Data-intensive Innovation and the State: Evidence from AI Firms in China

Martin Beraja David Yang Noam Yuchtman MIT Harvard LSE

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Research assistants: Haoran Gao, Shiyun Hu, Andrew Kao, Shuhao Lu, Junxi Liu, Shengqi Ni, Wenwei Peng, Yucheng Quan, Linchuan Xu, Peilin Yang, and Guoli Yin

Motivation: government data as input in Al innovation

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 - Many recent AI advances made with decades-old algorithms applied to newly available big data

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 - Many recent Al advances made with decades-old algorithms applied to newly available big data
- ► Literature has focused on how data collected by **private** firms shapes Al innovation (Agrawal et al., 2019; Jones and Tonetti, 2020)
- Yet, throughout history, states have also collected massive quantities of data (Scott, 1998)
- ▶ The state has a large role in many areas
 - ▶ Public security, health care, education, basic science...
 - ⇒ **Government data** can exceed privately-collected data in magnitude/scope; or lack good substitutes altogether

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- ► A common way in which Al firms **gain access** to valuable government data is by **providing services** to the state
- ► Think about facial recognition Al firms in China...
 - ► Train algorithms with, e.g., video streams of faces from many angles
 - ► The state's public security units collect this form of data through their surveillance apparatus, and contract AI firms for services
 - Al firms gaining access to surveillance data can use it to train algorithms and develop software

This paper

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The mechanism(s)

- If gov't data and algorithms are sharable across uses, they can be used to develop AI products for commercial markets (e.g., a facial recognition platform for retail stores)
- 2. Firms may **learn** to manage and utilize large datasets too

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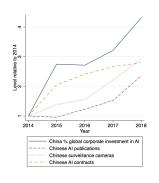
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⇒ a procurement contract with access to gov't data can fuel commercial innovation, overcoming **crowd-out** from the contract

Evidence of this in China's facial recognition Al sector

Two implications

- 1. Access to gov't data contributed to Chinese firms' emergence as leading innovators in facial recognition Al
 - ► Indeed, this has coincided with the expansion of the government's procurement of AI and surveillance capacity



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2. Novel role for the state in data-intensive economies

- ► So far, emphasis on the regulation of privately-collected data due to antitrust or privacy concerns (Tirole, 2020; Aridor et al., 2020)
- Al procurement and policies of gov't data collection and provision could, whether intentionally or not, stimulate and shape the direction of innovation in a range of sectors

Empirical challenges

Would like to compare software output changes after receipt of gov't procurement contracts giving access to more v. less data

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Data challenges

- 1. Dataset linking AI firms to govt. contracts did not exist
- Dataset on AI firms' software did not exist (our measure of product innovation). Also, critical for us to classify by use (commercial or not)
- 3. No available direct measures of firm-level use of gov't data

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Identification challenges

- 1. Non-random assignment of gov't contracts
- 2. Contracts work through other mechanisms unrelated to data

Data 1: linking Al firms to govt. contracts

1. Identify all facial recognition Al firms

- 7,837 firms
- Two sources: Tianyancha (People's Bank of China) and PitchBook (Morningstar)
- Include: (i) firms specialized in facial recognition AI (e.g., Yitu); (ii) hardware firms that devote substantial resources to develop AI software (e.g., Hik-Vision); (iii) facial recognition AI units of large tech conglomerates (e.g., Baidu AI)

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2. Obtain universe of **government contracts**

- 2,997,105 contracts
- Source: Chinese Govt. Procurement Database (Ministry of Finance)

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Data 2: Al firms' software production

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Categorize by intended customers:

- 1. **Commercial:** e.g., visual recognition system for smart retail;
- Government: e.g., smart city real time monitoring system on main traffic routes;
- 3. General: e.g., a synchronization method for multi-view cameras based on FPGA chips.

