Human Interactions and Financial Investment: A Video-Based Approach

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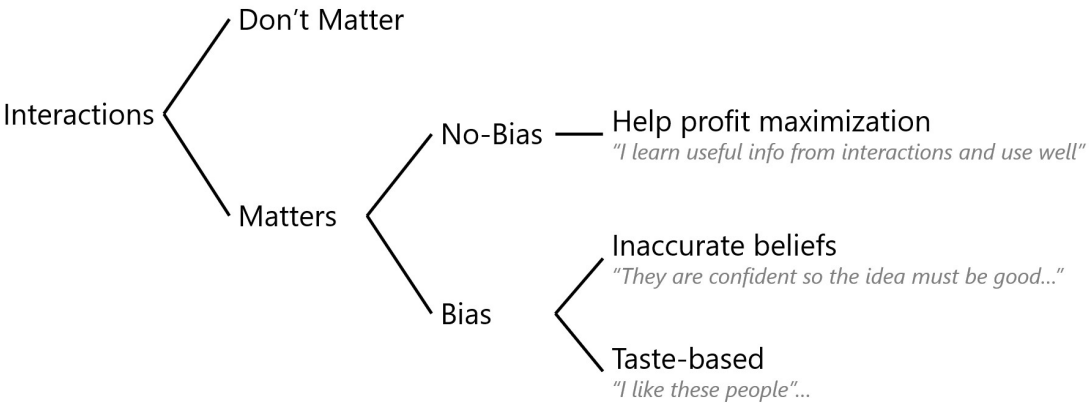
Human Interactions

- Many economic decisions are made after human interactions
  - Corporate executive pitch strategies, startup pitches, sell-side analysts pitch stocks, ...

Research Question

- Research Q #1: Do human interaction features matter for economic decision-making?
- Research Q #2: Why, through what economic mechanisms?

Human Interactions and Decisions-Making



What We Do

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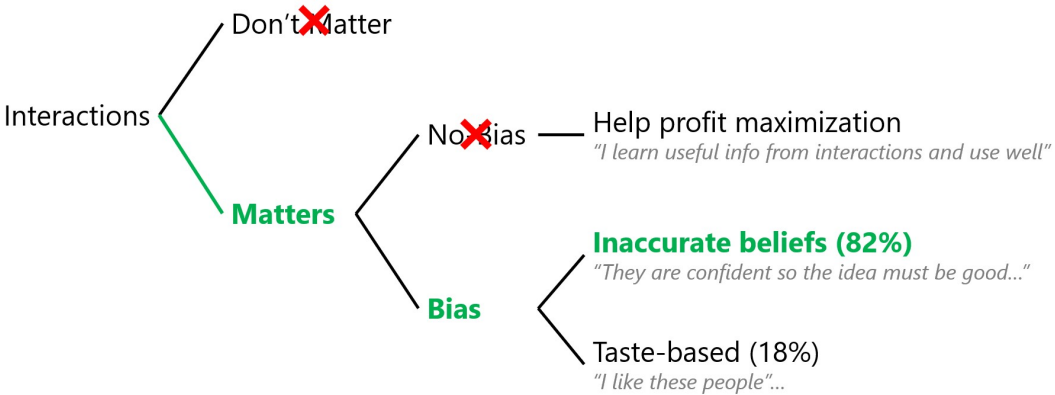
- **Methodology: Video as Data**
  - Video as data; machine-learning based framework for processing and variable construction
  - 3-V structure, visual, vocal, and verbal; a system of measurements

What We Do

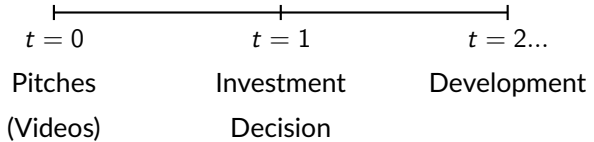
- **Methodology: Video as Data**
  - Video as data; machine-learning based framework for processing and variable construction
  - 3-V structure, visual, vocal, and verbal; a system of measurements
- **Setting: Startup Pitches and Venture Investment**
  - Use startup pitches as a setting, explore the effect of pitch features
  - Observe pitch videos, investment decisions, and long-term development of startups

Preview of the Results



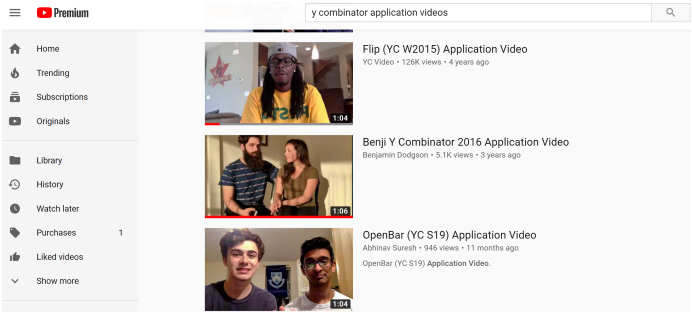
Setting and Data

Setting: Startup Pitches for Venture Investing



- Startups pitching to accelerators, **1-2** min, standard
- An important part of the application process
- Consider them as short video pitches on Zoom

Collecting Videos from YouTube/Vimeo/...

