# Online Appendix (Not For Publication)

## A. Collecting Video Data and Startup/Team Information

### *A.1. Collecting Videos from Video Platforms*

When startups apply to accelerator programs, they are required (or highly recommended) to record and submit a standardized self-introductory pitch video as part of the application process. Figure A.1 shows such examples from those accelerators' application systems. These videos, rather than being submitted to the accelerators directly, are submitted through uploading to a public multimedia platform, such as YouTube or Vimeo, and then providing the url links to these videos in application forms.

We use an automatic searching script for two public video-sharing websites, YouTube and Vimeo. Integrated with query APIs, our web crawler returns a list of video indices according to a set of predefined keywords, which include but are not limited to the names of these accelerators, "startup accelerator application video","accelerator application videos" and so on. We first obtain the full list of potential videos returned by each keyword search (there is a limit of returned videos by YouTube), and then filter the potential videos by a combination of different conditions on video info obtained along with the video itself. Filtering variables include but are not limit to data format, duration, title, and annotation.

**Table A.1. List of Searching Keywords for Collecting Videos**

| Keywords |
|---|
| YC Application Videos |
| Y Combinator Application Videos |
| MassChallenge Application Videos |
| 500 Startups Application Videos |
| Techstars Application Videos |
| AngelPad Application Videos |
| Y Combinator Application Videos + *YEAR* |
| Techstars Application Videos + *YEAR* |
| 500 Startups Application Videos + *YEAR* |
| AngelPad Application Videos + *YEAR* |

*Notes.* This table shows the list of keywords we use for searching and collecting the pitch videos from Youtube and Vimeo. The *YEAR* takes values from 2005 to 2019.

We also employ startup names listed on accelerators' web pages to expand our video data set. Specifically, we first obtain the full list of startups accelerated by the accelerator each year if such a list is published on the accelerator's website. Then our script automatically searches these startup names and checks the first three results returned by the search API. A match is defined as having both the startup name and the accelerator name appear in the video title or annotation.

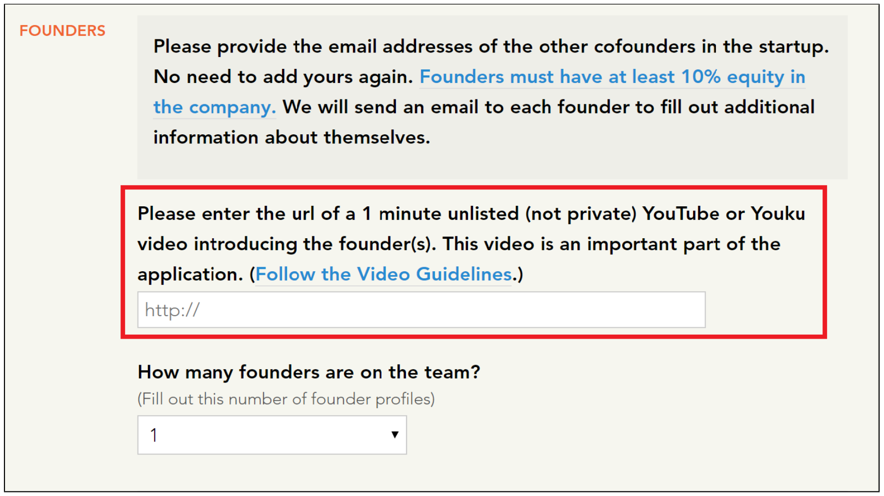
It is worth noting that if one company has more than one video in our sample, we only keep the video recorded first. There are 33 such firms in our analysis, which make up only 2.90% of our sample. These firms have multiple videos because of the following reasons. First, there are some entrepreneur teams applying to different accelerators. Second, there are some teams that applied to the same accelerator multiple times. For these firms, we only keep their videos and outcomes in the first application.

In total we obtain 1,139 videos. Table A.2 describes the sample, in which the number of videos is reported by accelerator (Panel A) and by year (Panel B). Y Combinator contributes the largest number of application videos, followed by MassChallenge and Techstars. Among all the companies that applied, 97 (8.52%) were chosen by the accelerator program, and 248 (21.77%) were invested by any venture investor (accelerator or angels/VCs). The videos are more available for recent years due to the increase in video requirements in the application.

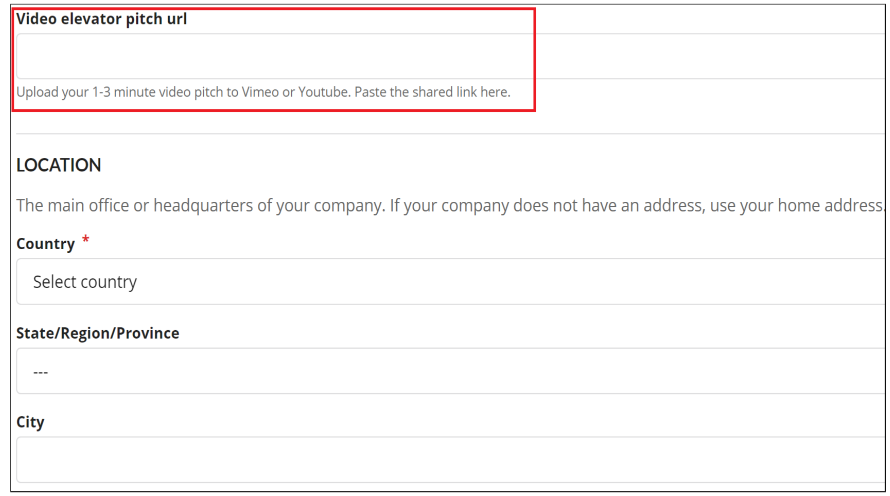
After collecting the videos, we parse each video web page to collect other relevant information. This includes the video's duration, upload date, title, annotation, subtitle, and uploader ID. This set of information also allows us to identify the startup almost perfectly. Specifically, by scrutinizing video titles and annotations, we double-check names of the startups and names of the accelerators they are applying for. If the startup name cannot be identified from these items, we search the uploader name on LinkedIn and back out the company information. It is common that many people have the same name on LinkedIn, so to verify that the person on Linkedin is the founder, we also double-check the name, background, experience, and even photos.

