How Robust are the Results?

A Bayesian Averaging Approach for Tackling Replication and Model Uncertainty in Research on Inbound Open Innovation

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Question.

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How do (inbound) open innovation practices influence innovation performance?

Motivation & Contribution.

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Develop a set of empirically robust results through replication and introduce a new empirical approach to ´research in strategic management.

Motivation & Approach.

- How robust are the findings? – Replication of the analyses.

  Step (1) Large scale robustness study for

  - DE, FR, & UK (7,841 firms)

  Step (2) Bayesian Averaging of Classical Estimators (BACE)

- Aim is to provide a **set of empirically robust results** on the determinants of firm-level innovation performance
  - introduction of **new to the firm** and
  - new to the world innovations

    (e.g., Cassiman and Veugelers, 2006; Laursen and Salter, 2006; Leiponen and Helfat, 2010; Garriga, von Krogh, and Spaeth, 2013)

- Implications for innovation research, and **explore the potential application of our approach** to other domains of research in strategic management

Data & Measures.

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Broad data set: CIS 4 for DE, FR, UK

Broad set of measures: Ballot et al. (2015), Cassiman and Veugelers (2006), Garriga et al. (2013), Grimpe and Kaiser (2010), Laursen and Salter (2006), Leiponen and Helfat (2010), Leiponen (2005a), Love et al. (2014), Roper et al. (2008), Schmiedeberg (2008)

Data & Measures

Dependent variables

- **INNOFIRM**: share of sales of products new to the firm (log)
- **INNOWORLD**: share of sales of products new to the world (log)

Potential predictors

- Inbound Open Innovation:
  - Search: **BREADTH** and **DEPTH**; information flows **USER**, **COMPINFO**, value of information **BASICINFO** and **PUBINFO**
  - Collaboration: **COLLAB** and depth **COLDEPTH**.
- **R&D**: total R&D share of expenditure in 2004
- Markets: **INTMKT** for international and **NATMKT** for national
- Appropriability strategy: formal **IPF** and informal appropriability **IPNF**
- Obstacles to innovation: financial obstacles to innovation (**OBSFIN**), knowledge obstacles to innovation (**OBSKNOW**), and market obstacles to innovation (**OBSMKT**)
- Make or buy: **MAKEONLY**, **BUYONLY**, **MAKEBUY**
- Firm demographics: Firm size (**LOGEMP**), **STARTUP**, **11 sector** and **3 country dummies.**

Step 1:
Replication / Robustness

Model Specification

- Focus on main models built in
  - **Laursen and Salter (2006)**
  - **Cassiman and Veugelers (2006)**
  - **Schmiedeberg (2008)**

- Dependent variables explained by **Tobit regressions**
  - INNOWORLD: share of sales of products new to the world (log)
  - INNOFIRM: share of sales of products new to the firm (log)
    - In this presentation only the results for the latter are documented.

Table X2: Regression of sales share of innovation new to the firm (INNOFIRM, N=7,384)