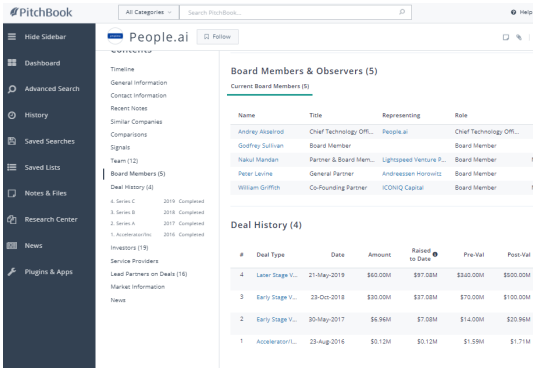


- **20+** keywords used to search: "startup accelerator application video", "accelerator videos"...
- Returns **1,139** videos in **5** top accelerators, **2010-2019**
- Hold your "video/sample selection" question...

▸ Sample Tabulation

▸ Sample Selection

Information on the Startups

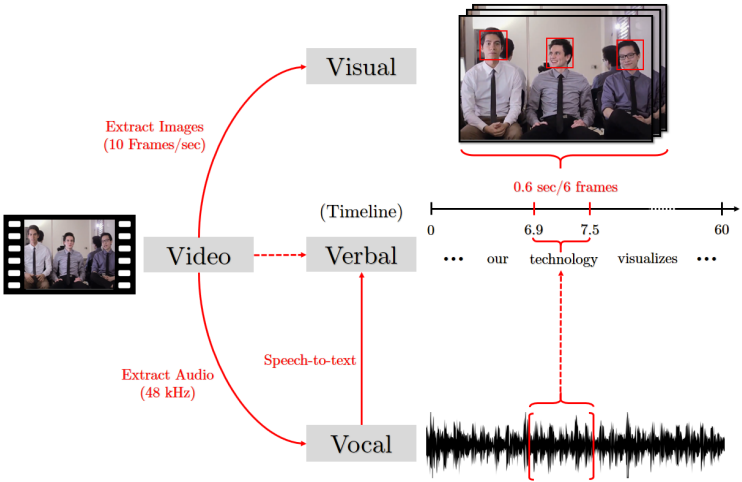


- Company information: Pitchbook (fig on the left), Crunchbase, VentureXpert
- Founders' background: LinkedIn
- Observe: industry, financing history, CEO turnover, founder education and work experience, growth and success (e.g., employment, survival)

▸ Caveats and Discussions
▸ Full Timeline

Methodology: Video As Data

Step 1: Decomposition and Representation

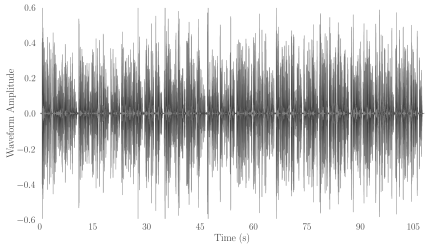


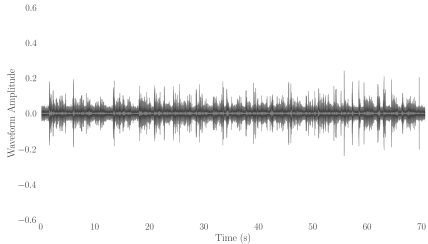
Step 2.1: Video $\Rightarrow$ Visual (Facial)

- Analyze video frame by frame through facial detection & emotion algorithms (Face++)
  - Example: More positive and less positive visual facial expressions

Step 2.2: Video $\Rightarrow$ Vocal (Voice)

- Analyze sound waves through audio analytics and vocal emotion algorithms
  - Example: High and low arousal in vocal communications



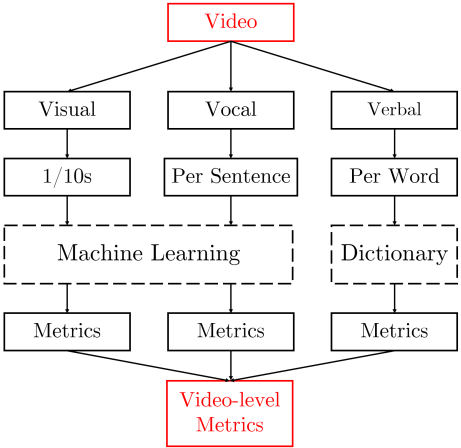


Step 2.3: Video ⇒ Verbal (Text)

- Merge with dictionaries from business (LM) and social psychology (NBF)
  - Example: Warmth shown in the script

Hello, I'm Marcus and I'm Rebecca and together we're the proud founders of Fine Print Fighters LLC. We help expose small and misleading content in contracts. We help consumers make much more informed decisions during the purchasing process both pre and post purchase. We like to help the consumers gain back control of the purchasing process, and we like to create value well through our pleasing personalities as you can tell. Well, we look forward to working with angel pad, and we appreciate the opportunity in advance. Look forward to working with the staff and the rest of the constituents and hopefully be a good representation of what angel angel pad represents. So we thank you again in advance, and we look forward to speaking with you all and seeing you all soon. Thank you.