## Figure A.1. Examples of Accelerator Online Application Forms

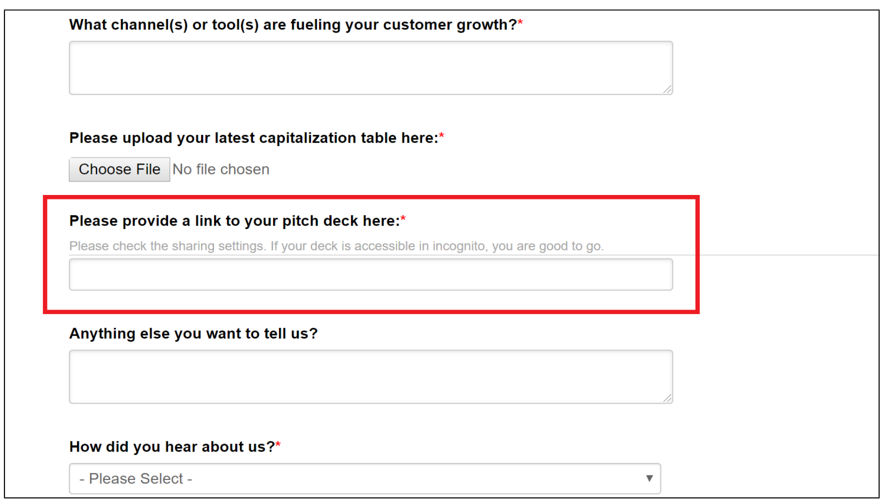
(a) Y Combinator



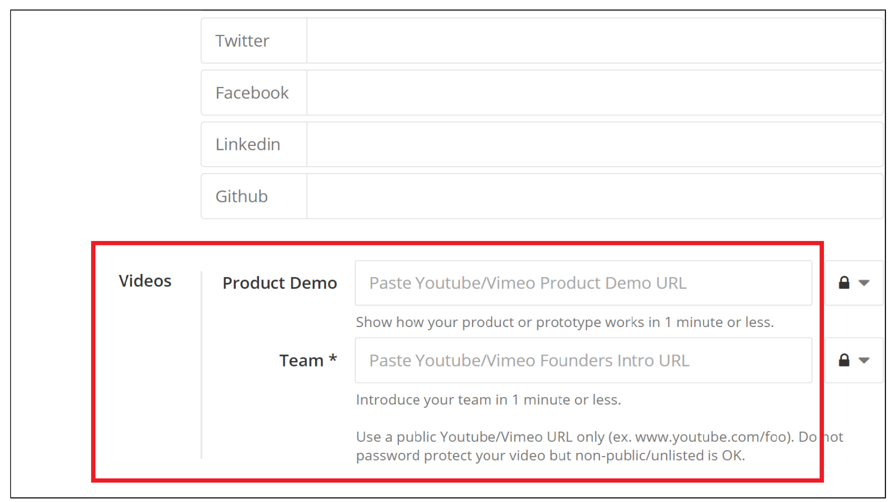

(b) MassChallenge




(c) 500 Startups

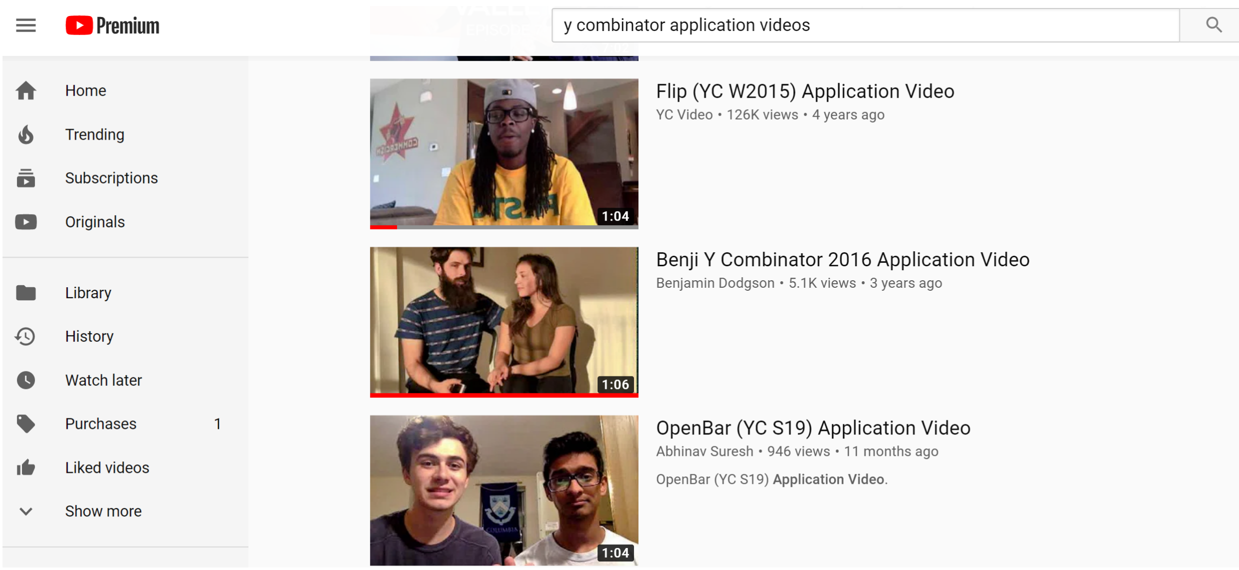



(d) Techstars




*Notes.* This figure shows screenshots of accelerators' online application forms. We show forms for Y Combinator, MassChallenge, 500 Startups, and Techstars. On each online application form, we highlight the question specifically asking for uploading pitch videos.

## Figure A.2. Screenshot of Search Results from YouTube



## Table A.2. Sample Description of Pitch Videos

**Panel A: Breakdown by Accelerators and Investment Status**

| Accelerator | Videos # | Accelerator Invested | Website Active | In Crunchbase | In PitchBook |
|---|---|---|---|---|---|
| 500 Startups | 33 | 1 | 15 | 19 | 8 |
| AngelPad | 83 | 2 | 33 | 36 | 18 |
| MassChallenge | 166 | 56 | 129 | 113 | 79 |
| Techstars | 136 | 3 | 67 | 53 | 21 |
| Y Combinator | 713 | 35 | 363 | 238 | 91 |
| YC Fellowship | 8 | 0 | 2 | 3 | 0 |
| Total | 1,139 | 97 | 609 | 462 | 217 |
| % of Full Sample | 100% | 8.52% | 53.47% | 40.56% | 19.05% |

**Panel B: Breakdown by Years**

| Accelerator | <=2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|
| 500 Startups | 1 | 1 | 7 | 7 | 2 | 8 | 5 | 2 |
| AngelPad | 11 | 7 | 13 | 4 | 12 | 14 | 21 | 1 |
| MassChallenge | 4 | 9 | 4 | 13 | 34 | 33 | 34 | 35 |
| Techstars | 9 | 17 | 12 | 15 | 8 | 30 | 32 | 13 |
| Y Combinator | 10 | 31 | 29 | 82 | 67 | 110 | 164 | 220 |
| YC Fellowship | 0 | 0 | 0 | 8 | 0 | 0 | 0 | 0 |
| Total | 35 | 65 | 65 | 129 | 123 | 195 | 256 | 271 |
| % of Full Sample | 3.07% | 5.71% | 5.71% | 11.33% | 10.80% | 17.12% | 22.48% | 23.79% |

*Notes:* This table provides descriptive statistics on collected videos by accelerators that the applications are made to (Panel A) and by year (Panel B). We obtain pitch videos using an automatic searching script for two public video-sharing websites, YouTube and Vimeo. Integrated with query APIs, our web crawler returns a list of video indices according to a set of predefined keywords, which include but are not limit to the names of these accelerators, "startup accelerator application video","accelerator application videos" and so on. We first obtain the full list of potential videos returned by each keyword search (there is a limitation of returned videos by YouTube), and then filter the potential videos by a combination of different conditions on video info obtained along with the video itself. Filtering variables include but are not limit to data format, duration, title, and annotation. We also obtain additional videos from accelerators' websites. Panel A reports the number of videos submitted to each accelerator and the proportion of each accelarator in the full sample. Panel B reports the breakdown by application year (typically the year of video uploading).

### A.2. *Details on Gathering Founder and Startup Information*

Founder-level control variables are constructed based on the information of the presenter(s) instead of the people listed as co-founders in external databases. To achieve this goal, our data collection processes involve comparing presenters' self-reported names and facial images with the names and pictures on individual profiles, and only information about the presenters are used. Below we offer more details, which we hope can mitigate any concerns.

- We obtain presenter names from self-introductions in pitches, video description text, and YouTube account names. These presenter names, along with startup names, are then used as keywords for searching on LinkedIn, our main data source to gather individual information.
- Among 1,139 startups in our sample, we are able to find the presenters on LinkedIn for 693 (61%) of them. For these startups, we collect information on presenters' educational backgrounds and work experiences. We code such information in an array of categorical variables, including whether presenters have a master's or a PhD degree, whether they attended an elite university, whether they have prior entrepreneurship experience, and whether they ever held a senior position in prior employment.
- For startups for which we are unable to find presenters' LinkedIn profiles, we construct the same array of categorical variables and code variables as the "missing" category. For example, the categorical variable of whether presenters have a master degree has three categories: "Yes", "No", and "Missing". We then add dummy variables that correspond to each categorical variable to our regressions as controls for team background.

In Table A.3, we conduct the following robustness tests, using the specification in Table 3. First, we focus on the subsample of startups whose presenters can be found on LinkedIn. The effect of the Pitch Factor on the probability of receiving an investment remains significant. And the effect is larger relative to the full-sample estimate. Second, we add a dummy variable I(*Has LinkedIn*) to the specification. The dummy variable takes the value of one if we are able to find LinkedIn profiles of presenters and zero otherwise. The coefficients of the Pitch Factor remain stable. Meanwhile, the positive and significant coefficients of I(*Has LinkedIn*) indicate that teams whose presenters have LinkedIn profiles have a higher probability of receiving an investment.

## Table A.3. Investment Decisions and Missing LinkedIn Profiles

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Dependent Var: I(*Invested*) | | | | | |
| Pitch-Factor | 0.030*** | 0.028*** | 0.045*** | 0.043*** | 0.029*** | 0.028*** |
| | (0.007) | (0.007) | (0.012) | (0.011) | (0.007) | (0.007) |
| I(*Has LinkedIn*) | | | | | 0.094*** | 0.118*** |
| | | | | | (0.029) | (0.040) |
| Observations | 1,139 | 1,139 | 693 | 693 | 1,139 | 1,139 |
| Pseudo $R^2$ | 0.193 | 0.239 | 0.158 | 0.171 | 0.229 | 0.239 |
| Sample | Full | Full | Has LinkedIn | Has LinkedIn | Full | Full |
| Startup/Team Controls | N | Y | N | Y | N | Y |
| Accelerator FE | Y | Y | Y | Y | Y | Y |

*Notes.* Logit regressions, marginal effect. The analysis is obtained using the following model:

$$I(Invested) = \alpha + \beta \cdot X + \delta_{FE} + \varepsilon.$$

I(*Invested*) takes a value of one if the startup team was chosen by the accelerator and zero otherwise. All pitch feature variables are standardized into a zero-mean variable with a standard deviation of one. All variables are identical to those in Table 3. The dummy variable I(*Has LinkedIn*) takes the value of one if we are able to find LinkedIn profiles of presenters and zero otherwise. Control variables include founders' education background (whether they have a master's or a PhD degree; whether they attended an elite university, defined as the U.S. News & World Report's Top 10), founders' prior work experience (whether they have prior entrepreneurship experience; whether they ever held a senior position in prior employment), team size, and video resolution. Standard errors clustered at the accelerator-year level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

# B. Method Appendix

This appendix provides more details on the steps to perform video analysis used in our paper. Compared to the more theoretical descriptions provided in Section II of the paper, this appendix proceeds with a more practical approach with information on our code structure, key functions, and notes on important steps.

### *B.1. Video Processing Example*

# Video Processing Example

This example shows how to use `interactionvideo` package to process a video for studies in human interactions. Please also refer to our research paper: Hu and Ma (2020), "Pursuading Investors: A Video-Based Study", available at: https://songma.github.io/files/hm_video.pdf.

