Venture Capital (Mis)Allocation in the Age of AI

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AI & BIG DATA IN FINANCE RESEARCH FORUM
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The Venture Capital Funnel

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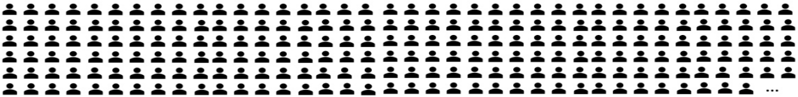

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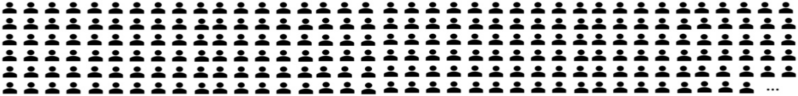

are considered by Venture Capitalists (VCs)

6% given opportunity to meet with VCs

2.5% reviewed by VC partners

1.5% pass due diligence

1.15% get term sheet

0.5% VC-backed

Outline

Model of VCs' Decisions

- Builds on Mullainathan and Obermeyer (2022)
- Based on firm features (X, Z), **rational** predictions of firms' performance can be formed
  - Both X and Z are observed by VCs, only X is in the data
  - $R(X, Z) \in [0, 100]$ the percentile rank of these predictions

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- VCs' **optimal** policy: $I = 1$ iff $R(X, Z) > \textit{threshold}$
  - $I = 1$ if VCs invest, $I = 0$ otherwise

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  - $I = 1$ if VCs invest, $I = 0$ otherwise
- VCs' **actual** policy: $I = 1$ iff $R(X, Z) > \textit{threshold} + \Delta(X, Z)$
  - $\Delta(X, Z)$ captures shifts in the investment threshold
  - shifts may arise due to VCs' biases, constraints, or private benefits

This Paper

1. **Create an algorithmic investment policy**
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   - estimate the **shadow cost of constraints** faced by VCs

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2. **Understand VCs' decisions through algorithmic predictions**
   - build a model that predicts VCs' decisions
   - contrast this model to the algorithmic investment policy
   - explore the role of **stereotypes**: do stereotypes bias VCs' decisions?

This Paper

Scoping exercise – algorithms as **tools** to help us understand how VCs' make their investment decisions

Not a "human vs. machine horse race" paper

- automation? No!
- study the differences between VC-backed and algorithm-selected ventures to **uncover sources of inefficiencies** in VCs' decision making

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We do not assume the algorithm is correct

- algorithmic predictions to identify **potential** inefficiencies
- **actual** inefficiencies are identified using **realized** outcomes

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Data Sources

Entrepreneur survey (French administrative data)	Financial statements (French administrative data)	Exits (Commercial data)

Entrepreneur survey (French administrative data)

4 cohorts every 4 years:
- 1998-2010

representative sample:
- 1/3 of all entrepreneurs

survey questions cover:
- demographics
- expertise
- experience
- motivation
- expectations
- **VC-backed**

Financial statements (French administrative data)

Corporate tax filings:
- all new firms

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SDC, Zephyr:
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representative sample: 1/3 of all entrepreneurs		
survey questions cover: demographics, expertise, experience, motivation, expectations, **VC-backed**		

Contains both VC-backed **and** non-VC-backed firms

→ **No "selective labels" problem!**

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→ **No "selective labels" problem!**

→ **No survivorship bias and no selection/reporting bias**

Algorithm Design

Features

Year of firm creation

Entrepreneur and firm characteristics in entrepreneur survey

Easily available to VCs in first-pass evaluation

k = 452

Outcome

5 or 7 years after firm creation

- "value added" (≈ ebitda) (log)
- 1[top 5% value added]
- EBITDA / initial capital (log)
- successful deals (M&A, IPO, subsequent funding round)

- n ≈ 124k new firms in four cohorts (1998, 2002, 2006, 2010)
  → drop firms in industries that never receive VC
- Train *XGBoost* model on first 3 cohorts of firms (69% of observations)
  → Predict outcome: $\widehat{m}(X_i) \longrightarrow M(X_i)$ percentile rank for entrepreneur *i*
  → Algorithmic policy: $I = 1 \; iff \; M(X_i) > threshold$
- Results only evaluated on 2010 cohort (31% of observations), never seen by algorithm