Step 3: Aggregation of Measurements



Project to 3V

Break to Unit

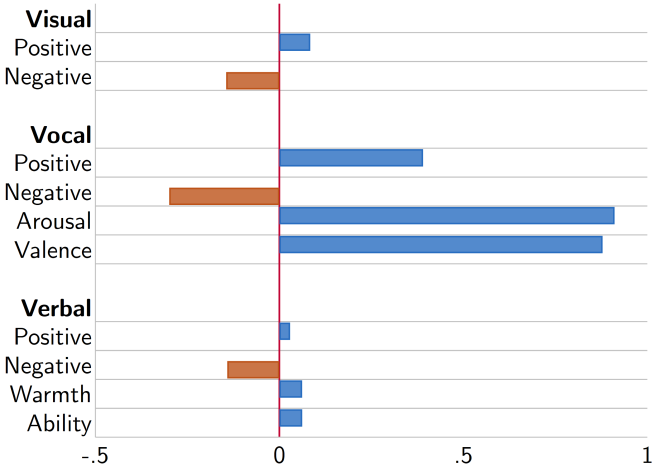
Feed into Algorithms

Construct Metrics at Person-Word Level

Aggregate to Video Level

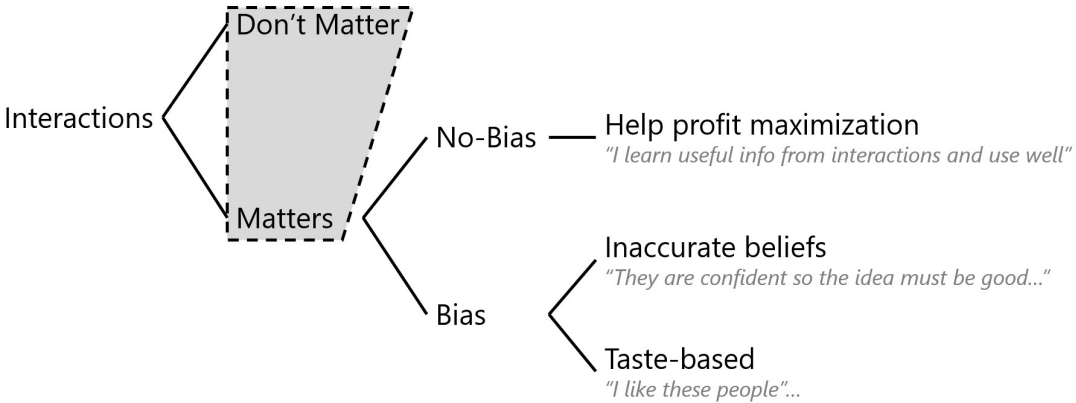
- Visual (Facial)
  - Positive, Negative
  - Beauty
- Vocal (Audio)
  - Positive, Negative
  - Arousal, Valence
- Verbal (Textual)
  - Positive, Negative
  - Warmth, Ability

Pitch Factor: Capturing the Overall "Positivity"



- Pitch Factor: further aggregation based on detailed 3-V features Tetlock 07
- Loadings: + on the "positivity" dimensions, and – on the "negativity" dimensions
- Naïve Interpretation: The Pitch Factor captures the unobserved overall positivity in the pitch

Baseline: Do Interactions Matter?

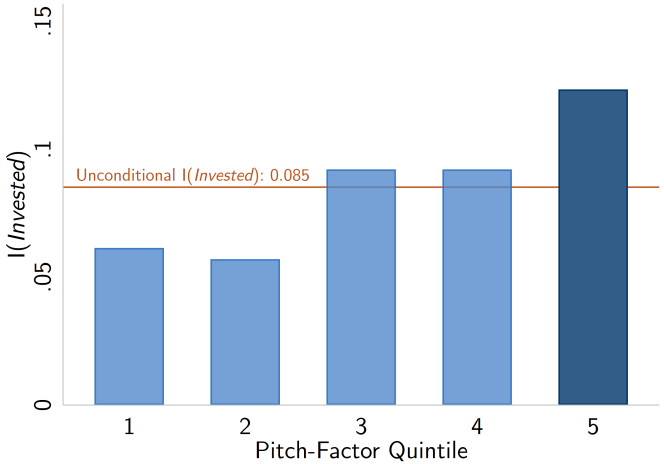


Investment Decision: Empirical Design

$$I(Invested)_{ijt} = \alpha + \beta \cdot X + \delta_j + \varepsilon_{ijt}$$

- Logit model: cross-sectional data of startup i, applying to investor j, in year t
  - I: Investment decisions of the accelerator investors
  - Xs: Pitch Factor; 3V features—from visual, vocal, and verbal
  - Xs: All standardized to mean 0 standard deviation 1
  - δ_{FE}: Accelerator FE, account for unobserved heterogeneities at the investor level
  - ε: Standard errors clustered at the level of accelerator-year