## Overview

The video processing involves the following steps:

1. Set up folders and check dependencies (requirements)
2. Extract images and audios from a video using `pliers`
3. Extract text from audios using Google Speech2Text API
4. Process images(faces) using Face++ API
5. Process text using Loughran and McDonald (2011) Finance Dictionary and Nicolas, Bai, and Fiske (2019) Social Psychology Dictionary
6. Process audios using pre-trained ML models in `pyAudioAnalysis and speechemotionrecognition`
7. Aggregate information from 3V (visual, vocal, and verbal) to video level

## Structure

```
├── interactionvideo
│   ├── __pycache__
│   ├── prepare.py
│   ├── decompose.py
│   ├── faceppml.py
│   ├── googleml.py
│   ├── textualanalysis.py
│   ├── audioml.py
│   ├── aggregate.py
│   └── utils.py
├── data
│   ├── example_video.mp4
│   └── VideoDictionary.csv
├── mlmodel
│   ├── pyAudioAnalysis
│   └── speechemotionrecognition
├── output
│   ├── audio_temp
│   ├── image_temp
│   └── result_temp
├── PythonSDK
├── example.py
├── Video Processing Example.ipynb
├── README.md
└── requirement.txt
```

## Dependencies

- pandas
- tqdm
- codecs
- pliers
- pydub
- PIL
- google-cloud-speech
- google-cloud-storage
- speechemotionrecognition
- pyAudioAnalysis

# 1. Set up folders and check dependencies (requirements)

In [1]:
```
from os.path import join
# Set your root path here
RootPath = r''
# Set your video file path here
VideoFilePath = join(RootPath,'data','example_video.mp4')
# Set your work path here
# Work path is where to store meta files and output files
WorkPath = join(RootPath,'output')
```

In [2]:
```
# Set up the folders
from interactionvideo.prepare import setup_folder
setup_folder(WorkPath)

# check the requirements for interactionvideo
from interactionvideo.prepare import check_requirements
check_requirements()
```

```
decompose.py requirements satisfied.

faceppml.py requirements satisfied.

googleml.py requirements satisfied.

audioml.py requirements satisfied.
```

Out[2]:
```
True
```

# 2. Extract images and audios from video

In [3]:
```
from interactionvideo.decompose import convert_video_to_images

# Decompose the video into a stream of images
# The default sampling rate is 10 frames per second
# Find the output at WorkPath\image_temp
convert_video_to_images(VideoFilePath, WorkPath)
```

```
Video is 70.12 seconds long.

100%|████████████████████████████████████████████████████████████████| 7
02/702 [06:03<00:00,  1.86it/s]


Video is sampled to 702 images.

Video to images finished.
```

Out[3]:
```
True
```

In [4]:
```
from interactionvideo.decompose import convert_video_to_audios

# Decompose the video into audios
# Find the output at WorkPath\audio_temp
convert_video_to_audios(VideoFilePath, WorkPath)
```

```
MoviePy - Writing audio in %s

MoviePy - Done.
Video to audios finished.
```

Out[4]: True

## 3. Extract text from audios using Google Speech2Text API

Set up your Google Cloud environment following

- [https://cloud.google.com/python (https://cloud.google.com/python)](https://cloud.google.com/python)
- [https://cloud.google.com/storage/docs/quickstart-console (https://cloud.google.com/storage/docs/quickstart-console)](https://cloud.google.com/storage/docs/quickstart-console)
- [https://cloud.google.com/speech-to-text (https://cloud.google.com/speech-to-text)](https://cloud.google.com/speech-to-text)

Create a Google Cloud Storage bucket.

In [5]:
```
from interactionvideo.googleml import upload_audio_to_googlecloud

# Set your Google Cloud Storage bucket name here
GoogleBucketName = ''

# Upload audio file to Google Cloud Storage
upload_audio_to_googlecloud(WorkPath, GoogleBucketName)
```

```
Uploaded the audio file to Google Cloud.
```

Out[5]: True

In [6]:
```
from interactionvideo.googleml import convert_audio_to_text_by_google

# Use Google Speech2Text API to convert audio to text
# Return a txt file of full speech script and a csv file of text and punctuation
# Find the output at
# - WorkPath\result_temp\script_google.txt (full speech script)
# - WorkPath\result_temp\text_panel_google.csv (text panel from Google)
google_result_text, google_result_df = convert_audio_to_text_by_google(WorkPath, GoogleB
ucketName)
```

```
Google Speech2Text begins. 70.12 seconds audio to process.

Google Speech2Text ends. 70.12 seconds audio processed.
```

In [7]:
```
# Check full speech script from Google
print(google_result_text)
```

```
Hello, everyone. First of all, we will like to thank you for your interest in our resear
ch in this paper. We try to understand how human interaction features such as facial exp
ressions vocal emotions and word choices might influence economic agents decision making
in order to study this question empirically, we build an empirical approach that uses vi
deos of human interactions as data input and and machine learning based algorithms as th
e tool. We apply an empirical approach in a setting where early stage Turn up Pitch Vent
ure capitalists for early-stage funding. We find that pitch features along visual vocal
and verbal damages all matter for the probability of receiving funding and we also show
that this event impact is largely due to interaction induced biases rather than that int
eractions provide additional valuable information the empirical structure that you see i
n this code example can hopefully help you to get started with using video in other impo
rtant settings such as As interviews classroom recordings among many other exciting thin
gs. We look forward to hearing your feedback and reading about your research. Thank you.
```

In [8]:
```
# Check text panel from Google
google_result_df.head(10)
```

Out[8]:

| | Text | Onset | Offset | Duration | Sentence End |
|---|---|---|---|---|---|
| **0** | Hello, | 0.1 | 0.7 | 0.6 | True |
| **1** | everyone. | 0.7 | 1.1 | 0.4 | True |
| **2** | First | 1.1 | 1.5 | 0.4 | False |
| **3** | of | 1.5 | 1.6 | 0.1 | False |
| **4** | all, | 1.6 | 1.9 | 0.3 | True |
| **5** | we | 1.9 | 2.0 | 0.1 | False |
| **6** | will | 2.0 | 2.2 | 0.2 | False |
| **7** | like | 2.2 | 2.3 | 0.1 | False |
| **8** | to | 2.3 | 2.4 | 0.1 | False |
| **9** | thank | 2.4 | 2.7 | 0.3 | False |

## 4. Process images(faces) using Face++ API

Get your key and secret from https://www.faceplusplus.com (https://www.faceplusplus.com).

If you register at https://console.faceplusplus.com/register (https://console.faceplusplus.com/register), use https://api-us.faceplusplus.com (https://api-us.faceplusplus.com) as the server.

If you register at https://console.faceplusplus.com.cn/register (https://console.faceplusplus.com.cn/register), use https://api-cn.faceplusplus.com (https://api-cn.faceplusplus.com) as the server.

The `Python SDK` of Face++ is included in this package.

You can also download it from https://github.com/FacePlusPlus/facepp-python-sdk (https://github.com/FacePlusPlus/facepp-python-sdk).

In [9]:
```python
from interactionvideo.faceppml import process_image_by_facepp

# Use Face++ ML API to process images
# Return csv files of facial emotion, gender, predicted age
# Find the output
# - WorkPath\result_temp\face_panel_facepp.csv (full returns from Face++)
# - WorkPath\result_temp\face_panel.csv (clean results)

# Set your key, secret, and server here
FaceppKey = ''
FaceppSecret = ''
FaceppServer = 'https://api-us.faceplusplus.com'

facepp_result_df, facepp_result_clean_df = process_image_by_facepp(VideoFilePath, WorkPa
th,\
                                                  FaceppKey, FaceppSecret, FaceppServer)
```

```
Face++ API begins. 702 images to process.

100%|██████████████████████████████████████████████████| 70
2/702 [1:13:21<00:06,  6.47s/it]

Face++ API ends. 702 images processed.
```

In [10]:
```python
# Check full returns from Face++
facepp_result_df.head(10)
```

Out[10]:

| | ImageName | Onset | Offset | Duration | face_rectangle#top | face_rectangle#left | face_rectangle#width |
|---|---|---|---|---|---|---|---|
| **0** | frame[0] | 0.0 | 0.1 | 0.1 | 405 | 868 | 249 |
| **1** | frame[3] | 0.1 | 0.2 | 0.1 | 406 | 867 | 250 |
| **2** | frame[6] | 0.2 | 0.3 | 0.1 | 404 | 866 | 252 |
| **3** | frame[9] | 0.3 | 0.4 | 0.1 | 403 | 867 | 253 |
| **4** | frame[12] | 0.4 | 0.5 | 0.1 | 401 | 866 | 258 |
| **5** | frame[15] | 0.5 | 0.6 | 0.1 | 405 | 867 | 261 |
| **6** | frame[18] | 0.6 | 0.7 | 0.1 | 407 | 867 | 261 |
| **7** | frame[21] | 0.7 | 0.8 | 0.1 | 404 | 869 | 258 |
| **8** | frame[24] | 0.8 | 0.9 | 0.1 | 403 | 867 | 262 |
| **9** | frame[27] | 0.9 | 1.0 | 0.1 | 402 | 868 | 262 |

10 rows × 193 columns

In [11]:
```
# Check clean results
facepp_result_clean_df.head(10)
```

Out[11]:

| | Onset | Offset | Duration | Number of Faces | Gender | Age | Visual-Positive | Visual-Negative | Visual-Beauty |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 0.1 | 0.1 | 1 | Male | 31 | 0.00007 | 0.26876 | 0.430900 |
| **1** | 0.1 | 0.2 | 0.1 | 1 | Male | 33 | 0.00008 | 0.22857 | 0.406690 |
| **2** | 0.2 | 0.3 | 0.1 | 1 | Male | 30 | 0.00115 | 0.33071 | 0.413915 |
| **3** | 0.3 | 0.4 | 0.1 | 1 | Male | 28 | 0.00152 | 0.33477 | 0.402910 |
| **4** | 0.4 | 0.5 | 0.1 | 1 | Male | 28 | 0.00040 | 0.92615 | 0.415210 |
| **5** | 0.5 | 0.6 | 0.1 | 1 | Male | 26 | 0.00734 | 0.98612 | 0.447690 |
| **6** | 0.6 | 0.7 | 0.1 | 1 | Male | 30 | 0.00196 | 0.80259 | 0.449480 |
| **7** | 0.7 | 0.8 | 0.1 | 1 | Male | 32 | 0.00021 | 0.09574 | 0.449665 |
| **8** | 0.8 | 0.9 | 0.1 | 1 | Male | 29 | 0.00095 | 0.60956 | 0.451470 |
| **9** | 0.9 | 1.0 | 0.1 | 1 | Male | 29 | 0.00046 | 0.05656 | 0.468895 |

## 5. Process text using LM and NBF Dictionaries

Use Loughran-McDonald (2011) Finance Dictionary (LM) to construct verbal positive and negative.