	(1)	(2)	(3)	(4)	(5)	(6)
BREADTH	0.328*** (0.050)	0.352*** (0.050)			0.235*** (0.055)	0.251*** (0.055)
BREADTH2	-0.019*** (0.004)	-0.022*** (0.004)			-0.015*** (0.004)	-0.017*** (0.004)
DEPTH	0.129** (0.056)				0.074 (0.056)	
DEPTH2	-0.012 (0.009)				-0.009 (0.009)	
DEPTH×RD					-0.003 (0.043)	
USER	0.167** (0.074)	0.271*** (0.061)			0.110 (0.075)	0.148** (0.064)
COMPINFO			0.278*** (0.031)		0.156*** (0.039)	0.165*** (0.038)
BASICINFO			0.028 (0.062)		-0.057 (0.071)	-0.082 (0.071)
PUBINFO			0.105** (0.054)		-0.001 (0.059)	0.001 (0.059)
COLLAB	0.376*** (0.063)				0.341*** (0.064)	
COLDEPTH		0.196*** (0.053)		0.196*** (0.020)		0.172*** (0.053)
COLDEPTH2		-0.010 (0.011)				-0.007 (0.011)
COLDEPTH×RD				-0.140 (0.132)		-0.019 (0.044)
RD	-0.089 (0.066)	-0.091 (0.068)	-0.063 (0.047)	0.109 (0.139)	-0.079 (0.177)	-0.044 (0.094)
INTMKT	0.337*** (0.088)	0.345*** (0.087)	0.307*** (0.088)	0.411*** (0.088)	0.265*** (0.088)	0.272*** (0.087)
NATMKT	0.170* (0.097)	0.150 (0.097)	0.153 (0.097)	0.182* (0.098)	0.128 (0.097)	0.107 (0.097)
OBSFIN			-0.078 (0.061)		-0.098 (0.061)	-0.108* (0.061)
OBSKNOW			-0.093 (0.081)		-0.098 (0.081)	-0.106 (0.081)
OBSMKT			0.247*** (0.070)		0.233*** (0.070)	0.236*** (0.069)
MAKEONLY			0.541*** (0.171)		0.429** (0.171)	0.447*** (0.171)
BUYONLY			0.130 (0.169)		0.00001 (0.170)	0.014 (0.169)
MAKEBUY			0.953*** (0.158)		0.723*** (0.160)	0.729*** (0.159)
LOGEMP	-0.024 (0.021)	-0.029 (0.021)	-0.023 (0.021)	-0.004 (0.021)	-0.046** (0.021)	-0.053** (0.021)
STARTUP	0.090 (0.242)	0.106 (0.242)			0.131 (0.240)	0.141 (0.240)
STARTUP×RD	0.895* (0.472)	0.910* (0.472)			0.924** (0.469)	0.885* (0.473)
CONSTANT	-1.467*** (0.211)	-1.347*** (0.211)	-1.103*** (0.210)	-0.144 (0.158)	-1.538*** (0.243)	-1.437*** (0.243)
Sector controls	Yes	Yes	Yes	Yes	Yes	Yes
Country controls	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-11,425.600	-11,418.490	-11,408.430	-11,481.520	-11,371.030	-11,361.140
Wald Test	436.529*** (df = 24)	451.310*** (df = 23)	472.346*** (df = 25)	334.754*** (df = 18)	539.124*** (df = 34)	559.107*** (df = 33)

Note: ***, ** and * indicate significance at 1 per cent, 5 per cent and 10 per cent levels respectively. Six industry dummies, Coefficients of Tobit regressions, standard errors in parentheses. Underlining indicates that variables loose or gain significance depending on the other variables in the model.

Model 1, 2
~ Laursen & Salter (2006)

Model 3
~ Cassiman & Veugelers (2006)

Model 4
~ Schmiedeberg (2008)

Model 5, 6
~ Combination of all models / all variables

One Insight From the Regressions.

- Variable gain or lose significance depending on other variables included in the models

  - Results must be interpreted **conditional on the assumption that in each case, the estimated model is the 'true' model:** where predictors are appropriate to explain innovation performance

- But: Do we know the 'true' model?
  - **Which predictors** should be included in the regression model.
    - It is unclear **which model** to be estimated.
    - Different sets of **predictors** and different models with dramatically different conclusions.

- Disregarding model uncertainty leads **to overconfident** inferences based on statistical estimates.

Step 2:
Model Uncertainty and Model Averaging.

Model Uncertainty & Model Averaging.

- Model averaging techniques provide a solution to model uncertainty based
  - on **several plausible models**,
  - (weighted) **averaging** over those models, and
  - **drawing inferences based on their weighted averages**.
    - Model parameters are estimated
    - and also structure of the model are estimated

- Non-Bayesian and Bayesian approaches

- Key idea of model averaging: **Using several models rather than a single model to make inferences**

Specification.

- Account for model uncertainty and modify the **Bayesian Averaging of Classical Estimators** BACE approach (Sala-i-Martin et al., 2004; Jones and Schneider, 2006) for the Tobit regressions
  - Entire model space $\{M_1,...M_k,...M_\kappa\}$ of κ models where each model consists of a different set of predictors
  - Typically: after regressing the κ models, BACE approach **computes the weighted average of the estimation results** with weights (Sala-i-Martin et al., 2004)

- Full enumeration (2^{29} = 540 million Tobit models) **is not possible**.
  - We implement a **Markov Chain Monte Carlo Model Composition** (MCMCMC or MC3): search the model space and collect information from the relevant parts of the posterior model distribution
    - 600,000 MC3 iterations: discard first 300,000 iterations "burn-in steps"
    - Analysis based on the results of the remaining 300,000 MC3 iterations

Specification.

- The averaging

$$E(\beta|D) = \sum_{k=1}^{\kappa} P(M_k|D) \cdot \beta^k$$

- Weights for the averaging is the posterior model probability $P(M_k|D)$:

$$P(M_k|D) = \frac{P(D|M_k) \cdot P(M_k)}{\sum_{j=1}^{\kappa} P(D|M_j) \cdot P(M_j)}$$

- $P(D|M_k)$ measures how well M_k explains the data D. For the Tobit models we use

$$P(D|M_k) = g(BICk)$$

- Prior model probability

$$P(M_k) = \prod_{j=1}^{z} \pi_j^{\delta_{kj}} (1-\pi_j)^{1-\delta_{kj}}.$$

$\pi_j = 0.5$ is the prior probability that β_j is not zero (robustness with 0.3 and 0.7).