The "Pitch Factor" and Investment



- Higher Pitch Factor is associated with a higher probability of obtaining funding
- Top quintile vs. lowest quintile, **12.5%** v.s. **6%**
- One std.dev increase in Pitch Factor, **35.2%** increase in prob. of obtaining funding

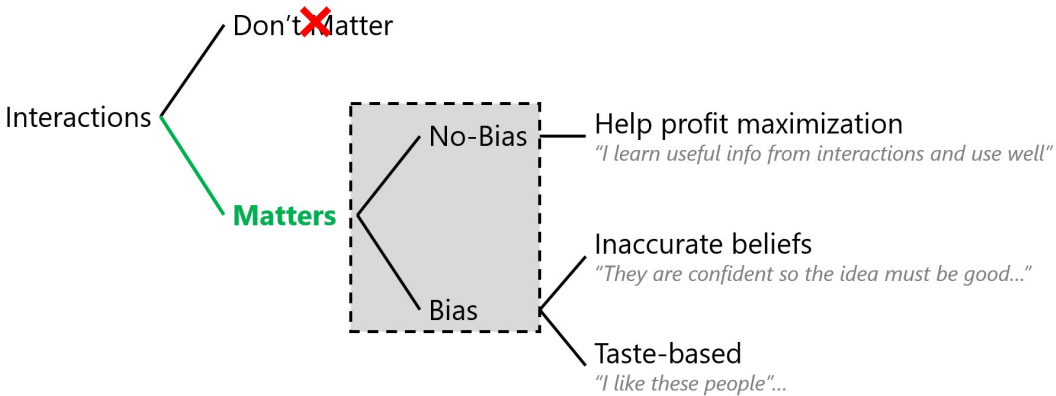
▸ Alternative Magnitude

▸ Positivity

Results—Three-V Breakdown

		Marginal Effect	S.E.	Stat. Sig.	Pseudo R^2	Econ. Magnitude of 1-SD
Visual	Visual-Positive	0.015	(0.005)	***	0.178	**17.6%**
	Visual-Negative	−0.027	(0.007)	***	0.187	**−31.8%**
	Visual-Beauty	0.015	(0.006)	**	0.178	**17.6%**
Vocal	Vocal-Positive	0.009	(0.005)	**	0.174	**10.6%**
	Vocal-Negative	−0.045	(0.016)	***	0.183	**−52.9%**
	Vocal-Arousal	0.023	(0.009)	***	0.184	**27.1%**
	Vocal-Valence	0.023	(0.006)	***	0.185	**27.1%**
Verbal	Verbal-Positive	−0.010	(0.009)		0.174	**−11.8%**
	Verbal-Negative	−0.026	(0.007)	***	0.186	**−30.6%**
	Verbal-Warmth	0.026	(0.008)	***	0.190	**30.6%**
	Verbal-Ability	−0.049	(0.009)	***	0.243	**−57.6%**

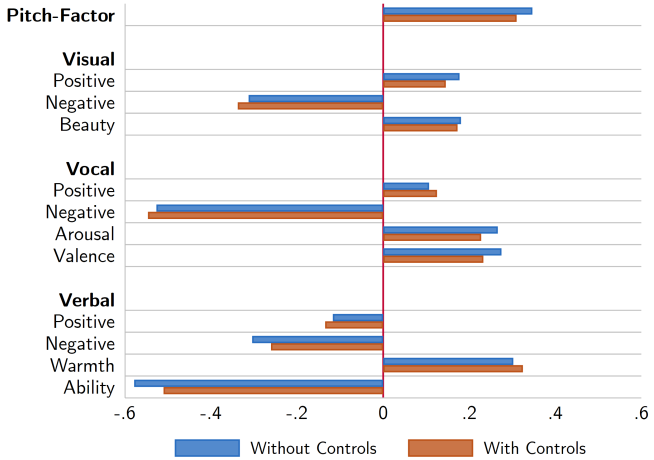
Human Interactions Matter... Why?



No Bias—Better Pitchperson Runs Better Startups?