For more details, please check https://sraf.nd.edu/textual-analysis/resources (https://sraf.nd.edu/textual-analysis/resources).

Use Nicolas, Bai, and Fiske (2019) Social Psychology Dictionary (NBF) to construct verbal warmth and ability.

For more details, please check https://psyarxiv.com/afm8k (https://psyarxiv.com/afm8k).

In [12]:
```
from interactionvideo.textualanalysis import process_text_by_dict

# Set LM-NBF dictionary path
DictionaryPath = join(RootPath,'data','VideoDictionary.csv')

# Dictionary-based textual analysis to get verbal measures
# (e.g., verbal positive, negative, warmth, ability)
# Return csv files of verbal positive, negative, warmth, and ability
# Find the output at
# - WorkPath\result_temp\text_panel.csv
text_result_df = process_text_by_dict(WorkPath, DictionaryPath)
```

```
LM and NBF Dictionaries loaded.

Dictionary-based textual analysis begins. 183 words to process.

Dictionary-based textual analysis ends. 183 words processed.
```

In [13]:
```
# Check text panel from Dictionary
text_result_df.head(10)
```

Out[13]:

| | Text | Onset | Offset | Duration | Sentence End | Verbal-Negative | Verbal-Positive | Verbal-Warmth | Verbal-Ability |
|---|---|---|---|---|---|---|---|---|---|
| **0** | Hello, | 0.1 | 0.7 | 0.6 | True | 0.0 | 0.0 | 0.0 | 0.0 |
| **1** | everyone. | 0.7 | 1.1 | 0.4 | True | 0.0 | 0.0 | 0.0 | 0.0 |
| **2** | First | 1.1 | 1.5 | 0.4 | False | 0.0 | 0.0 | 0.0 | 0.0 |
| **3** | of | 1.5 | 1.6 | 0.1 | False | 0.0 | 0.0 | 0.0 | 0.0 |
| **4** | all, | 1.6 | 1.9 | 0.3 | True | 0.0 | 0.0 | 0.0 | 0.0 |
| **5** | we | 1.9 | 2.0 | 0.1 | False | 0.0 | 0.0 | 0.0 | 0.0 |
| **6** | will | 2.0 | 2.2 | 0.2 | False | 0.0 | 0.0 | 0.0 | 0.0 |
| **7** | like | 2.2 | 2.3 | 0.1 | False | 0.0 | 0.0 | 1.0 | 0.0 |
| **8** | to | 2.3 | 2.4 | 0.1 | False | 0.0 | 0.0 | 0.0 | 0.0 |
| **9** | thank | 2.4 | 2.7 | 0.3 | False | 0.0 | 0.0 | 1.0 | 0.0 |

# 6. Process audios by pre-trained ML models

Construct vocal arousal and vocal valence from pre-trained SVM ML models in `pyAudioAnalysis` .

The pre-trained models are located at mlmodel\pyAudioAnalysis

- svmSpeechEmotion_arousal
- svmSpeechEmotion_arousalMEANS
- svmSpeechEmotion_valence
- svmSpeechEmotion_valenceMEANS

For more details, please check https://github.com/tyiannak/pyAudioAnalysis/wiki/4.-Classification-and-Regression (https://github.com/tyiannak/pyAudioAnalysis/wiki/4.-Classification-and-Regression).

Construct vocal positive and vocal negative from pre-trained LSTM ML models in `speechemotionrecognition` .

The pre-trained models are located at mlmodel\speechemotionrecognition

- best_model_LSTM_39.h5

For more details, please check https://github.com/harry-7/speech-emotion-recognition (https://github.com/harry-7/speech-emotion-recognition).

Note: speechemotionrecognition requires tensorflow and Keras.

In [14]:
```python
from interactionvideo.audioml import process_audio_by_pyAudioAnalysis

# Set the model path
pyAudioAnalysisModelPath = join(RootPath,'mlmodel','pyAudioAnalysis')

# Construct vocal arousal and vocal valence
# Find the output at
# - WorkPath\result_temp\audio_panel_pyAudioAnalysis.csv
audio_result_df1 = process_audio_by_pyAudioAnalysis(WorkPath, pyAudioAnalysisModelPath)
```

```
pyAudioAnalysis vocal emotion analysis begins. 70.12 seconds audio to process.

pyAudioAnalysis ML model loaded.

pyAudioAnalysis vocal emotion analysis ends. 70.12 seconds audio processed.
```

In [15]:
```python
# Check audio panel from pyAudioAnalysis
audio_result_df1.head()
```

Out[15]:

| | Onset | Offset | Duration | Vocal-Arousal | Vocal-Valence |
|---|---|---|---|---|---|
| **0** | 0 | 70.12 | 70.12 | 0.404089 | -0.01519 |

In [16]:
```python
from interactionvideo.audioml import process_audio_by_speechemotionrecognition

# Set the model path
speechemotionrecognitionModelPath = join(RootPath,'mlmodel','speechemotionrecognition')

# Construct vocal positive and vocal negative
# Find the output at
# - WorkPath\result_temp\audio_panel_speechemotionrecognition.csv
audio_result_df2 = process_audio_by_speechemotionrecognition(WorkPath, speechemotionreco
gnitionModelPath)
```

```
speechemotionrecognition vocal emotion analysis begins. 70.12 seconds audio to process.


Using TensorFlow backend.


_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 128)               86016
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 32)                4128
_________________________________________________________________
dense_2 (Dense)              (None, 16)                528
_________________________________________________________________
dense_3 (Dense)              (None, 4)                 68
=================================================================
Total params: 90,740
Trainable params: 90,740
Non-trainable params: 0
_________________________________________________________________

speechemotionrecognition ML model loaded.

speechemotionrecognition vocal emotion analysis ends. 70.12 seconds audio processed.
```

In [17]:
```
# Check audio panel from speechemotionrecognition
audio_result_df2.head()
```

Out[17]:

| | Onset | Offset | Duration | Vocal-Positive | Vocal-Negative |
|---|---|---|---|---|---|
| **0** | 0 | 70.12 | 70.12 | 0.459319 | 0.006388 |

# 7. Aggregate information from 3V to video level

In [18]:
```
from interactionvideo.aggregate import aggregate_3v_to_video

# Aggregate 3V information
# Find the output at
# - WorkPath\result_temp\video_panel.csv
video_result_df = aggregate_3v_to_video(WorkPath)
```

```
3V to video aggregation finished.
```

In [19]:
```
# Check video panel
video_result_df.T
```

Out[19]:

| | 0 |
|---|---|
| **Number of Faces** | 1 |
| **Gender** | Male |
| **Age** | 32 |
| **Visual-Positive** | 0.0142308 |
| **Visual-Negative** | 0.443333 |
| **Visual-Beauty** | 0.450598 |
| **Vocal-Positive** | 0.46 |
| **Vocal-Negative** | 0.01 |
| **Vocal-Arousal** | 0.4 |
| **Vocal-Valence** | -0.02 |
| **Verbal-Positive** | 0.010929 |
| **Verbal-Negative** | 0.010929 |
| **Verbal-Warmth** | 0.0327869 |
| **Verbal-Ability** | 0.0382514 |

### B.2. *Textual Analysis on Pitch Content*

In this appendix, we provide more technical details on the construction of informational content measures for the pitches.

**Measures of idea novelty based on textual similarity.** We measure the novelty of ideas in video pitches by comparing their textual content with business descriptions of startups and public firms extant around the same time. The idea is that if the pitch of the focal startup is different from existing businesses (i.e., not a me-too startup) but could be influential in the future (i.e., the idea will have some traction), we consider the pitching startup to be more novel. Kelly et al. (2021) at the *AER: Insights* takes a similar empirical strategy to measure the technological novelty of patents.

To implement this idea, we obtain a panel of business descriptions of existing startups from PitchBook and of publicly-traded firms from the business description section (Item 1) from 10-K filings of these firms. Combining these data, we observe the business descriptions of startups founded each year and the descriptions of public firms each year.

Our measure construction process closely follows that of Kelly et al. (2021). For a focal startup $i$ in our pitch sample that applied to an accelerator in year $t$, we construct its idea novelty measure in three steps.[31]

- **Step 1:** We calculate "backward textual similarity" as the average textual similarity (more on this below) between $i$'s pitch script and business descriptions of all startups that were first financed by early-stage VCs before or in year $t$. A low backward textual similarity indicates that startup $i$'s idea is distinct from the business models of previously and contemporaneously funded startups.

- **Step 2:** We calculate "forward textual similarity" as the average textual similarity between $i$'s pitch script and business descriptions of all startups that were first financed by early-stage VCs after year $t$. A high forward textual similarity indicates that startup $i$'s idea is similar to the business models of startups funded in the future.

- **Step 3:** We calculate the novelty measure using both the backward and forward textual similarities—dividing the forward one by the backward one. Together, a high forward-to-

[31]To keep the description concise, we skipped the standard processes of textual cleaning in this description. We are happy to provide more details if needed.

backward ratio indicates a high novelty for startup $i$'s idea: it is different enough from previous ideas but is potentially impactful for the future. The same logic applies to the measure using public firms' business descriptions as benchmarks.

A key component in the calculation above is the definition of textual similarity. We calculate textual similarities using both BERT and Bag-of-Words (BoW), and the results are robust to both.

- To quantify the information embedded in text, we first need to represent the textual data in a numerical format. We use Bidirectional Encoder Representations from Transformers (BERT), a state-of-the-art NLP model of word embeddings that maps words into vectors of real numbers. BERT proves to be superior in many NLP tasks (Devlin et al., 2018) and has been increasingly used in economic studies (Gorodnichenko et al., 2021). We use "all-mpnet-base," the current best-performing version of BERT in sentence embedding[32].