δ_{kj} is an indicator for variable j to be part of the model M_k

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Results

- Col (1): **Posterior inclusion probability** (PIP) is the sum of the probabilities of those models that include this predictor
  - Probability of each of the potential predictors to be part of the 'true' model
    - 0.50 ≤ PIP < 0.75: weak evidence
    - 0.75 ≤ PIP < 0.90: positive evidence
    - 0.90 ≤ PIP < 0.99: strong evidence
    - PIP ≥ 0.99: decisive evidence
- Column (2): mean parameter estimate for all the models that include the corresponding variable
- Robustness of the estimate of the effect:
  - Column (3): fraction of the models with a positive parameter conditional on inclusion
  - Column (4): fraction of the models with a significant parameter conditional on inclusion

Table Y2: Model averaging results – sales share of innovations new to the firm (INNOFIRM)

Variables	(1) Posterior inclusion probability (PIP)	(2) Posterior mean conditional on inclusion	(3) Sign certainty probability	(4) Fraction of regressions with p<10%
BREADTH	**1.000**	**0.267**	**1.000**	**1.000**
BREADTH2	**1.000**	**-0.019**	**0.000**	**1.000**
BREADTH×RD	0.000	-0.018	0.000	0.211
DEPTH	0.000	0.065	1.000	1.000
DEPTH2	0.000	-	-	-
DEPTH×RD	0.049	0.022	0.333	0.667
USER	0.017	0.161	1.000	1.000
COMPINFO	**1.000**	**0.195**	**1.000**	**1.000**
BASICINFO	0.000	-0.028	0.000	0.000
PUBINFO	0.000	-0.025	0.001	0.000
COLLAB	0.000	0.346	1.000	1.000
COLDEPTH	**0.997**	**0.133**	**1.000**	**1.000**
COLDEPTH2	0.003	0.024	1.000	1.000
COLDEPTH×RD	0.325	-0.054	0.000	0.116
RD	0.000	-0.243	0.000	0.000
RD2	0.000	-0.089	0.000	0.005
INTMKT	0.215	0.291	1.000	1.000
NATMKT	0.000	0.227	1.000	0.707
IPF	0.350	0.075	1.000	1.000
IPNF	0.003	0.062	1.000	1.000
OBSFIN	0.000	-0.075	0.000	0.000
OBSKNOW	0.000	-0.092	0.000	0.000
OBSMKT	**0.682**	**0.210**	**1.000**	**1.000**
MAKEONLY	**1.000**	**0.471**	**1.000**	**1.000**
BUYONLY	0.000	-0.232	0.293	0.707
MAKEBUY	**1.000**	**0.737**	**1.000**	**1.000**
LOGEMP	0.010	-0.050	0.000	0.906
STARTUP	0.000	0.266	1.000	0.000
STARTUP×RD	0.009	0.916	1.000	1.000

Note: Analysis based on 600,000 MCMC iterations which includes 300,000 burn-in iterations. CorrPMP = 0.998. Sector controls and country controls are always part of the models. The parameters base on the 1.000 best models. Variables with a PIP > 0.500 are in bold.

Results

- Model averaging approach provides
  - Decisive evidence for
    - BREADTH (+)
    - BREADTH2 (-) … inverse U-shape
    - COMPINFO (+)
    - COLDEPTH (+)
    - MAKEONLY (+)
    - MAKEBUY (+)
  - Weak evidence for
    - OBSMKT (+)

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Conclusion.

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- Accounting for model uncertainty allows us to investigate the robust determinants of innovation performance.
- Innovation new to the firm (INNOFIRM) closely related to
  - **external search breadth** and **an inverted U-shaped relationship** between openness and innovation, **collaboration** matters, **make or buy decision** influences innovation, **market obstacles** (positive)
  - **information from competitors** is important for new to firm innovation
  - **little support for the more traditional variables**: R&D, size, firm age, or appropriability strategy, obstacles to innovation, and market orientation

- More radical innovations (INNOWORLD) closely related to
  - **user involvement, international market,** capturing rents through formal and informal **appropriability strategies**, **collaboration depth when interacted with internal R&D** (absorptive capacity), **make or buy decision, market obstacles** (negative) **.**
  - **little evidence of some more traditional innovation variables**: R&D, size, collaboration, breadth of external search

Thank You for Your Attention.

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