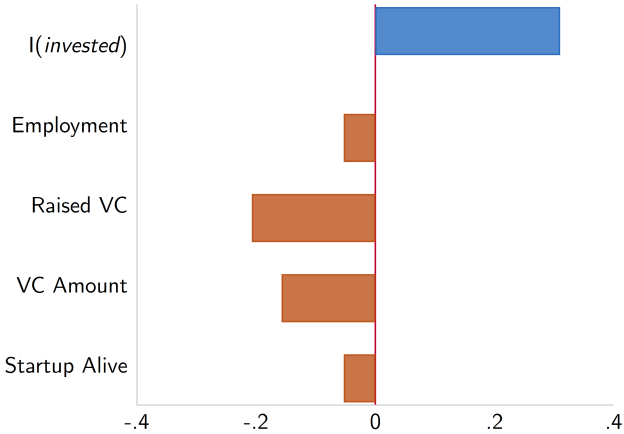
- Test: The robustness to quality controls
  - If yes, the usefulness of this will be crowded out by quality controls
  - Motivated by Altonji-Elder-Taber 05, Oster 19
- Test: Long-term performance
  - If yes, this should drive *better* outcomes conditional investment
  - Similar to Fisman-Paravisini-Vig 17, Ewens-Townsend 20
- Preview: Little support to this line of argument

Results: Stable and Robust to Adding Quality Controls



- Add quality controls including education, work experience, entrepreneurship history
- Finding: Robust, and importantly, Stable coefficients—limiting the room for "omitted quality" interpretation (Oster 19)

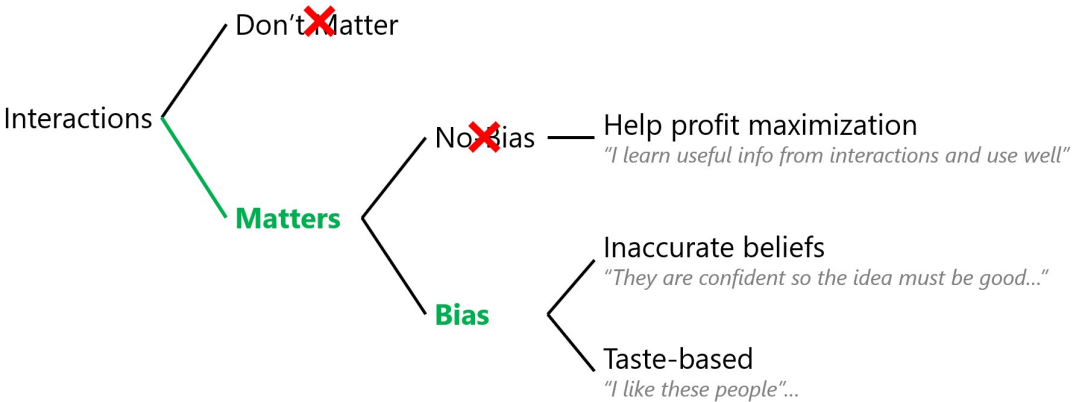
Results: Poorer Performance



- Finding: Conditional on funding, positive teams underperform
- Interpretation: Investors lower investment bar for teams with higher Pitch Factor

▸ More Discussions

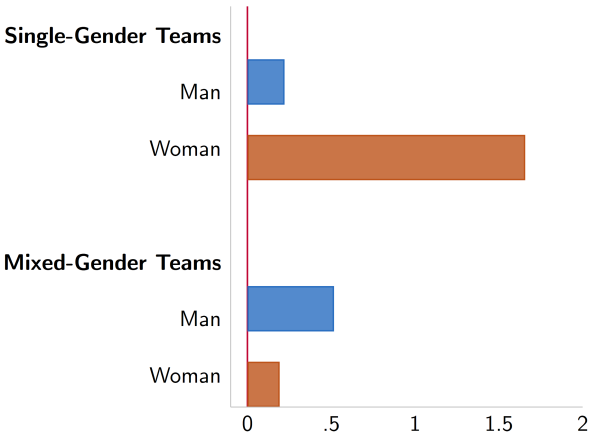
Interaction-Induced Bias



Interaction-Induced Biases?—Suggestive Evidence

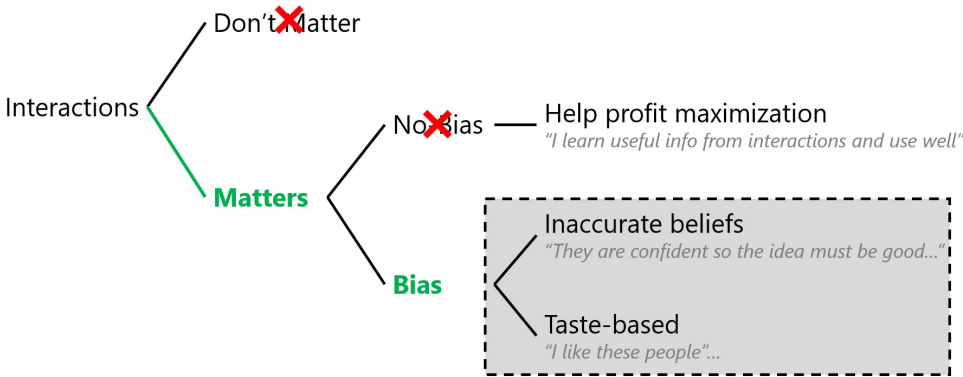
- Motivation: Differences across subsamples with different social dynamics?
  - Women are judged by non-substantive appearance (Fredrickson-Roberts 97)
  - Women face gender stereotyping/inequality (Kite-Deaux-Haines 08, Ellemers 18)
- Test: Pitch Factor of women and men in
  - Single-gender teams (i.e., women-only or men-only)
  - Mixed-gender teams, and Pitch Factor can be separately constructed using our method
- Preview: there are differences for female and male entrepreneurs