- As a robustness test, we use the "bag of words" (BoW) representation with the "term-frequency-inverse-document-frequency" (TF-IDF) weighting scheme and obtain similar results. For each video pitch or business description, we use BERT to transform it to a vector. We then define the textual similarity between video pitch and business description as the cosine similarity between each pair of vectors.

**Dictionary-based measures of pitch content.** We use a dictionary-based approach to directly capture the topics that are discussed in video pitches. We focus on the topics that are most relevant in the setting of early-stage startup financing. These topic categories include concrete numbers, cash flow, competition, employment, readiness, technology, data, and AI. We compile a list of keywords that are representative of these topic categories. For example, the keywords for the "cash flow" category include "sale(s)", "revenue(s)", and "profit(s)", among others, which capture whether a startup discusses the profitability in the video pitch. The "technology" category is concerned with whether the pitch explicitly discusses the technologies or patents. We define the category of concrete numbers as all numbers mentioned in video pitches. Table A.4 shows a complete list of categories and keywords.

[32]For a complete list of BERT versions, see `https://www.sbert.net/docs/pretrained_models.html`

For each video pitch, we examine whether the keywords of each topic are included. The dummy variable of each topic takes a value of one if any keyword of that topic appears in the content of a pitch. For example, the measure "Competition" has a mean of 0.06, which indicates that 6% of startups in our sample discuss competition explicitly in their video pitches.

**LIWC.** We use LIWC to extend the word categories of our dictionary-based approach. LIWC is widely used in computational linguistics and includes word categories that capture soft information and psychological meanings of text (Tausczik and Pennebaker, 2010). Over 20,000 scientific articles have already been published using LIWC. Similar to our practice above, for each LIWC category, we calculate its percentage of total words within a video pitch.

To complement the word categories in the finance dictionary (Loughran and McDonald, 2011), the social psychology dictionary (Nicolas et al., 2019), and our startup financing word list described above, we focus on communication styles (e.g., concrete and informal words) and time orientations (e.g., past, present, or future focus) in LIWC.

**Table A.4. List of Keywords of Content Control Categories**

| Category | Keywords | Category | Keywords | Category | Keywords |
|---|---|---|---|---|---|
| Cash Flow | sale(s) | Technology | patent(s) | Data and AI | digitalization |
| | revenue(s) | | innovation(s) | | digitalize(s) |
| | profit(s) | | invention(s) | | digitally |
| | profitability | | inventor(s) | | digitize(s) |
| | income(s) | | technique(s) | | digitized |
| | earning(s) | | technology(ies) | | digitizing |
| | cash flow(s) | | technological | | program |
| Employment | employ(s) | Competition | compete(s) | | programmed |
| | employing | | competing | | programming |
| | employed | | competition(s) | | programmer(s) |
| | employment | | competitive | | programmatic |
| | employee(s) | | competitiveness | | programmable |
| | employer(s) | | competitor(s) | | artificial intelligence |
| | recruit(s) | Data and AI | data | | machine learning |
| | recruited | | database | | |
| | recruiting | | information | | |
| | recruiter(s) | | analysis | | |
| | recruitment | | analyses | | |
| Readiness | prototype(s) | | analytic | | |
| | prototyping | | analytical | | |
| | customer(s) | | analytics | | |
| | commercialize(s) | | analyze(s) | | |
| | commercialized | | analyzed | | |
| | commercialise(s) | | analyzing | | |
| | commercialised | | developer(s) | | |
| | commercialization | | digital | | |

*Notes.* This table lists the keywords for constructing dictionary-based measures of informational content controls.

## Table A.5. Summary Statistics of Informational Content Controls

| | N | Mean | STD | 25% | 50% | 75% |
|---|---|---|---|---|---|---|
| *Textual Similarity* | | | | | | |
| Idea Novelty (PB) | 1,139 | 1.06 | 0.03 | 1.03 | 1.05 | 1.07 |
| Idea Novelty (10K) | 1,139 | 1.09 | 0.23 | 1.05 | 1.07 | 1.11 |
| *Dictionary-based* | | | | | | |
| Concrete Number | 1,139 | 0.61 | 0.49 | 0.00 | 1.00 | 1.00 |
| Cash Flow | 1,139 | 0.16 | 0.37 | 0.00 | 0.00 | 0.00 |
| Competition | 1,139 | 0.06 | 0.23 | 0.00 | 0.00 | 0.00 |
| Employment | 1,139 | 0.08 | 0.28 | 0.00 | 0.00 | 0.00 |
| Readiness | 1,139 | 0.20 | 0.40 | 0.00 | 0.00 | 0.00 |
| Technology | 1,139 | 0.25 | 0.43 | 0.00 | 0.00 | 0.00 |
| Data AI | 1,139 | 0.42 | 0.49 | 0.00 | 0.00 | 1.00 |
| *LIWC* | | | | | | |
| Focus Past | 1,139 | 2.54 | 1.90 | 1.14 | 2.21 | 3.64 |
| Focus Present | 1,139 | 11.63 | 3.41 | 9.35 | 11.43 | 13.53 |
| Focus Future | 1,139 | 1.28 | 1.12 | 0.53 | 1.09 | 1.85 |
| Concreteness | 1,139 | 0.71 | 3.07 | –1.26 | 0.69 | 2.76 |
| Informal | 1,139 | 0.70 | 1.77 | 0.00 | 0.47 | 0.95 |

*Notes.* This table provides descriptive statistics of informational content controls. For each variable, we report the number of observations, mean, standard deviation, and 25th, 50th, and 75th percentiles.

## C. Analysis Using the University Sample

To examine the robustness of our results, we analyze a new sample from the Yale Tsai Center for Innovative Thinking (CITY) using the same video analysis technique and empirical strategy. We show below that the empirical results of the Yale Sample Analysis are very similar to our original results in the paper, both in terms of economic magnitudes and statistical significance. With this administrative-level data set, we also perform a test on the sample selection problem which arises from the initial decision to submit and publicize a video pitch. We find that the availability of a video is neither related to measures of pitch features nor investment decisions, which suggests that the selection issue may not be a major concern.

### *C.1. Data*

Yale Tsai CITY is an institute at Yale University that aims to inspire innovation and entrepreneurship. Yale Tsai CITY runs an accelerator program, taking applications three times a year (Spring, Summer, Fall) from startup teams formed among Yale students. The application process is very similar to the accelerator programs studied in our main analysis (albeit on a much smaller scale). The applications are reviewed, and accepted teams receive an investment of $2,000 and additional resources such as mentorship, expert services (on accounting, legal services, and communication), and community activities—again, similar to the commercial accelerators.

Our data include all 316 Yale Tsai CITY accelerator applications between Fall 2018 and Fall 2020. For each application, we obtain the information submitted through the online form and the pitch video submitted together with the application. Among 316 startups in our sample, 166 (53%) include videos in their applications and 150 (47%) do not. Among 166 startups with videos included in their applications, 61 (37%) are funded by Yale Tsai CITY. For those 150 startups that do not include a video in their applications, 28 (19%) are funded by Yale Tsai CITY. Together, 89 (28%) are funded in the full sample.

**[Insert Table A.6 Here.]**

Table A.6 presents summary statistics of startups and videos, and it shows that the Yale sample is quite similar to our main sample in the paper. Similar to our original sample, the majority of these startups are still in an early stage—about 90% of them have not launched their products yet at the time of application. The videos in the Yale Tsai CITY sample are slightly longer (111 seconds on average) than those in our original sample (83 seconds on average) since Yale Tsai CITY does not have a hard restriction on the length of video pitches, while some accelerators in our original sample require videos to be less than one minute. In general, these two samples are quite comparable in terms of startup characteristics and video features.

### *C.2. Robustness of Main Results*

Table A.7 repeats the video analysis procedure used on our original sample. Specifically, we then estimate the same model in Table 3 to examine the relationship between Pitch Factor and the investment decisions by the accelerator. We show that in this Yale sample, Pitch Factor is significantly positively correlated with the probability for a startup to obtain funding from the accelerator. Our results are robust to alternative specifications with different sets of controls, such as team and video controls and time and startup-stage fixed effects. In terms of economic magnitude, take the coefficient in column (4) for example—a one-standard-deviation higher in Pitch Factor is associated with a 9.8 percentage point higher funding probability, which is equivalent to a 34.8 percent increase from the baseline funding rate of 28.16 percentage points. Such an estimate of 34.8 percent is very close to the one estimated in our original sample, which is 35.2 percent.

**[Insert Table A.7 Here.]**

### *C.3. Sample Selection Analysis*

One potential sample selection problem could arise from the initial decision to submit and publicize a video pitch. Since we collect the main sample from public domains and are unable to observe videos that were uploaded to private domains, our original sample is unable to speak to such a concern of sample selection. To better address this issue, we use the Yale Tsai CITY sample, which includes links to videos that are on private domains as well. Such a sample allows us to test whether the decision of making videos public is related to the key variables in our analysis. As shown in Table A.8, making the video public is unrelated to Pitch Factor, whether the startup is funded by the accelerator, and whether the startup receives funding from other investors and how much it receives.

**[Insert Table A.8 Here.]**

A key difference between the Yale sample and the main sample in the paper, however, is that student-led startup teams in the former have a lower probability of turning into more serious startups post-graduation, limiting our ability to study their long-term results in employment, obtaining VC funding, etc.