Algorithm Performance

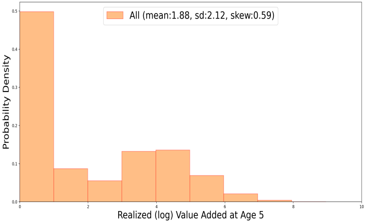
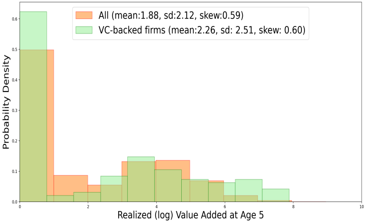


Figure 1: Distribution of firm performance in test set

Algorithm Performance



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- The average VC-backed firm is much more profitable than the average firm

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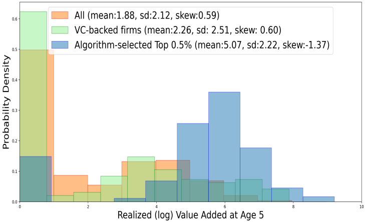

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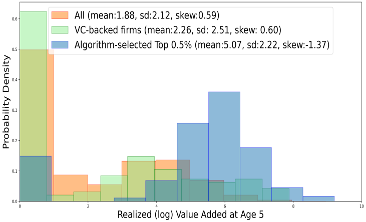

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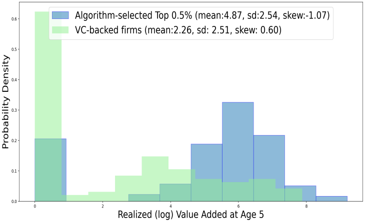

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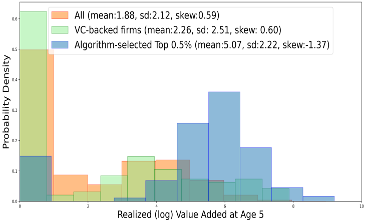

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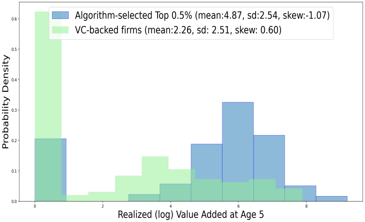

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- VCs invest in some firms that perform **predictably poorly** and pass on other firms that perform **predictably well** $\rightarrow \Delta(X, Z) \neq 0$

Predicting various measures of firm performance

- Firms selected by a model that predicts one measure of success also outperform VCs' selections on **all** other measures of success

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Algorithm trained on	Algorithm evaluated on					
	VA_5 (log)	VA_7 (log)	Top 5% VA_5	Top 5% VA_7	$Ebitda_5$ / $capital_0$(log)	Successful Deals
VA_5 (log)	5.07	4.86	0.55	0.55	3.09	4
VA_7 (log)	5.01	4.89	0.49	0.50	2.92	4
Top 5% VA_5	4.97	4.60	0.60	0.56	3.09	4
Top 5% VA_7	4.90	4.64	0.56	0.55	3.09	4
$Ebitda_5$ /$capital_0$(log)	4.69	4.50	0.45	0.44	2.86	3
Successful Deals	3.07	2.66	0.28	0.26	1.78	11
	Comparison: Average performance measures					
	VA_5 (log)	VA_7 (log)	Top 5% VA_5	Top 5% VA_7	$Ebitda_5$ / $capital_0$(log)	Successful Deals
All firms in test set	1.88	1.61	0.05	0.05	1.01	56
VC-backed firms	2.26	1.94	0.14	0.13	1.06	4

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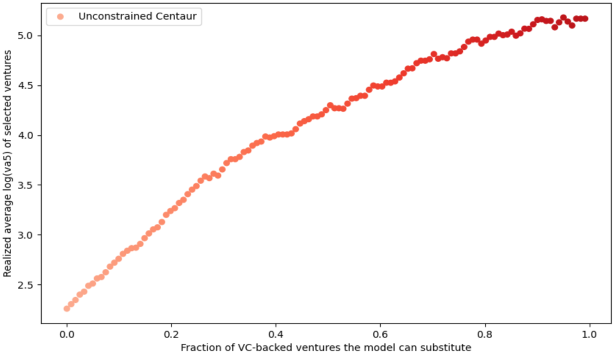
- Even measures that account for VCs' preference for skewness

Estimating the Shadow Cost of VCs' Constraints



- The centaur model:

1- ranks VC-backed firms on $\widehat{m}(X_i)$

2- drops VC-backed firms one by one, starting with lowest $\widehat{m}(X_i)$

3- replaces dropped VC-backed firm with firm with highest $\widehat{m}(X_i)$

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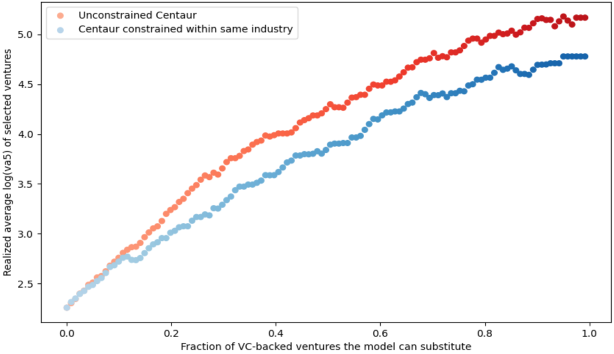

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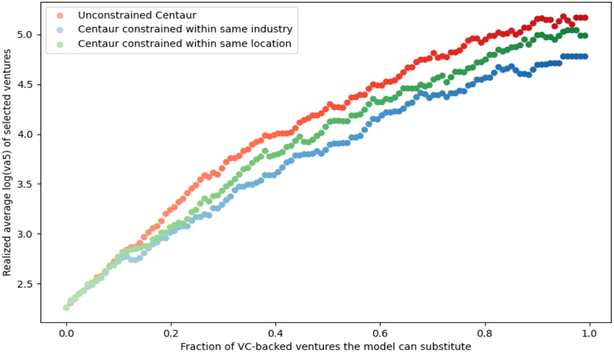

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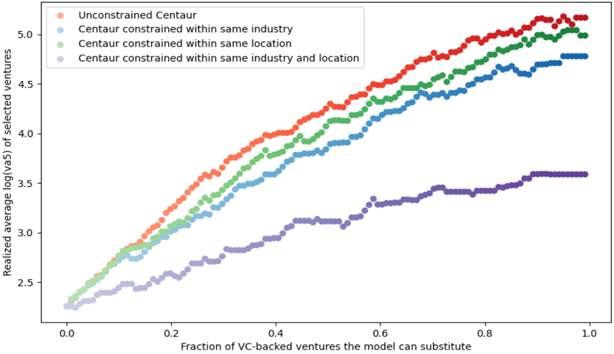

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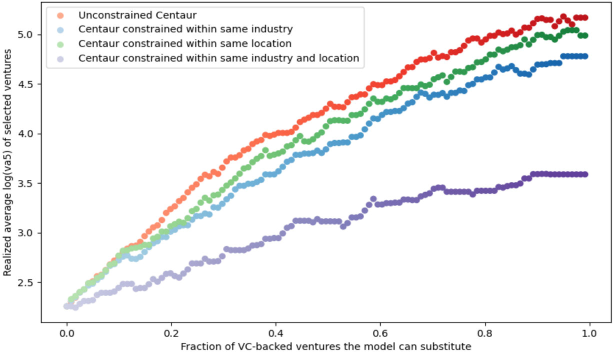

💡 Shadow cost: difference between performance of the **unconstrained** Centaur model and that of **constrained** Centaur models

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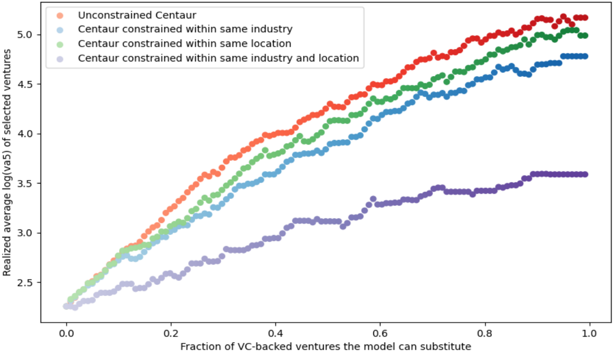

- Shadow price of constraining firms to be in the same
  - Industry: 30%
  - Location: 13%

