ATT, propensity score models

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Concepts

- Job training program
- Program evaluation
- Treatment effect
- Treatment group or The treated vs. Control group or Comparison group

Rubin causal model (RCM)

- Dummy Varible D_i : If i attend the program(1 or 0)
- Y_i is future income or outcome of interest after attending the program.
- $Y_i = Y_{1i}$, if $D_i = 1$
  $Y_i = Y_{0i}$, if $D_i = 0$
- $(Y_{1i} - Y_{0i})$ is treatment effect.

ATE

- Can't observe Y_{1i} and Y_{0i} simultaneously

$$Y_i = (1 - D_i) * Y_{0i} + D_i * Y_{1i} = Y_{0i} + (Y_{1i} - Y_{0i}) * D_i$$

- ATE (average treatment effect): is a measure used to compare treatments (or interventions) in randomized experiments, evaluation of policy interventions, and medical trials. The ATE measures the difference in mean (average) outcomes between units assigned to the treatment and units assigned to the control.

$$ATE = E(Y_{1i} - Y_{0i})$$

ATT & ATU

- ATT (average treatment effect on treated ATET, or treatment effect on treated TOT)

$$ATT = E(Y_{1i} - Y_{0i}|D_i = 1)$$

- In general, $ATE \neq ATT$
- ATU (average treatment effect on untreated)

$$ATU = E(Y_{1i} - Y_{0i}|D_i = 0)$$

- However, the individual may consider whether to attend the program by "self selection" through the expected return $E(Y_{1i} - Y_{0i})$, that may cause difficulties in the evaluation of ATE, which called "the selection problem".

Selection Problem

- Solving the selection problem by random assignment:
- If D_i is independent from (Y_{1i}, Y_{0i}), $ATE = ATT$

$$E(Y_{1i}|D_i = 1) - E(Y_{0i}|D_i = 0) = E(Y_{1i}) - E(Y_{0i}) = ATE = ATT$$

- Selection on observables,Rosenbaum and Rubin(1983) Ignorability:

$$F(Y_{0i}, Y_{1i}|X_i, D_i = 1) = F(Y_{0i}, Y_{1i}|X_i, D_i = 0)$$

Matching Estimator

- On the premise that this hypothesis is valid, X_i can be introduced into the regression equation as a control variable to solve the problem of missing variables. But there is a problem, we may be missing nonlinear terms, so there are still missing variables.
- Solutions:
  1. PSM matching estimator based on counterfactual framework.
  2. Find as many control variables as possible. (Very complicated)

Matching Estimator

- Therefore, we only need to find a match between the measurable observed value x_i of individual i in the treatment (intervention) group and the measurable observed value x_j of similar individual j, $x_i = x_j$. So D depends entirely on x, according to the measurable variable selection hypothesis, and individuals i and j are similar.
- If we can find similar individual j for individual i in each treatment group, then we can think: $y_{0i} \approx y_{0j}$. The approximate mean treatment effect $y_{1i} - y_{0i} \approx y_{1i} - y_{0j}$ is further calculated, and RHS is the matching estimator.

Matching Estimator

- Replacement: With replacement & No replacement
- Ties: Allowed & Not allowed
- 1 vs. ?: 1 vs. 1 & 1 vs n

Propensity Score Matching

- When x_i includes multiple variables and the data is sparse, it is difficult to get x_j matching with x_i through high latitude space.
- The solution is to use the vector norm, the distance function defined in the vector space.
- In 1983, Rosenbaum and Rubin used P-Score to measure distance. The propensity score of individual i is the conditional probability of individual i entering the treatment group under the given x_i, that is,$P(x_i) = P(D_i = 1 \mid x = x_i)$

Propensity Score Matching

- Propensity score matching: use propensity score as distance function for matching.
- Advantages: it is not only a unique variable, but also has a value between 0 and 1.Even if x_i are far away from x_j , you can still get $P(x_i) \approx P(x_j)$
- Definition: if the assumption of ignorability holds, $(y_{0i}, y_{1i})$is independent of D_i only when $p(x)$ is given.