Results in Female- and Male-Only Teams



- Single-gender teams: Largely similar with different intensities. Investors judge/"punish" more based on pitch features with woman-only teams
- Mixed-gender teams: Woman are essentially "ignored", i.e., the focus is more on the men

Interaction-Induced Bias



Experiment of VC Investment

- Subjects: Yale MBA students in "PE and VC" and "Entrepreneurial Finance" classes
- Experiment: watch 10 randomly selected pitch video, random order
- Key Questions:
  - Question #1: Are you going to make investment in this startup—I
  - Question #2.1: What is the probability, μ, that you think this startup will be successful, conditional on obtaining funding?
  - Question #2.2: How confident is your answer, σ?
- Incentive: Flat compensation + performance-based compensation

Test Framework

- Test #1 (Beliefs): Do pitch features affect beliefs?

$$\text{Beliefs} = \psi \cdot \textit{Pitch} + \varepsilon$$

- Test #2 (Full Model): Do pitch features still matter after controlling for beliefs?

$$I_{ij} = \underbrace{\kappa \cdot \theta_i}_{\text{Taste}} + \underbrace{\gamma_\mu \cdot \mu_{ij} + \gamma_\sigma \cdot \sigma_{ij}}_{\text{Beliefs}} + \delta_j + \varepsilon_{ij}.$$

Scenario	$\psi_{\mu,\sigma}$	κ	Beliefs Channel	Taste Channel	Decompose β
1	$\neq 0$	$= 0$	✓	×	$\beta = \psi_\mu \gamma_\mu + \psi_\sigma \gamma_\sigma$
2	$= 0$	$\neq 0$	×	✓	$\beta = \kappa$
3	$\neq 0$	$\neq 0$	✓	✓	$\beta = \kappa + \psi_\mu \gamma_\mu + \psi_\sigma \gamma_\sigma$

Result (1): The Beliefs and Inaccurate Beliefs

	P($alive|invested$)		$alive|invested$
	μ	σ	Realized
Pitch Factor (θ)	0.020**	−0.020	−0.117**
	(0.009)	(0.027)	(0.053)
Observations	952	952	495
R^2	0.569	0.545	0.673
Startup/Team Controls	Y	Y	Y
Subject FE	Y	Y	Y

- Beliefs channel exists: Pitch Factor affects μ, not so much σ
- Sign of inaccurate beliefs: **0.020** vs. **−0.117**, in other words, an inaccurate belief update of **0.137**

Result (2): Decomposition Through Two Channels

	Dependent Var: I(*Invested*)			
Pitch Factor (θ)	0.125***			0.067***
	(0.037)			(0.022)
$\mu(alive\|invested)$		2.309***		2.208***
		(0.120)		(0.132)
$\sigma(alive\|invested)$			−0.171***	−0.054**
			(0.041)	(0.026)
Observations	952	952	952	952
Pseudo R^2	0.157	0.423	0.135	0.436
Startup/Team Controls	Y	Y	Y	Y
Subject FE	Y	Y	Y	Y

- Invest in: more positive Pitch Factor, higher μ, lower σ
- Economic magnitude: The inaccurate beliefs channel explains **0.302** $= 2.208 \times 0.137$; and the preference channel explains **0.067**
- Decomposition: This means, **82%** vs. **18%**