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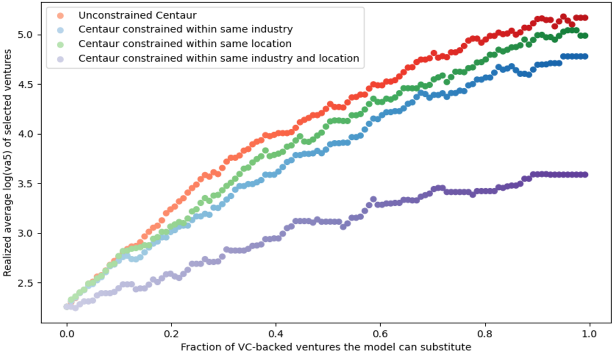

- Even our most constrained algorithm significantly outperforms VC-backed firms
  → **VCs' constraints cannot fully explain the difference in performance between VC-backed and algorithm-selected firms**

Discussion of Assumptions

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2. Same results when restricting pool of entrepreneurs the algorithmic policy can pick from to those with the **same growth aspirations** as dropped VC-backed entrepreneurs
3. Same results when restricting **within** the set of **VC-backed** firms, and when algorithm is **trained on VC-backed** firms only
4. We observe whether a firm was VC-backed by **any** VC, **not one VC in particular** (accounts for two-sided matching)
5. VCs invest in some firms that perform predictably poorly
   $\rightarrow$ suggests VCs do not follow optimal policy: $\Delta(X, Z) < 0$
   $\rightarrow$ opens possibility that they also pass on firms that perform predictably well: $\Delta(X, Z) > 0$

Outline

VC-Backed vs. Algorithm-Selected Entrepreneurs

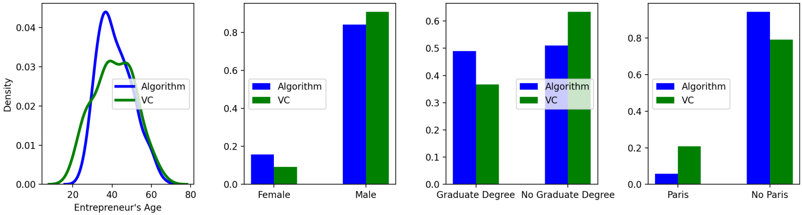

Figure 3: Entrepreneur demographics for VC-backed and algorithm-selected ventures

Compared to VCs, the algorithm selects:

- less young entrepreneurs
- more female entrepreneurs
- entrepreneurs with higher education levels
- less firms incorporated in Paris

ttests

Stereotypes of Best Performing Entrepreneurs

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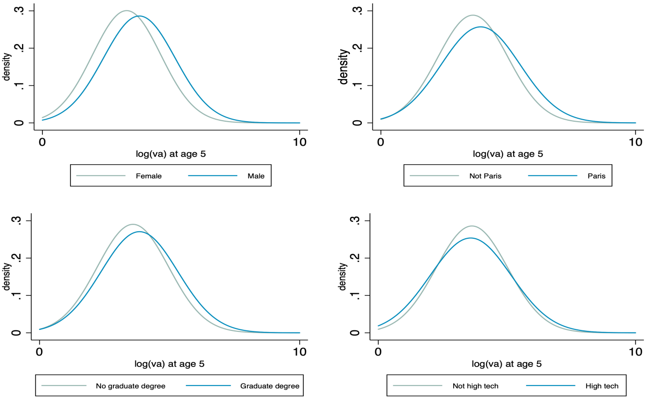

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Feature	Top 5%	Bottom 95%	Representativeness of best performers $\frac{Pr(X_i \mid \text{Top5})}{Pr(X_i \mid \text{Bottom95})}$	Representativeness of VC-backed firms $\frac{Pr(X_i \mid \text{VC-backed})}{Pr(X_i \mid \text{non-VC-backed})}$	Overreaction $\frac{\frac{Pr(X_i \mid \textbf{VC-backed})}{Pr(X_i \mid \textbf{non-VC-backed})}}{\frac{Pr(X_i \mid \textbf{Top5})}{Pr(X_i \mid \textbf{Bottom95})}}$
	(1)	(2)	(3)	(4)	(5)
Male	85%	72%	1.17	1.26	1.08
Graduate Degree	22%	15%	1.53	2.5	1.63
Grande Ecole	10%	5%	2.12	4.52	2.13
Optimism	52%	20%	2.63	2.31	.88
Serial Entrepreneur	39%	22%	1.77	1.42	.8
Paris-based	15%	8%	1.81	2.48	1.37
High tech	5%	3%	1.41	2.95	2.09

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→ VCs select founders whose characteristics fit the **stereotypes of the best performing entrepreneurs**