Propensity Score Matching

- Calculate the average treatment effect by PSM:
  1. Select covariate x_i
  2. Estimated propensity score (logit)
  3. Propensity score matching: if the propensity score is estimated accurately, x_i will be evenly distributed between the matched treatment group and the control group. (data balancing)
  4. Calculate the average processing effect according to the matched samples

Propensity Score Matching

- Different methods:
  1.K-nearest neighbor matching
  2.Caliper matching
  3.Nearest-neighbor matching with caliper inner
  4.Kernel matching:
  5.Local linear regression matching
  E. Fix and JL Hodges(1951), Rosenbaum and Rubin(1983), Heckman et al. (1997, 1998), Pearl(2000)

- Stata code: psmatch2, pstest

Overview

- Misty L. Heggeness, Donna K. Ginther, Maria I. Larenas and Frances D. Carter-Johnson, 2018, "**The Impact of Postdoctoral Fellowships on a Future Independent Career in Federally Funded Biomedical Research**", NBER Working Paper 24508.

- Based on the National Research Service Award (NRSA) project in the field of biomedicine in the United States, this paper uses the matching method to study the impact of obtaining postdoctoral scholarships on postdoctoral scientific research performance in the future.

Data and methods

- Application data of NRSA postdoctoral Scholarship (F32) from 1996 to 2008.
- Data on the application status are from the American Institutes of health.
- The personal data of postdoctoral comes from the annual survey of postdoctoral by the National Science Foundation (NSF).
- Data on NIH scholarship applications and research fund applications in 2015.

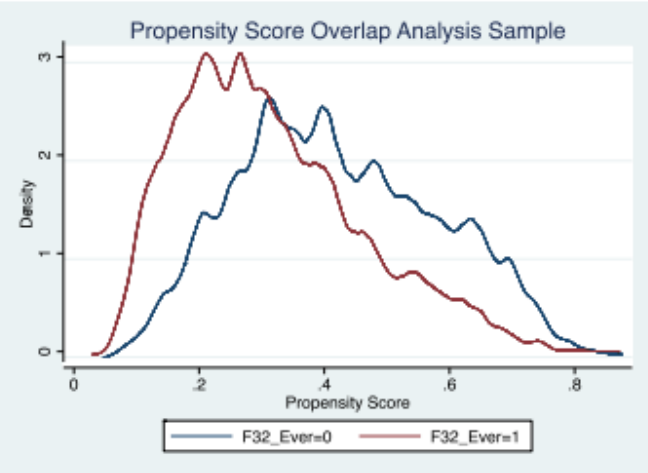
Identification strategy and results

- In the matching process, King and Nielson (2016) and Imbens (2015) pointed out that if the fitting accuracy of the model used for propensity score matching is too high for the original sample, the propensity score matching method will fail. Therefore, the author did not put the expert score into the model as a matching covariate.
- The premise of the propensity score matching method is to meet the common support hypothesis, that is, there is enough overlap between the treatment group and the control group.