## Table A.6. Summary Statistics of Videos and Startups: Yale Tsai CITY

**Panel A: Breakdown by Periods and Stages**

| Period | Ideation | Well-developed Idea | Prototyping | Alpha/ Beta | Launched | Total | % of Full Sample |
|---|---|---|---|---|---|---|---|
| Fall 2018 | 14 | 9 | 11 | 6 | 2 | 42 | 13.29% |
| Spring 2019 | 11 | 12 | 25 | 13 | 3 | 64 | 20.25% |
| Summer 2019 | 1 | 8 | 24 | 11 | 5 | 49 | 15.51% |
| Fall 2019 | 10 | 8 | 14 | 2 | 4 | 38 | 12.03% |
| Spring 2020 | 3 | 7 | 17 | 4 | 3 | 34 | 10.76% |
| Summer 2020 | 7 | 1 | 21 | 15 | 6 | 50 | 15.82% |
| Fall 2020 | 10 | 0 | 7 | 13 | 9 | 39 | 12.34% |
| Total | 56 | 45 | 119 | 64 | 32 | 316 | 100% |
| % of Full Sample | 17.72% | 14.24% | 37.66% | 20.25% | 10.13% | 100% | |

**Panel B: Summary Statistics of Video and Startups**

| | N | Mean | STD | 25% | 50% | 75% |
|---|---|---|---|---|---|---|
| Duration (second) | 166 | 111.72 | 27.30 | 100.20 | 118.03 | 121.32 |
| Video Size (MB) | 166 | 24.38 | 44.52 | 7.16 | 15.66 | 21.35 |
| Number of Words | 166 | 303.83 | 73.52 | 259.00 | 304.50 | 353.00 |
| Number of Sentences | 166 | 33.63 | 9.10 | 28.00 | 33.00 | 38.00 |
| Number of People | 316 | 2.14 | 1.26 | 1.00 | 2.00 | 3.00 |
| I(*Invested*) | 316 | 0.28 | 0.45 | 0.00 | 0.00 | 1.00 |
| I(*Other Funding*) | 316 | 0.18 | 0.39 | 0.00 | 0.00 | 0.00 |
| Other Funding Amount ($000) | 316 | 9.34 | 58.28 | 0.00 | 0.00 | 0.00 |

*Notes.* This table provides descriptive statistics of pitch videos and the underlying startups in our sample of Yale Tsai CITY. For each variable, we report the number of observations, mean, standard deviation, and 25th, 50th, and 75th percentiles. Panel A reports the total number of teams in each stage and in each period. Panel B reports characteristics of videos and teams.

**Table A.7. Investment Decisions: Yale Tsai CITY**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Dependent Var: I(*Invested*) | | | |
| Pitch Factor | 0.091** | 0.091*** | 0.087*** | 0.098*** |
| | (0.036) | (0.035) | (0.029) | (0.023) |
| Observations | 166 | 166 | 166 | 166 |
| Pseudo $R^2$ | 0.027 | 0.028 | 0.092 | 0.224 |
| Team/Video Controls | N | Y | Y | Y |
| Period FE | N | N | Y | Y |
| Stage FE | N | N | N | Y |

*Notes.* Logit regressions, marginal effect. The analysis is obtained using the following model:

$$I(Invested) = \alpha + \beta \cdot X + \delta_{FE} + \varepsilon.$$

I(*Invested*) takes a value of one if the startup team was chosen by the accelerator and zero otherwise. All pitch feature variables are standardized into a zero-mean variable with a standard deviation of one. Control variables include team size and video resolution. Standard errors clustered at the period level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

**Table A.8. Sample Selection: Yale Tsai CITY**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | I(*Public Video*) | | | | |
| I(*Invested*) | −0.089 | | | | −0.107 |
| | (0.082) | | | | (0.095) |
| I(*Other Funding*) | | −0.006 | | | 0.239 |
| | | (0.056) | | | (0.202) |
| Other Funding Amount | | | −0.003 | | −0.027 |
| | | | (0.005) | | (0.021) |
| Pitch Factor | | | | 0.000 | 0.010 |
| | | | | (0.011) | (0.017) |
| Observations | 166 | 166 | 166 | 166 | 166 |
| Pseudo R2 | 0.138 | 0.127 | 0.128 | 0.127 | 0.147 |
| Period FE | Y | Y | Y | Y | Y |
| Stage FE | Y | Y | Y | Y | Y |

*Notes.* Logit regressions, marginal effect. This table investigates the sample selection issue of the video sample. The analysis is restricted to the sample of startups that includes videos in their applications. I(*Public Videos*) takes a value of one if the startup team uploads its video to a public domain and zero otherwise. I(*Invested*) takes a value of one if the startup team was chosen by the accelerator and zero otherwise. I(*Other Funding*) takes a value of one if the startup team has received funding from other investors at the time of application and zero otherwise. Other Funding Amount is the inverse hyperbolic sine of total amount of investment that a startup has raised from other investors at the time of application. All pitch feature variables are standardized into a zero-mean variable with a standard deviation of one. Standard errors clustered at the period level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

# D. Appendix: MTurk Rating Survey

This appendix presents details of our survey designs. The goal of these exercises is to bridge our ML-algorithm that rates pitch videos with the traditional approach of using human raters.

Both exercises take the form of an online survey that participants complete using their own electronic devices (e.g., computers and tablets), and they are distributed through Amazon Mechanical Turk (MTurk). In both surveys, we require the participants to be located in the U.S. and to be identified as masters at completing our types of tasks by the MTurk platform through its statistical performance monitoring. The experiments recruit 115 and 100 participants respectively. Our experiments on MTurk provide relatively high payments compared to the MTurk average to ensure quality responses.

Sample survey designs are attached toward the end of this appendix.

## *D.1. Survey 1: Rating on Pitch Positivity*

In the first survey, we elicit ratings of positivity from MTurkers. In each survey, a respondent is allocated a random set of six pitch videos. For each video, we first mandate the completion of watching the full video, and the respondent is not able to skip the video before answering the rating questions. Then, on the next survey screen, we elicit the rating of positivity, defined as passion, enthusiasms, based on the video just watched. The rating is on a 1-9 scale with nine choices. The evaluations of the videos are completed one by one, and ratings may not be revised after moving to the next video.

We then compare the ratings from MTurkers with the Pitch Factor. Figure A.3 shows the binned scatter plot of the relation between the two variables. The clearly positive correlation provides the first assurance of the validity of the ML-generated measure. In a regression analysis, as shown in Table A.9, we also show a strong correlation between the two variables.

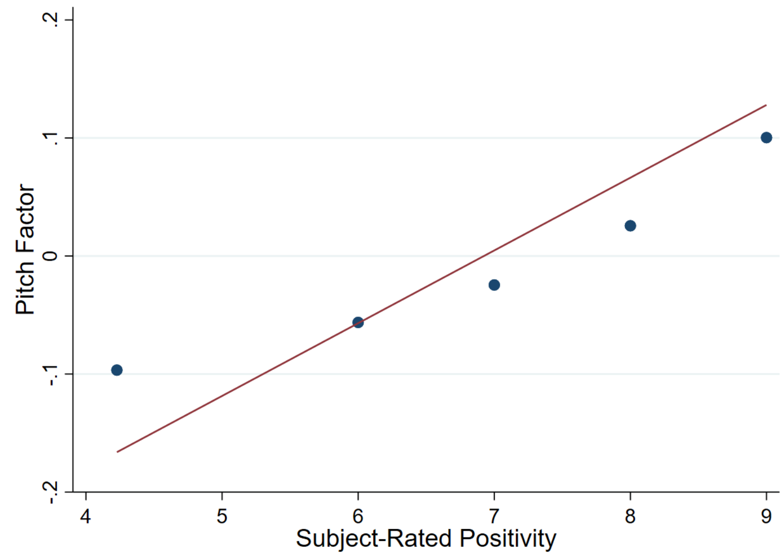



**Figure A.3. Pitch Factor and Respondent-Rated Positivity**

**Table A.9. Pitch Factor and Respondent-Rated Positivity**

| | (1) | (2) |
|---|---|---|
| | Pitch Factor | |
| Respondent-Rated Positivity | 0.062** | 0.088*** |
| | (0.028) | (0.034) |
| Observations | 690 | 690 |
| $R^2$ | 0.011 | 0.167 |
| Respondent FE | No | Yes |

### *D.2. Survey 2: Comparing Pitches*

In our second and separate survey, we ask MTurker respondents to compare pitch positivity in pairs of randomly-drawn videos. By asking respondents to directly compare pitches, we mitigate noise that could arise from the rating survey in Survey 1 due to the small sample—such as the impact of the order of videos and individual fixed effects in interpreting scales, among others.

In this survey, each respondent is allocated four pairs of videos. For each of these random pairs, we require both videos, clearly labeled as "Video 1" and "Video 2," to be completely watched. Then on the next screen, the respondents are asked to choose the pitch video that gives them the more positive impression (passionate, enthusiastic). Finally, we evaluate the consistency between our ML-based ranking and the human ranking. In other words, does the algorithm pick the same winners as the raters?

We find that the same winner is picked with nearly 89.5% consistency. Interestingly, we also find strong disagreement among MTurker raters themselves when the two videos in the same pair have close algorithm-generated Pitch Factors. In other words, our method seems to be able to provide a more decisive ranking when there are high levels of noise.

Yale University

**Video Pitch Experiment Introduction**

This survey will take you about 10 minutes. You will get a base payment of $3 as long as you finish this survey. We will also award you bonus payment (up to $3), which is determined by how well you did in the survey.

During the survey, you are going to watch 6 videos where company founders are describing their startup. You will then rate how positive (e.g. passionate, happy, enthusiastic) each video is on four dimensions: **facial expressions, voices, word choices, and overall**.