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1. We create new **simple** predictive models of firm performance with the same prediction setup, but **restricting the set of input features**

2. We regress VCs' decisions on our **full** model predicting which firms are most likely to be among the best performers, as well as our simple models:

$$\textit{VC-backed}_i = \beta_0 + \widehat{m}_{full}(X_i)\beta_1 + \widehat{m}_{simple}(X_i)\beta_2 + \epsilon_i \qquad (1)$$

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1. We create new **simple** predictive models of firm performance with the same prediction setup, but **restricting the set of input features**

2. We regress VCs' decisions on our **full** model predicting which firms are most likely to be among the best performers, as well as our simple models:

$$\textit{VC-backed}_i = \beta_0 + \widehat{m}_{full}(X_i)\beta_1 + \widehat{m}_{simple}(X_i)\beta_2 + \epsilon_i \quad (1)$$

3. Simple models should **not** predict VC decisions over and above full model of firm performance!

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    - $\beta_2 = 0 \rightarrow$ features X used in $\widehat{m}_{\textit{simple}}(\cdot)$ do not matter for VCs' decisions beyond their effect on firm performance through $\widehat{m}_{\textit{full}}(\cdot)$
    - $\beta_2 > 0 \rightarrow$ VCs **over-weight** features in simple model
    - $\beta_2 < 0 \rightarrow$ VCs **under-weight** features in simple model

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Panel A: Entrepreneurs' features

	VC-backed									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\widehat{m}_{full}(X)$	.0293***	.0255***	.0295***	.0277***	.0264***	.0209***	.0292***	.0294***	.0243***	.0279***
	(.00332)	(.00342)	(.00334)	(.00335)	(.00336)	(.00317)	(.00332)	(.00333)	(.00358)	(.00335)
$\widehat{m}_{simple}$(age)			-.0115							
			(.0237)							
$\widehat{m}_{simple}$(male)				.0703***						
				(.0211)						
$\widehat{m}_{simple}$(graduate degree)					.175***					
					(.032)					
$\widehat{m}_{simple}$(grande ecole)						.199***				
						(.0233)				
$\widehat{m}_{simple}$(French nationality)							.0259			
							(.0829)			
$\widehat{m}_{simple}$(relatives)								-.0275		
								(.0627)		
$\widehat{m}_{simple}$(optimism)									.032***	
									(.00867)	
$\widehat{m}_{simple}$(serial entrepreneur)										.0543***
										(.0176)

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- VCs over-weight entrepreneurs' personal features, and in particular **gender**, **education**, **optimism**, and **serial entrepreneurs** in their decision to back a new firm

Do Stereotypes Bias VCs' Decisions?

Panel B: New ventures' features

	VC backed								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{m}_{full}(X)$	.0293***	.0284***	.0293***	.0294***	.0293***	.0289***	.0293***	.0293***	.0251***
	(.00332)	(.00332)	(.00332)	(.00332)	(.00332)	(.00332)	(.00333)	(.00333)	(.00441)
$\widehat{m}_{simple}$(Paris-based)		.282***							
		(.0645)							
$\widehat{m}_{simple}$(Marseille-based)			.691						
			(6.8)						
$\widehat{m}_{simple}$(Lyon-based)				-.147					
				(.156)					
$\widehat{m}_{simple}$(Bordeaux-based)					.423				
					(.615)				
$\widehat{m}_{simple}$(high tech)						.568***			
						(.154)			
$\widehat{m}_{simple}$(business services)							-.00777		
							(.0457)		
$\widehat{m}_{simple}$(energy)								-.00183	
								(.0132)	
$\widehat{m}_{simple}$(startup traction)									.01
									(.00686)

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	VC backed								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{m}_{full}(X)$	.0293***	.0284***	.0293***	.0294***	.0293***	.0289***	.0293***	.0293***	.0251***
	(.00332)	(.00332)	(.00332)	(.00332)	(.00332)	(.00332)	(.00333)	(.00333)	(.00441)
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- VCs over-weight certain **locations** and **industries** in their decision to back a new firm

Conclusion

- **We use machine learning to study how VCs make investment decisions**
  - No selective label and selection issues, no survivorship bias
  - VCs invest in firms that perform predictably poorly and pass up on firms that perform predictably well
  - Constraints cannot fully explain this result