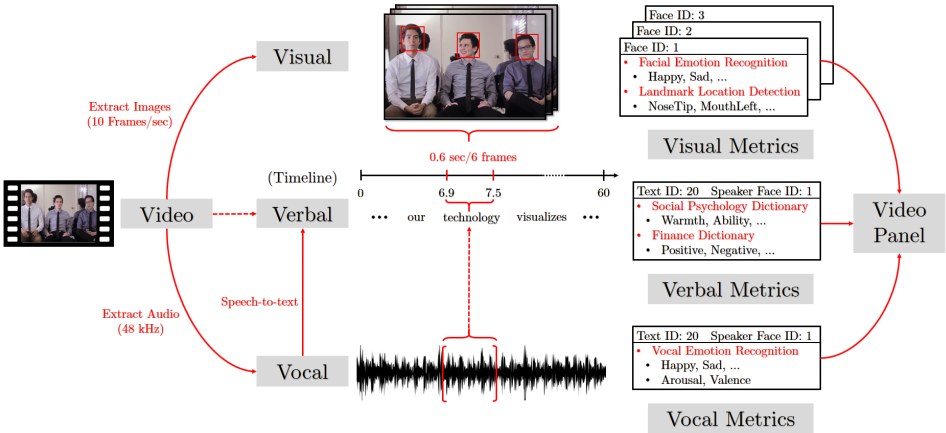
▸ Limitations
▸ Positivity in Decision

Concluding Remarks

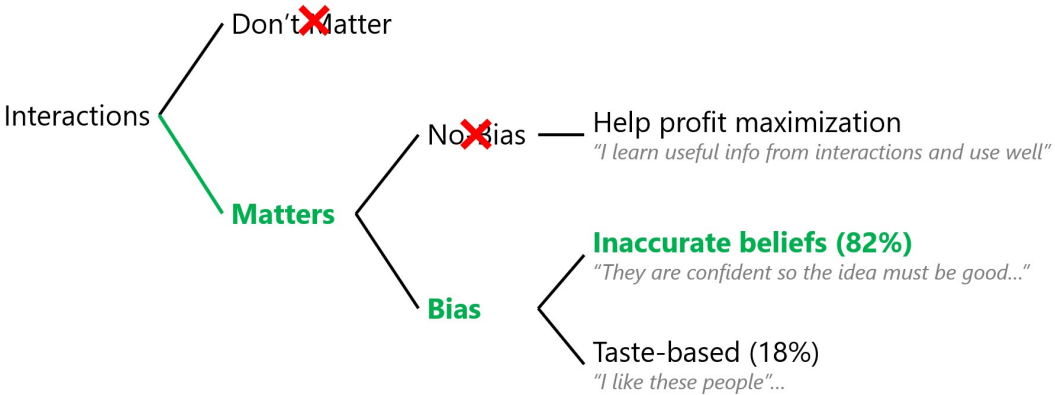
Conclusion

- Research Question #1: Do interaction features matter for economic decision-making?
- Research Question #2: Why, through what economic mechanisms?

Conclusion: Methodology



Conclusion: Economic Takeaway



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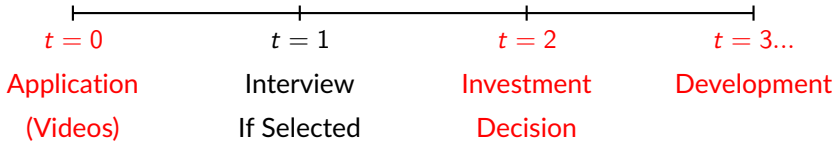
Full Timeline of the Setting



- Standard contracts: most, if not all incubators, do "standard deals"
  - Say, $50K of SAFE, with the right to convert to 7% of equity shares.
- Skipped the formal interview stage: what are we getting from the videos?
  - Push you to the interview stage
  - Capture the "first impression" and "persistent component" in human interactions

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Tabulation of Videos

Accelerator	<=2012	2013	2014	2015	2016	2017	2018	2019
Y Combinator	14	33	32	92	75	113	179	229
MassChallenge	5	14	6	15	38	41	42	40
500 Startups	1	2	8	8	2	10	5	5
Techstars	12	20	13	17	9	33	37	15
AngelPad	11	8	14	5	13	15	23	2
Total	43	77	73	137	137	212	286	291
% of Full Sample	3.42%	6.13%	5.81%	10.91%	10.91%	16.88%	22.77%	23.17%

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Caveats of the Setting

- Unidirectional communication or interaction: no Q&A, back-and-forth
  - Common in the economy and a building block for bi- or multi-directional interactions
  - One needs to believe that part of unidirectional features can be generalized
- $Distance(Video, In\text{-}Person)$: how big and how important?
  - $Distance \neq 0$, but people react to same factors likely similarly
  - Sensitivity may differ—will affect the generalizability of the estimates
- Future Research:
  - Capture more factors: gestures, team dynamics, reaction to questions, ...
  - Potential heterogeneities when reviewing in-person and videos, across different tasks, ...

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Sample/Video Selection: Where Do the Videos Come From?

- The source of video selection: startups may choose to unlist or remove the videos
  - We worry—if "better" videos and invested companies are more likely to be available...
- The empirical selection question:
  - Is the selected-out decision related to pitch features, investment decision, etc.?
- Our approach: explore the selection process by tracking YouTube
  - Collect a sample available in Apr 2019 (original sample)
  - Re-search the sample to identify the unlisted, privatized, and removed (i.e., selected-out)

Selection Does Not Seem To Drive Our Results

	Video Selected Out = 1			
Pitch Factor	0.006	0.014		
	(0.021)	(0.023)		
I(invested)			-0.040	-0.016
			(0.161)	(0.149)
Observations	527	527	527	527
Controls		Yes		Yes
Accelerator FE		Yes		Yes
Year FE		Yes		Yes

- What we do: track the "disappearing" of videos from **Apr 2019** to **Apr 2020**
- Results suggest: the "disappearing" (selection out) does not relate to pitch features or future investment outcomes, thus is not driving our findings

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How Important Do Interactions Matter?

- We ask: how much would investment decisions change with human interactions
- Our approach: with the risk of making many crazy assumptions...
  - We estimate an investment model with and without human interactions
  - We then calculate—how many firms are actually affected by this change?
- Answer: roughly **20%** of the firms on the margin
  - With a threshold investment rule (top 10%)—**124** are chosen based on hard info only
  - After adding interaction features, **12** moved out and **12** moved in

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Why Positivity Matters in Our Setting?