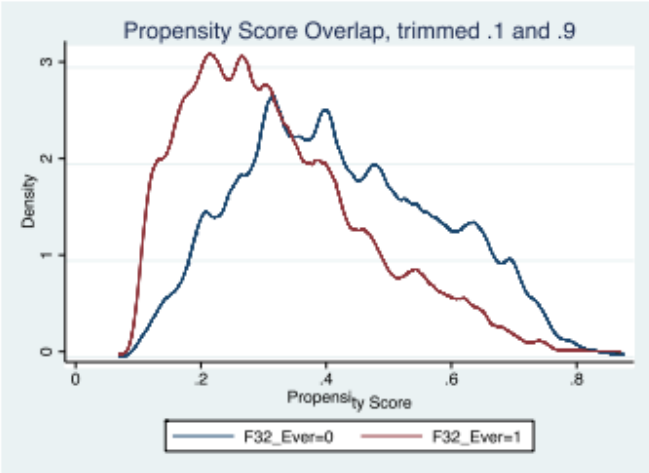
Identification strategy and results

Figure 4: Score overlap by F32 Award

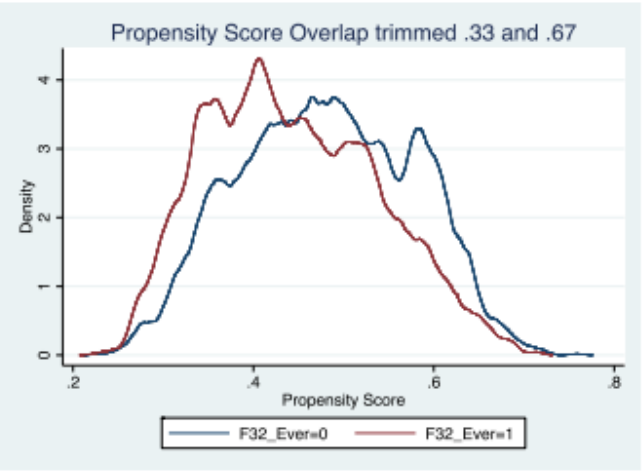
Panel A.



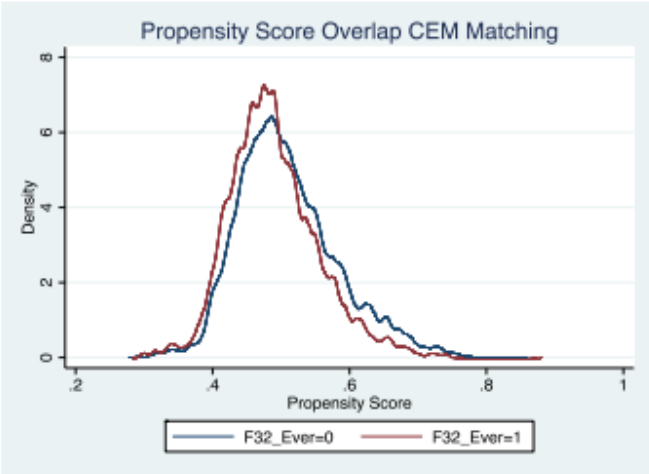
Panel B.



Panel C.



Panel D.



Identification strategy and results

Table 4. Propensity Score Matching Estimates

VARIABLES	Number of RPG Awards	Number of RPG Applications	Probability RPG	Probability R01	Probability Never RPG
ATE					
Full Sample	0.149***	0.731***	0.082***	0.060***	-0.112***
	[0.026]	[0.098]	[0.009]	[0.008]	[0.010]
Trimmed .1,.9	0.127***	0.584***	0.064***	0.048***	-0.098***
	[0.026]	[0.109]	[0.009]	[0.008]	[0.011]
Trimmed .33, .67	0.111***	0.671***	0.067***	0.048***	-0.102***
	[0.030]	[0.129]	[0.011]	[0.010]	[0.013]
ATT					
Full Sample	0.159***	0.775***	0.088***	0.065***	-0.118***
	[0.030]	[0.113]	[0.010]	[0.009]	[0.012]
Trimmed .1,.9	0.143***	0.605***	0.068***	0.050***	-0.100***
	[0.031]	[0.134]	[0.011]	[0.010]	[0.013]
Trimmed .33, .67	0.117**	0.642***	0.070***	0.049***	-0.108***
	[0.036]	[0.160]	[0.012]	[0.011]	[0.015]
Observations	14,273	14,273	14,273	14,273	14,273

Full sample = 14, 273 observations
Trimmed 1 = 14,021
Trimmed 2 = 6,516

Identification strategy and results

Table 5. Counterfactual Treatment Effects with Pseudo Treatments

VARIABLES	(1) PhD Degree	(3) Biomedical Degree	(5) Fellowship or Scholarship PhD Funding
ATE	0.007	0.001	0.005
	[0.007]	[0.010]	[0.010]
ATT	0.005	0.007	0.004
	[0.008]	[0.012]	[0.012]
Observations	14,273	14,273	14,273

Identification strategy and results

- The regression results of this paper show that strengthening the scientific research reward for postdoctoral personnel is conducive to encouraging postdoctoral personnel to engage in scientific research, and then retaining scientific research talents for relevant fields.
- The highlight of the article lies in the original author's in-depth understanding of the process of selecting postdoctoral scholarships and the selection of identification methods. The application and detail processing of matching method in this article is worthy of in-depth study.