Categorization: analyze text using machine learning

- ► Recurrent Neural Network (RNN) model using tensorflow
 - Corpus: 13,000 manually labeled software programs
 - Word-embedding: converted sentences to vectors based on word frequencies and used the words from full datasets as dictionary
 - Long Short-Term Memory (LSTM) algorithm: 2 layers of 32 nodes
 - 90% of corpus for training, 10% for validating
 - 10,000 training cycles are run for gradient descent on loss function
- Results robust to perturbing parameters of learning model

Data 3: measuring access to government data

Within Al public security contracts: variation in the data collection capacity of the public security agency's local surveillance network

- 1. Identify non-Al contracts: police department purchases of street cameras
- 2. Measure quantity of advanced cameras in a prefecture at a given time
- Categorize public security contracts as coming from "high" or "low" camera capacity prefectures

Baseline empirical strategy

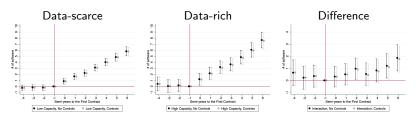
► **Triple diffs:** compare cumulative software releases before and after firms received 1st data-rich contracts, relative to the data-scarce ones

$$y_{it} = \sum_{T} \beta_{1T} T_{it} \frac{Data_i}{Data_i} + \sum_{T} \beta_{2T} T_{it} + \alpha_t + \gamma_i + \sum_{T} \beta_{3T} T_{it} X_i + \epsilon_{it}$$

- T_{it}: 1 if, at time t, T semi-years have passed before/since firm i received 1st contract
- Data_i: 1 if firm i receives "data rich" contract (i.e., from "high" camera capacity prefecture at time of contract receipt)
- X_i controls for pre-contract firm characteristics: age, size (cap), and software production

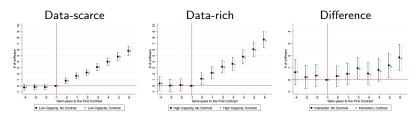
Public security contract "richer in data" & firm innovation

Commercial use cumulative software releases



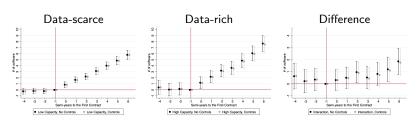
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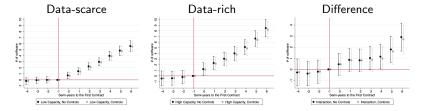


Magnitude: 2 new software products over 3 years

Public security contract "richer in data" & firm innovation Commercial use cumulative software releases



Government use cumulative software releases



Commercial innovation overcomes crowd-out of inputs by gov't

Evaluating alternative hypotheses

1. **Selection** at a given time differs by contract

- Firm controls. No differential pre-contract levels/trends of software

2. Terms and tasks differ by contract Language distance

- Descriptions of data-rich and -scarce contracts are similar in content
- Similar govt soft produced after data-rich and -scarce contracts too

3. Importance of capital differs by contract Capital

 Control for time-period x: pre-contract market cap or amount of external financing, and monetary value of contract

4. **Signals** differ by contract Signals

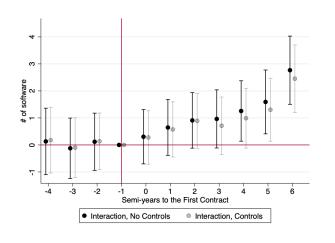
- Subsamples of firms: (i) from a *mother* firm that has already received contract, or (ii) receiving a 2nd data-rich contract

5. Govt connections or opportunities differ by contract • Local

- Drop contracts with Beijing/Shangai or firm's home province.
- Control for time-period × GDP-per-cap

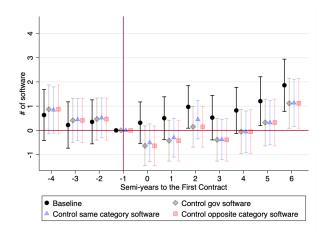
Additional evidence for our mechanism(s)

Data-complementary software (e.g., storage/transmission) differentially increases after data-rich contract. **Learning?**



Additional evidence for our mechanism(s)

- Include pre-contract Al production interacted with Time period fixed-effects. (Over)controls for learning potential
- Baseline estimate still positive, but halves in magnitude.
 Direct effect due to sharability of data/algorithms?