- Remaining Question: Why positivity may introduce interaction-induced biases
  - What is the root of this bias favoring "positivity"—on taste and expectations?
- Possibility #1: Emotions and moods
  - ... are contagious (Smith 1759; Hatfield et al. 93)
  - in turn influence beliefs and risk assessment (Johnson-Tversky 83; Loewenstein et al. 01)
- Possibility #2: Stereotyping
  - ... overweight its representative types (Bordalo et al. 16)
  - and seeing confidence successful entrepreneurs lead incorrect beliefs (Åstebro et al. 14)

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Performance Test Framework: Illustrative Example

- Illustrative example: why performance test, conditional on funding, is useful?
  - With simple assumptions, no-bias, taste-based, and inaccurate-beliefs can be clearly shown
  - Lower performance is more consistent with interaction-induced biases
- To be super clear: This is NOT a complete rejection of the no-bias view
  - There are cases, by tweaking distributions, in which performance is a noisy signal
  - Applies to prior research with similar tests Fisman-Paravisini-Vig 17, Ewens-Townsend 20
- Simplifying assumptions:
  - High positivity pitch (H) and low positivity pitch (L)
  - The expected performance distributions of H & L is just a mean shift

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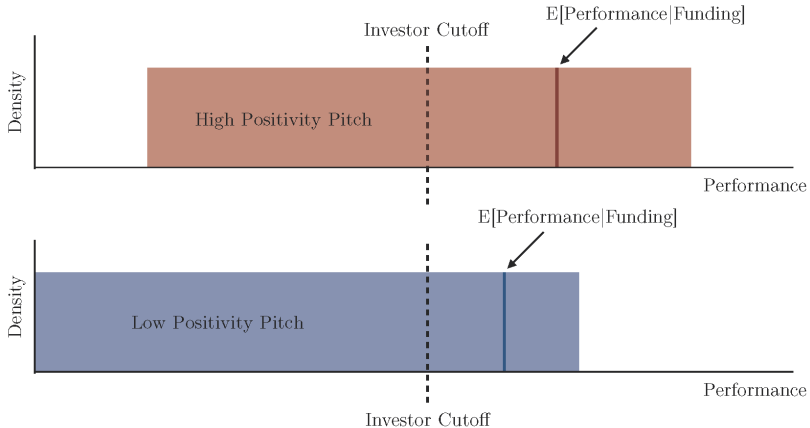
Performance Test Framework (1): No Bias



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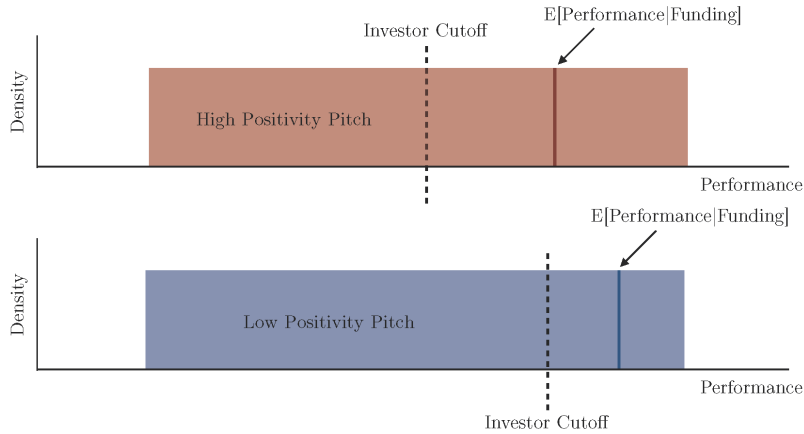
Performance Test Framework (2): Taste-Based Bias



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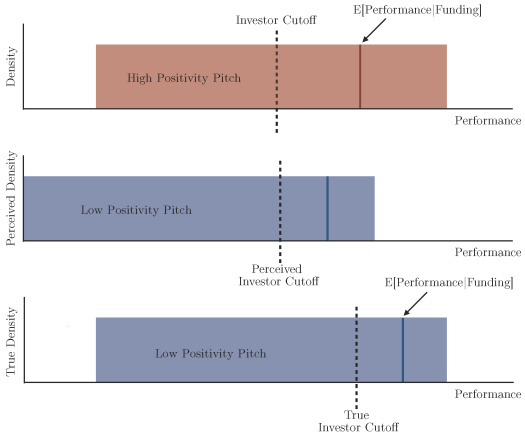
Performance Test Framework (3): Inaccurate Beliefs



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Limitations of the Experiment

- We may under-estimate the importance of the taste-based channel (**18%**)
- The sense of presence and collaborating (common problem in the literature)
  - Experiment subjects will not really "collaborate" with the entrepreneurs
  - They may thus less likely to care about taste-based forces
- Measurement errors when eliciting beliefs
  - Subjects may incorrectly allocate taste-based forces to expectation responses
  - "I think they can succeed because I really like them and want to support them..."
- Unfortunately, these are common problems... comments are welcome!

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