Overview

- **Corporate Venture Capital, Value Creation,and Innovation**

Thomas J. Chemmanur,Carroll School of Management, Boston College
Elena Loutskina,Darden School of Business, University of Virginia
Xuan Tian,Kelley School of Business, Indiana University and PBC School of Finance,Tsinghua University

Overview

- Corporate Venture Capital, Value Creation,and Innovation
  They analyze how corporate venture capital (CVC) differs from independent venture capital (IVC) in nurturing innovation in entrepreneurial firms. They find that CVC-backed firms are more innovative, as measured by their patenting outcome, although they are younger, riskier, and less profitable than IVC-backed firms. Their baseline results continue to hold in a propensity score matching analysis of IPO firms and a difference-in-differences analysis of the universe of VC-backed entrepreneurial firms.They present evidence consistent with two possible underlying mechanisms: CVC's greater industry knowledge due to the technological fit between their parent firms and entrepreneurial firms and CVC's greater tolerance for failure.

Data and Sample Selection

- Identifying CVCs
  1,846 VCs that enjoy investments from corporations as reported by the Thomson VentureXpert database.
  926 distinct CVC firms, out of which 562 are affiliated with publicly traded parent firms. They define an entrepreneurial firm as a CVC-backed firm if it receives financing from at least one CVC investor.
- Baseline sample
  IPO firms that went public between 1980 and 2004.
  2,129 VC-backed IPO firms, of which 462 are CVC-backed.

Data and Sample Selection

- They construct two measures for a firm's annual innovation output.
- The first measure, $Ln(Patents)$, is the natural logarithm of annual truncation-adjusted patent count for a firm.
- second measure, $Ln(Citations/Patent)$, that intends to capture the importance of patents by counting the number of citations received by each patent in the subsequent years.

Empirical Results

- Baseline findings
  To evaluate the effect of CVC backing, They use three measures for the degree of CVC participation: CVC Backing Dummy, which equals one if the firm is classified as a CVC-backed IPO and zero if the firm is classified as an IVC-backed IPO, Number of CVCs, which counts the number of CVCs in an investing VC syndicate, and CVC Share, which measures the percentage investment made by the CVCs within a VC syndicate.

Empirical Results

Table 3
Pre-IPO innovation productivity of CVC- and IVC-backed IPO firms

	Panel A: Ln(patents)			Panel B: Ln(citations/patent)		
	(1)	(2)	(3)	(4)	(5)	(6)
CVC backing dummy	0.269***			0.176**		
	(3.02)			(2.21)		
Number of CVCs		0.159***			0.066*	
		(2.91)			(1.75)	
CVC share			0.618**			0.471**
			(2.17)			(2.09)

Table 4
Post-IPO innovation productivity of CVC- and IVC-backed firms

	Panel A: Ln(patents)			Panel B: Ln(citations/patent)		
	(1)	(2)	(3)	(4)	(5)	(6)
CVC backing dummy	0.449***			0.132*		
	(4.01)			(1.91)		
Number of CVCs		0.219***			0.057*	
		(3.66)			(1.64)	
CVC share			0.812**			0.434**
			(2.19)			(2.10)