**Please get your audio device (e.g., earphone and computer speaker) ready now.**

***Note: The submission button will appear only after you watch the video. If the submission button does not appear even after* you watch the video*, please wait several seconds and do not reload the web page.***

**Video Pitch -Kru865yB-M (Example)**


**Please watch the video. You will then rate how positive (e.g. passionate, happy, enthusiastic) this video is on four dimensions: facial expressions, voices, word choices, and overall.**
**(The submission button will appear after the video is played.)**

**Video Pitch -Kru865yB-M Question (Example)**

Which of the following industry or industries best describe the business of this startup?

- ○ Consumption Goods
- ○ Health Care
- ○ Information Technology
- ○ Consumer Services
- ○ Industrials

What is your rating for the **overall positivity** of this video?

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Most negative | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Most positive |

What is your rating for the **visual positivity** of this video?

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Most negative | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Most positive |

What is your rating for the **vocal positivity** of this video?

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Most negative | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Most positive |

What is your rating for the **verbal positivity** of this video?

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Most negative | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | Most positive |

**Questions on Basic Information**

What is your year of birth? (e.g., 1990)

Choose one or more races that you consider yourself to be:

- ☐ White
- ☐ Asian
- ☐ Black or African American
- ☐ Hispanic or Latino
- ☐ Other

What is your gender?

- ○ Male
- ○ Female
- ○ Other

What is the highest level of school you have completed or the highest degree you have received?

- ○ Less than High School
- ○ High School
- ○ College
- ○ Graduate or Professional (JD, MD)

**Ending**

This is the end of the survey. Thank you for your valuable time.

To obtain your payment, please input your unique ID below to MTurk.

Here is your unique ID: ${e://Field/Random%20ID}. Copy this value to paste into MTurk.

When you have copied this ID, please click the Submit button to submit your answers.

Yale University

**Video Pitch Experiment Introduction**

This survey will take you about 15 minutes. You will get a base payment of $3 as long as you finish this survey. We will also award you bonus payment (up to $3), which is determined by how well you did in the survey.

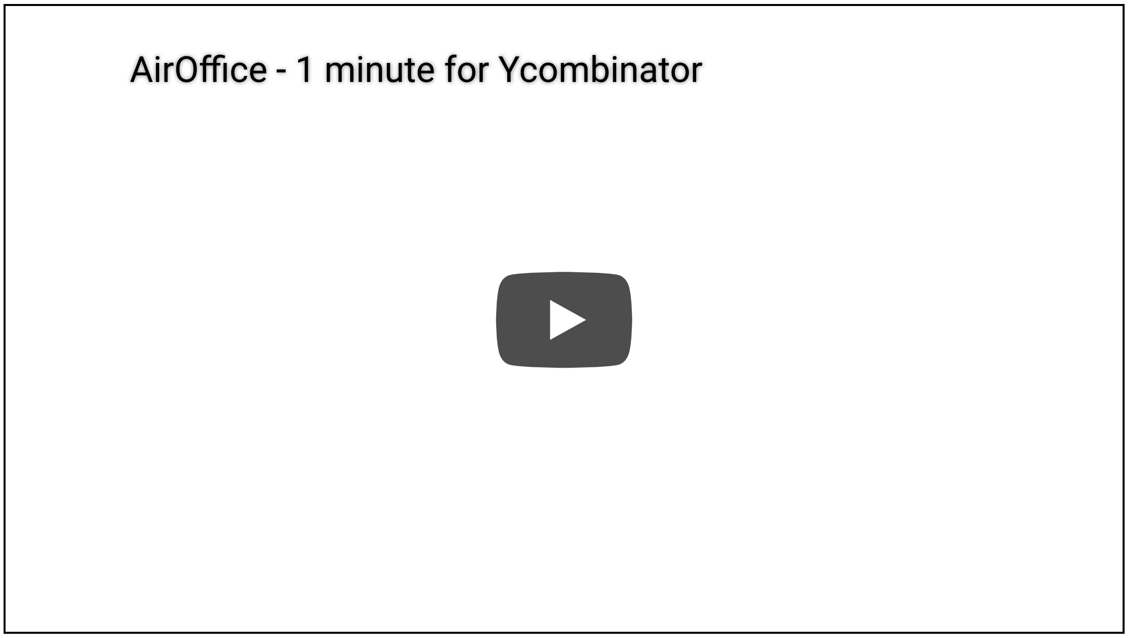
During the survey, you are going to watch 4 pairs of videos where company founders are describing their startup. You will then select which video is more positive (e.g. passionate, happy, enthusiastic) on four dimensions: **facial expressions, voices, word choices, and overall**.

**Please get your audio device (e.g., earphone and computer speaker) ready now.**

***Note: The submission button will appear only after you watch both videos. If the submission button does not appear even after*** **you watch the video*****, please wait several seconds and do not reload the web page.***

**Video Pitch le3s6qSV1Ck and n4d1TXm-RUk (Example)**

# Video 1




# Video 2


**Please watch both videos. You will then select which video is more positive (e.g. passionate, happy, enthusiastic) on four dimensions: facial expressions, voices, word choices, and overall.**
**(The submission button will appear after both videos are played.)**

**Video Pitch Ie3s6qSV1Ck and n4d1TXm-RUk Question (Example)**

Which of the following industry or industries best describe the business of the startup in video 1?

- ○ Consumption Goods
- ○ Health Care
- ○ Information Technology
- ○ Consumer Services
- ○ Industrials

Which of the following industry or industries best describe the business of the startup in video 2?

- ○ Consumption Goods
- ○ Health Care
- ○ Information Technology
- ○ Consumer Services
- ○ Industrials

Which video is more positive in terms of **overall positivity**?

| | Video 1 | Video 2 |
|---|---|---|
| Overall Positivity | ○ | ○ |

Which video is more positive in terms of **visual positivity**?

| | Video 1 | Video 2 |
|---|---|---|
| Visual Positivity | ○ | ○ |

Which video is more positive in terms of **vocal positivity**?

| | Video 1 | Video 2 |
|---|---|---|
| Vocal Positivity | ○ | ○ |

Which video is more positive in terms of **verbal positivity**?

| | Video 1 | Video 2 |
|---|---|---|
| Verbal Positivity | ○ | ○ |

**Questions on Basic Information**

What is your year of birth? (e.g., 1990)

Choose one or more races that you consider yourself to be:

- ☐ White
- ☐ Asian
- ☐ Black or African American
- ☐ Hispanic or Latino
- ☐ Other

What is your gender?

- ○ Male
- ○ Female
- ○ Other

What is the highest level of school you have completed or the highest degree you have received?

- ○ Less than High School
- ○ High School
- ○ College
- ○ Graduate or Professional (JD, MD)

### Ending

This is the end of the survey. Thank you for your valuable time.

To obtain your payment, please input your unique ID below to MTurk.

Here is your unique ID: ${e://Field/Random%20ID}. Copy this value to paste into MTurk.

When you have copied this ID, please click the Submit button to submit your answers.

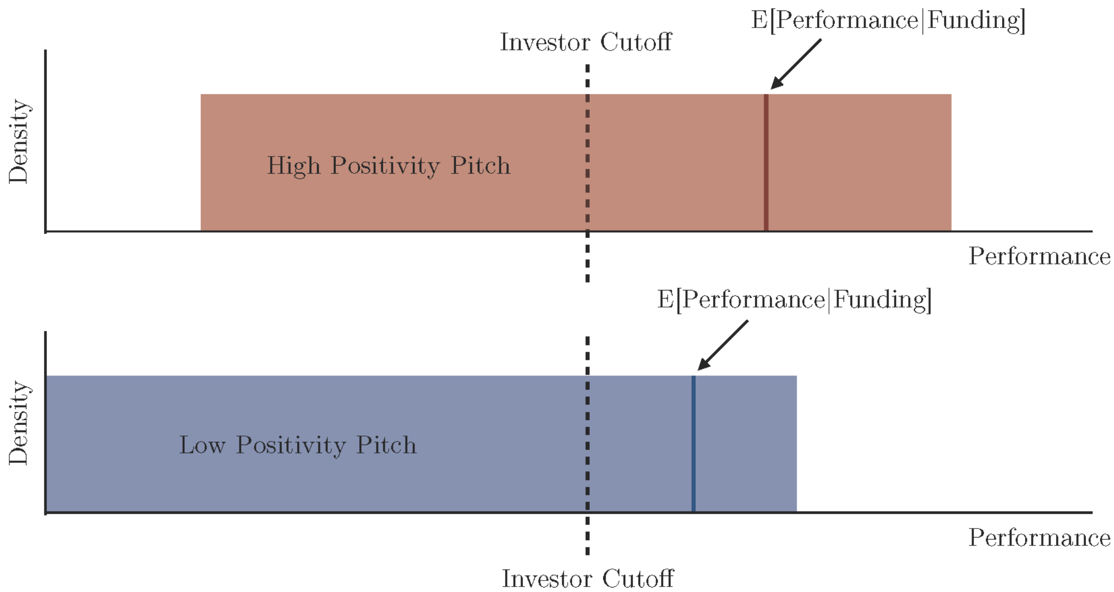
# E. Appendix: Performance Analysis and Sources of Bias

This appendix presents a simple conceptual framework, visualized in Figure A.4, to illustrate how pitch deliveries could introduce investment bias that then leads to poorer startup performance. Panel (a), presenting the no-bias scenario, shows hypothetical performance/quality distributions for startups that an investor may be considering funding. Separate overlapping distributions are assumed for startups with high- versus low-positivity pitches. The distributions shown are identical, except that the high-positivity distribution is shifted to the right of the low-positivity distribution. In other words, the high-positivity teams first-order stochastically dominates the low-positivity distribution. We assume the investor funds startups according to a simple cutoff rule, offering funding to all startups above a certain threshold. Since the investor is unbiased, he or she applies the same cutoff rule to all startups, regardless of the pitch positivity. In this case, because the high-positivity distribution first-order stochastically dominates the low-positivity distribution, the investor will invest in startups with high-positivity pitches with greater probability. In addition, expected performance, conditional on funding, will be higher for high-positivity startups.