Contributions to literature

- To the literature on the economics of Al and data (e.g., Aghion et al., 2017; Agrawal et al., 2018; Farboodi et al., 2019; Jones and Tonetti, 2019)
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 - Mechanisms similar to other government policies (e.g., learning spillovers from space exploration) but distinct too (direct effect of sharability)

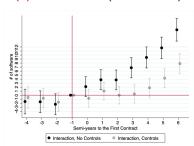
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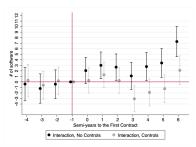
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- To the literature on the rise of China emphasizing the role of the state (e.g., Lau et al., 2000; Brandt and Rawski, 2008; Song et al., 2011)
 - Highlight the role of the surveillance apparatus in commercial innovation
 - Next project: Al-tocracy. Alignment between innovation and autocracy?
 Contrasts with e.g., North (1991); Acemoglu and Robinson (2006, 2012)

Appendix

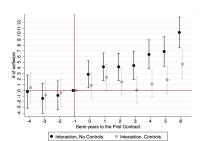
(a) Government (for video-AI)

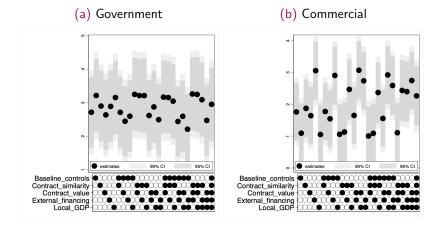
(b) Commercial (for video-AI)





(c) Data-complementary (for video-AI)





▶ Back

Table A.11: Scale effects and learning-by-doing

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	Government Commercial		Data-complementary			
	(1)	(2)	(3)			
Panel A: Baseline						
4 Semiyears Before	-0.177	-0.239	-0.310			
	(0.268)	(0.231)	(0.270)			
6 Semiyears After	5.595***	5.811***	6.383***			
•	(0.444)	(0.378)	(0.443)			
4 Semiyears Before × High Capacity	-0.279	0.633	0.130			
, , ,	(0.620)	(0.539)	(0.627)			
6 Semiyears After × High Capacity	2.911***	1.861***	2.766***			
,	(0.642)	(0.550)	(0.644)			
Panel B: Control for government pre-contract software production						
4 Semiyears Before	0.138	-0.076	-0.081			
ŕ	(0.233)	(0.220)	(0.252)			
6 Semiyears After	1.769***	3.846***	3.652***			
,	(0.386)	(0.362)	(0.415)			
4 Semiyears Before × High Capacity	0.170	0.869*	0.489			
, , , , , , , , , , , , , , , , , , , ,	(0.538)	(0.514)	(0.586)			
6 Semiyears After × High Capacity	1.477***	1.116**	1.722***			
	(0.556)	(0.525)	(0.602)			
Panel C: Control for same category pre-contract software production						
4 Semiyears Before	0.138	0.034	-0.047			
,	(0.233)	(0.209)	(0.253)			
6 Semiyears After	1.769***	2.577***	3.173***			
,	(0.386)	(0.344)	(0.418)			
4 Semiyears Before × High Capacity	0.170	0.841*	0.361			
yy	(0.538)	(0.487)	(0.589)			
6 Semiyears After × High Capacity	1.477***	1.132**	2.013***			
o sensy cars rates wrager capacity	(0.556)	(0.498)	(0.605)			
Panel D: Control for opposite category pre-contract software production						
4 Semiyears Before	0.080	-0.076	-0.061			
•	(0.250)	(0.220)	(0.256)			
6 Semiyears After	2.399***	3.846***	3.474***			
	(0.416)	(0.362)	(0.423)			
4 Semiyears Before × High Capacity	-0.078	0.869*	0.302			
, xxigit empticity	(0.579)	(0.514)	(0.596)			
6 Semiyears After × High Capacity	2.231***	1.116**	2.111***			
,,,	(0.599)	(0.525)	(0.612)			
	(0.077)	(0.020)	(0.012)			