Conclusion

- **We use machine learning to study how VCs make investment decisions**
  - No selective label and selection issues, no survivorship bias
  - VCs invest in firms that perform predictably poorly and pass up on firms that perform predictably well
  - Constraints cannot fully explain this result
- **Model of VCs' decisions to understand why VCs' and algorithm's selections differ**
  - VCs are more likely to back firms whose characteristics are representative of the most successful entrepreneurs
  - VCs exaggerate some representative features of success in their decisions (e.g., male, highly educated, Paris-based, and high-tech entrepreneurs)

Appendix

Why VCs and Algo Policy Differ

		Test Set										
	variable	VC-backed			Algorithm-selected ($s = 0.5\%$)			Algorithm-selected ($s = 1\%$)			Difference ($s = 0.5\%$)	Difference ($s = 1\%$)
		Mean	SD	N	Mean	SD	N	Mean	SD	N	T-Test	T-Test
Outcomes												
	Value Added at Age 5 (log)	2.26	2.52	120	5.07	2.23	190	4.79	2.23	379	-2.81***	-2.53***
	Value Added at Age 5	140.66	432.54	120	540.51	1019.67	190	435.12	869.09	379	-399.85***	-294.47***
	Alive at Age 5	0.69	0.46	120	0.91	0.29	190	0.89	0.31	379	-0.22***	-0.20***
Founder Demographics												
	Entrepreneur's Age	41.26	10.58	120	41.68	8.70	190	41.27	8.70	379	-0.42	-0.02
	Entrepreneur's Nationality (FR)	0.94	0.24	120	0.98	0.14	190	0.98	0.12	379	-0.04	-0.04*
	Female	0.09	0.29	120	0.16	0.37	190	0.18	0.38	379	-0.07*	-0.09***
Founder Professional Background												
	Same Prior Industry	0.52	0.50	120	0.91	0.29	190	0.88	0.33	379	-0.39***	-0.36***
	Serial Entrepreneur	0.42	0.50	120	0.35	0.48	190	0.32	0.47	379	0.07	0.10*
	Previously Employed in Small Firm	0.29	0.46	120	0.37	0.48	190	0.35	0.48	379	-0.08	-0.05
	Graduate Degree	0.37	0.48	120	0.49	0.50	190	0.41	0.49	379	-0.12**	-0.04
	Grande École	0.27	0.44	120	0.11	0.31	190	0.10	0.30	379	0.16***	0.17***
Founder Motivation and Expectations												
	Expectation: Growth	0.58	0.50	120	0.52	0.50	190	0.57	0.50	379	0.06	0.01
	Motivation: Successful Peer Entrepreneurs	0.06	0.24	120	0.11	0.31	190	0.11	0.31	379	-0.05*	-0.05*
	Expect to Hire	0.51	0.50	120	0.54	0.50	190	0.56	0.50	379	-0.03	-0.05
	Motivation: New Idea	0.39	0.49	120	0.08	0.27	190	0.09	0.29	379	0.31***	0.30***
	Motivation: Opportunity	0.38	0.49	120	0.56	0.50	190	0.54	0.50	379	-0.19***	-0.17***
	Innovation	0.73	0.44	120	0.41	0.49	190	0.43	0.50	379	0.32***	0.31***
Venture Characteristics												
	Paris-based	0.21	0.41	120	0.06	0.23	190	0.05	0.22	379	0.15***	0.16***
	High-tech Services Industry	0.10	0.30	120	0.01	0.10	190	0.02	0.13	379	0.09***	0.08***
Organization												
	Outsourcing: Accounting	0.90	0.30	114	0.89	0.31	190	0.91	0.29	379	0.01	-0.01
	Outsourcing: Management	0.10	0.30	114	0.28	0.45	190	0.23	0.42	379	-0.19***	-0.14***
	Outsourcing: Logistics	0.16	0.37	114	0.25	0.44	190	0.23	0.42	379	-0.09**	-0.08*
	Number of Employees	2.37	2.87	114	6.01	4.78	190	5.41	4.47	379	-3.64***	-3.04***
Industries-Locations												
	Number of Industries	-	-	29	-	-	23	-	-	29	-	-
	Number of Regions	-	-	68	-	-	96	-	-	145	-	-
Financial Characteristics (not included in input features)	Total Assets (k euros)	660.58	2233.84	118	584.20	1805.17	187	626.75	2166.54	375	76.38	33.83

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