Empirical Results

Table 6
Propensity score matching: Diagnostic tests

	Panel A Comparing sample characteristics					Panel B Probit regressions	
		Prematch		Postmatch		Prematch	Postmatch
	CVC-backed (1)	IVC-backed (2)	Difference (3)	IVC-backed (4)	Difference (5)	(1)	(2)
Ln(total assets)	4.161	3.938	0.222***	4.132	0.029	0.280***	−0.043
			(3.80)		(0.41)	(5.41)	(0.85)
ROA	−0.154	0.018	−0.172***	−0.084	−0.070***	−1.235***	−0.394**
			(11.62)		(3.61)	(6.64)	(2.14)
R&D in total assets	0.135	0.092	0.042***	0.111	0.023	−0.267	0.0758
			(5.87)		(1.51)	(0.73)	(0.22)
PPE in total assets	0.166	0.228	−0.062***	0.168	−0.002	0.237	0.032
			(5.34)		(0.16)	(0.68)	(0.08)
Leverage	0.052	0.103	−0.051***	0.056	−0.003	−1.556***	0.299
			(5.74)		(0.38)	(4.16)	(0.71)
CE in total assets	0.064	0.073	−0.009*	0.062	0.002	0.284	−0.904
			(1.91)		(0.43)	(0.40)	(1.18)
HHI	0.145	0.251	−0.106***	0.145	0.000	−0.681	0.744
			(6.24)		(0.02)	(1.41)	(1.51)
HHI^2	0.070	0.166	−0.095***	0.068	0.002	0.144	−0.549
			(5.71)		(0.15)	(0.28)	(0.98)
Tobin's q	6.328	3.892	2.436***	5.517	0.811	0.011**	0.011
			(6.43)		(1.40)	(2.09)	(1.24)
KZ index	−31.934	−31.584	−0.350	−32.699	0.765	0.001	0.001*
			(0.03)		(0.09)	(1.17)	(1.73)
Age at IPO	6.555	9.448	−2.893***	7.015	−0.460	−0.011**	0.004
			(5.20)		(0.81)	(2.13)	(0.67)

Empirical Results

Table 7
Propensity score matching results

Nearest neighbors	Exact match	Pre-IPO			Post-IPO		
		CVC-	IVC-	Difference	CVC-	IVC-	Difference
Panel A: Ln(patents)							
Unmatched		1.215	0.605	0.610***	1.929	1.094	0.834***
One	No restriction	1.215	0.814	0.401***	1.929	1.328	0.601***
	Industry	1.215	0.974	0.242*	1.929	1.496	0.432**
	Year	1.215	0.897	0.318**	1.929	1.392	0.537***
	Industry and year	1.215	0.854	0.361**	1.929	1.421	0.508***
Three	No restriction	1.215	0.994	0.222*	1.929	1.572	0.356**
	Industry	1.215	0.958	0.257**	1.929	1.505	0.424***
	Year	1.215	0.922	0.294**	1.929	1.459	0.470***
	Industry and year	1.215	0.978	0.237**	1.929	1.519	0.410***
Five	No restriction	1.215	0.965	0.250***	1.929	1.527	0.401***
	Industry	1.215	0.978	0.237**	1.929	1.543	0.386***
	Year	1.215	0.916	0.299***	1.929	1.474	0.455***
	Industry and year	1.215	0.963	0.252**	1.929	1.490	0.438***
Panel B: Ln(citations per patent)							
Unmatched		1.007	0.638	0.369***	1.087	0.837	0.250***
One	No restriction	1.007	0.850	0.157	1.087	0.899	0.188**
	Industry	1.007	0.933	0.074	1.087	1.019	0.067
	Year	1.007	0.772	0.235**	1.087	0.921	0.166
	Industry and year	1.007	0.755	0.252**	1.087	0.992	0.095
Three	No restriction	1.007	0.856	0.151	1.087	1.010	0.077
	Industry	1.007	0.928	0.079	1.087	1.026	0.060
	Year	1.007	0.827	0.180*	1.087	0.950	0.136
	Industry and year	1.007	0.859	0.148	1.087	1.022	0.065
Five	No restriction	1.007	0.829	0.178*	1.087	0.961	0.126
	Industry	1.007	0.849	0.158*	1.087	0.988	0.099
	Year	1.007	0.840	0.167*	1.087	0.959	0.128
	Industry and year	1.007	0.848	0.159*	1.087	1.010	0.077

Conclusion

- CVC-backed firms achieve a higher degree of innovation output, as measured by their patenting, although these firms are younger, riskier, and less profitable.
- The results of our propensity score matching and DID analyses suggest that there is a significant treatment effect of CVC financing on innovation. Our analysis reveals two possible mechanisms through which CVCs are able to better nurture innovation: the technological fit between CVCs' parent firms and the entrepreneurial firms backed by them and the greater failure tolerance by CVCs relative to IVCs.

Reference

- Misty L. Heggeness, Donna K. Ginther, Maria I. Larenas & Frances D. Carter-Johnson. (2018) The Impact of Postdoctoral Fellowships on a Future Independent Career in Federally Funded Biomedical Research. NBER Working Paper 24508.
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