Table A.12: Effects of 2nd public security contracts

	Government Commercial		Data-complementary	
	(1)	(2)	(3)	
Panel A: Baseline				
4 Semiyears Before	-0.177	-0.239	-0.310	
	(0.268)	(0.231)	(0.270)	
6 Semiyears After	5.595***	5.811***	6.383***	
	(0.444)	(0.378)	(0.443)	
4 Semiyears Before × High Capacity	-0.279	0.633	0.130	
	(0.620)	(0.539)	(0.627)	
6 Semiyears After × High Capacity	2.911***	1.861***	2.766***	
	(0.642)	(0.550)	(0.644)	
Panel B: Sample — not first contract w	ithin mother fir	m		
4 Semiyears Before	-0.078	-0.431	-0.184	
	(0.213)	(0.362)	(0.283)	
6 Semiyears After	4.606***	6.730***	6.370***	
•	(0.332)	(0.557)	(0.438)	
4 Semiyears Before × High Capacity	1.035	1.047	0.820	
	(0.786)	(1.384)	(1.081)	
6 Semiyears After × High Capacity	2.753***	1.975*	1.024	
	(0.710)	(1.200)	(0.947)	
Panel C: Sample — second contract w	ithin subsidiary	firm		
4 Semiyears Before	-1.577*	2.214***	2.015***	
•	(0.916)	(0.656)	(0.697)	
6 Semiyears After	8.533***	7.856***	13.538***	
•	(1.430)	(1.025)	(1.088)	
4 Semiyears Before × High Capacity	1.090	-1.943**	-1.819*	
. 0 1 7	(1.287)	(0.923)	(0.980)	
6 Semiyears After × High Capacity	29.042***	2.876**	17.833***	
, , ,	(1.881)	(1.349)	(1.432)	

Table A.13: Robustness — firm geography

·	Government	Commercial	Data-complementary
	(1)	(2)	(3)
Panel A: Baseline			
4 Semiyears Before	-0.177	-0.239	-0.310
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6 Semiyears After	5.595***	5.811***	6.383***
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4 Semiyears Before × High Capacity	-0.279	0.633	0.130
, , , ,	(0.620)	(0.539)	(0.627)
6 Semiyears After × High Capacity	2.911***	1.861***	2.766***
, , , , , , , , , , , , , , , , , , , ,	(0.642)	(0.550)	(0.644)
Panel B: Drop Beijing, Shanghai			
4 Semiyears Before	-0.179	-0.242	-0.277
,	(0.264)	(0.166)	(0.249)
6 Semiyears After	5.511***	5.873***	6.286***
,	(0.423)	(0.264)	(0.397)
4 Semiyears Before × High Capacity	-0.114	0.763*	0.235
, , ,	(0.634)	(0.404)	(0.603)
6 Semiyears After × High Capacity	2.983***	1.118***	2.863***
, , ,	(0.641)	(0.403)	(0.605)
Panel C: Firm based outside contract province			
4 Semiyears Before	-0.195	-0.165	-0.293
100111,0110 001010	(0.209)	(0.245)	(0.218)
6 Semiyears After	5.254***	5.862***	6.153***
,	(0.333)	(0.387)	(0.346)
4 Semiyears Before × High Capacity	-0.053	0.721	0.177
	(0.555)	(0.658)	(0.586)
6 Semiyears After × High Capacity	2.365***	2.747***	2.815***
,,,,,	(0.542)	(0.636)	(0.567)