquirer and target
  - Product market,
  - Managerial scope or style

- This paper argues that all the above are affected by the costs of integrating **production** processes.

2. Methods

- Consider 2 firms with production processes p_i^*
  - $y_1^* \equiv y_1\left(p_1^*\right), y_2^* \equiv y_2\left(p_2^*\right)$

- $d_{12} = y_2\left(p_1^*\right) - y_2\left(p_2^*\right)$
  - Distance to cross if firm 1 acquires firm 2

- Assumption -- firm 1 must impose its style on firm 2 or learn about firm 2's methods

- High $d_{12} \Rightarrow$ hard to do this, so M&A is less likely.

2. Methods

- Compute $d_{ij} \forall \{i, j\}$ Fama-French 12 industries.
  - Use machine learning methods
  - "Transfer" learning reflects changes in weights rather than input quantities
- Hypothesis is that d_{ij} impacts
  - M&As
  - M&A completion probability
  - M&A announcement effects
  - Post-M&A survival (?)

Overall

1. Interesting exercise and findings
   - ML in corporate finance research
   - Less sure that it is about ML and practice
2. Some big picture, some small comments
3. Where should the boundaries of the paper lie?

Comments

1. Interpreting "distance"

2. Pin down what ML contributes

3. Keep-Divest-Close Decisions

4. Allocative Efficiency Literature

5. Other Remarks

1. Interpreting distance

- Can we say more on the economics of the distance variable?

- Optimality or hubris? Can one tell?

Optimality

$$M \,\&\, A \Leftrightarrow B^* - C^* > 0; \frac{\partial B^*}{\partial d} < 0, \frac{\partial C^*}{\partial d} > 0$$

Hubris

Acquirer acts out of habit(Rajan et al, RFS 2022)

$$M \Leftrightarrow B - C > 0; \frac{\partial C}{\partial d} > 0$$

1. Interpreting distance

- Does distance reflect costs of learning or costs of integration?
- Is distance related to product synergy?
  - Paper has a clever control for product similarity s_{ij} using textual data a la Hoberg and Phillips
  - But product distance s_{ij} may impact production synergies.
  - May need to interact s_{ij} with d_{ij}
    - Or, put s_{ij} into machine learning algorithm.
- Is it possible to do more that is firm-specific?
  - Firm's internal investment versus M&A?

1. Interpreting distance

- The paper is probably right that all manners of synergies are less likely when d_{ij} is high.

- Nevertheless, more color on d_{ij} through heterogeneity or other tests would add to the economics quotient of the paper.

2. Pin down what ML contributes

- Authors focus on varieties of ML. I wonder if a more useful question is what ML adds in the first place.

- Start with a traditional production function
  - Cobb-Douglas or CES technology
  - Stochastic frontier with technical efficiencies?

- Reestimate gains from this approach relative to ML.

2. Pin down what ML contributes

- What would happen in pseudo-mergers?
  - We don't have placebo mergers
  - Randomly shuffle inputs and pretend the mergers happened with different companies

2. Pin down what ML contributes

- Dynamics. M&A today determines future costs, distances. Firms probably understand that.

- Is there learning from past acquisitions?

- Something about repeated acquirers?

3. Keep-Close-Divest Decisions

- Are inter-firm M&As the right level of granularity? Firms are typically multidivisional, especially acquirers.

- Issue 1 is partial firm acquisitions.
  - This may complicate life not only in data terms but also because of divisional production functions.

- Issue 2 is that in M&A's, firms keep what they need and divest what they don't in partial asset sales.
  - What they keep is related to core expertise and also generalized management skill (Lucas 1978).
  - See Maksimovic et al. JFE 2013.

4. Efficient Allocation of Capital

- M&A is one piece of capital reallocation.

- Economics literature on capital allocation
  - Hsieh and Klenow 2009
  - Hsieh and Klenow 2017 "The Reallocation Myth"
    - "Most innovation comes from existing firms improving their own products"

- I wonder whether the paper's technology can be applied to understand the consequences of capital reallocation from low to high productivity firms.

5. Other Remarks

- Public and private firms differ systematically.
  - Worry about using models off one set for the other
  - Maksimovic, Phillips, Yang (JF 2013, WP 2020)

- Equally weighting acquirer and target M&A abnormal returns didn't make sense to me. Combined gains, acquirer gains, target gains are the (more useful) traditional classifications

- Survival rates. 2 years seems short and death rather extreme.
  - What about divisional divestments and partial asset sales?
  - Try ex-post analysis based on Barber-Lyon long-term performance, or analyst forecasts and their revisions.

5. Other Remarks

- Nitpicky empirical issues
  - Omitted variables: common ownership and behavioral variables came to mind. Patents?
  - Probit versus linear probability models
    - Or even ML based classifiers
  - Hoberg-Phillips industries or Fama-French 12?
  - Residualization is often viewed as illegitimate. It also introduces EIV.
  - In Table 2, distances seem to increase in recent times. Why?

Overall

1. Interesting exercise and findings
    - Machine learning in M&A research
2. I'd like to see more economics, value added by ML
3. Several comments, some big picture, some small.
4. Boundaries of the paper?