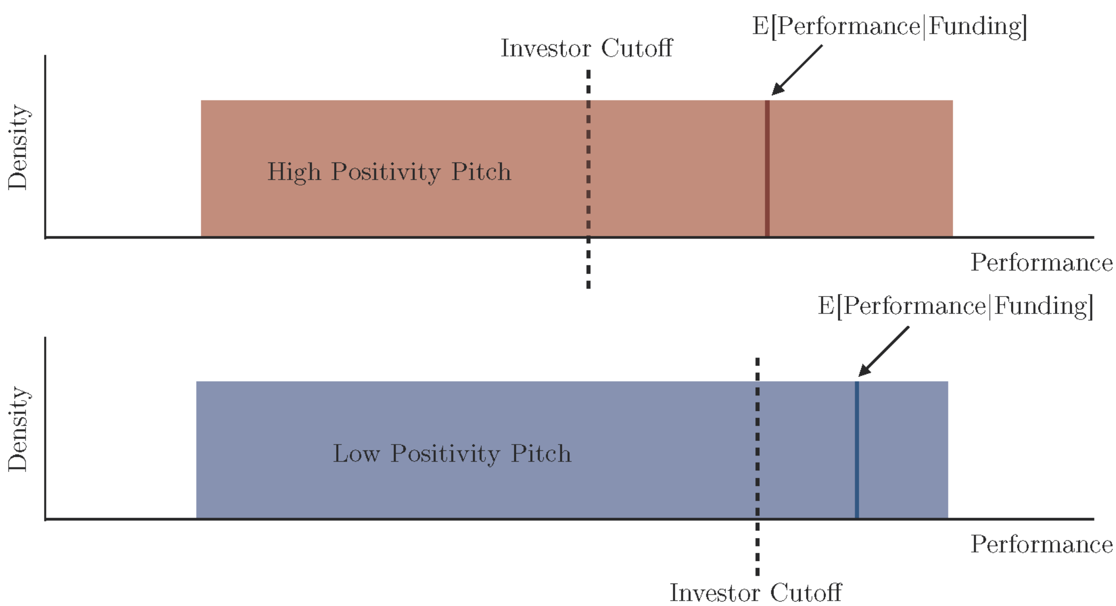
In contrast, if investors are biased, either due to a taste-based channel or inaccurate beliefs, it is possible that high-positivity startups may underperform. Figure A.4 Panel (b) illustrates taste-based bias. In the example, the performance distributions of high- and low-positivity teams are assumed to be the same. The investor continues to derive utility from startup performance. But she or he now also derives disutility from investing in startups with low positivity pitches—as a result, the investor sets a higher cutoff for them. With a taste-based channel, the investor will again fund founders with more positive pitches with greater probability. However, now expected performance, conditional on funding, will be lower for these investments. Figure A.4 Panel (c) illustrates the case of inaccurate beliefs. Inaccurate beliefs imply a gap between the investor's perceived performance distribution for low-positivity (or high-positivity) startups and the true performance distribution. In the example shown, the investor acts exactly like an investor with no bias according to the investor's *perceived* performance distribution. Inaccurate beliefs can also lead investors to fund founders of high-positivity with greater probability while having lower (true) expected performance for those investments.

**Figure A.4. Startup Performance Under Different Investment Models**

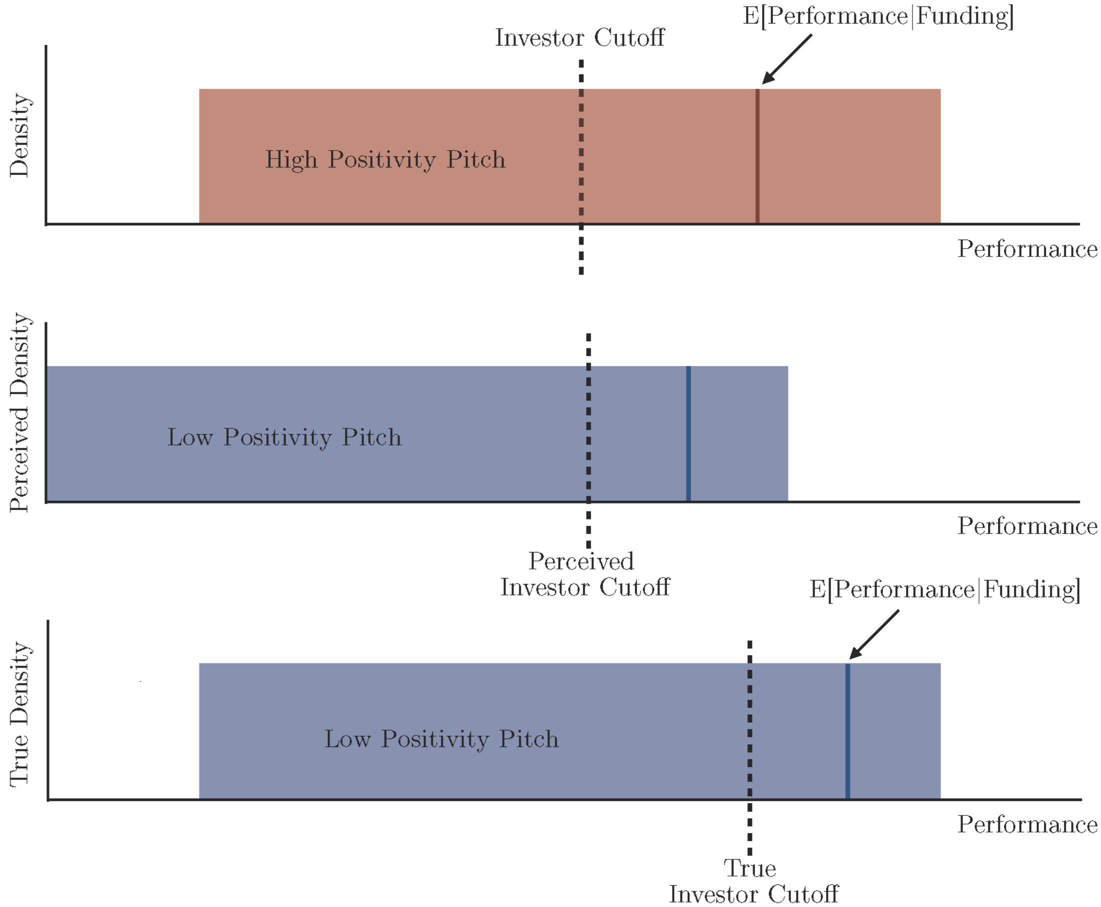
**(a)** No Bias




**(b)** Taste-Based Bias



**(c)** Inaccurate Beliefs




*Notes.* These figures present hypothetical startup performance distributions combined with investor decision rules. Panel (a) considers the situation where the investors have no bias and startups with low-positivity pitches underperform high-positivity startups. Investors use the same performance cutoff rule (the vertical dashed line) and the solid vertical lines represent the expected performance conditional on the funding decision. Panel (b) considers the situation where investors exhibit taste-based bias and founders of both high- and low-positivity have the same performance distribution. The taste-based bias leads investors to have a higher cutoff rule (the vertical dashed line) for low-positivity startups. This, in turn, leads to higher performance outcomes conditional on funding. Panel (c) presents the situation where investors have inaccurate beliefs about startups with different pitch features. The low-positivity startups' distribution is shifted to the left because of the miscalibration, which has the effect of increasing the expected performance conditional on funding.

# F. Appendix Figures and Tables

## Table A.10. Features in Pitch Delivery and Investment Decisions: MSFT Azure

| Dependent Var: I(*Invested*) | Logit without Controls | | | Logit with Startup/Team Controls | | |
|---|---|---|---|---|---|---|
| | Marginal Effect | S.E. | Pseudo $R^2$ | Marginal Effect | S.E. | Pseudo $R^2$ |
| Pitch Factor | 0.028*** | (0.007) | 0.191 | 0.025*** | (0.007) | 0.251 |
| *Visual (Facial)* | | | | | | |
| Visual-Positive | 0.012** | (0.006) | 0.176 | 0.012* | (0.007) | 0.239 |
| Visual-Negative | −0.013* | (0.007) | 0.176 | −0.012 | (0.008) | 0.253 |
| Visual-Beauty | 0.015** | (0.006) | 0.178 | 0.015** | (0.007) | 0.242 |
| *Vocal (Audio)* | | | | | | |
| Vocal-Positive | 0.009** | (0.005) | 0.174 | 0.011* | (0.006) | 0.239 |
| Vocal-Negative | −0.045*** | (0.016) | 0.183 | −0.047*** | (0.017) | 0.248 |
| Vocal-Arousal | 0.023*** | (0.009) | 0.184 | 0.019** | (0.008) | 0.245 |
| Vocal-Valence | 0.023*** | (0.006) | 0.185 | 0.020*** | (0.007) | 0.246 |
| *Verbal (Text)* | | | | | | |
| Verbal-Positive | −0.010 | (0.009) | 0.174 | −0.011 | (0.009) | 0.239 |
| Verbal-Negative | −0.026*** | (0.007) | 0.186 | −0.022*** | (0.008) | 0.246 |
| Verbal-Warmth | 0.026*** | (0.008) | 0.190 | 0.028*** | (0.008) | 0.256 |
| Verbal-Ability | −0.049*** | (0.009) | 0.243 | −0.043*** | (0.007) | 0.298 |

*Notes.* Logit regressions, marginal effect, $N = 1,139$. The analysis is obtained using the following model:

$$I(Invested) = \alpha + \beta \cdot X + \delta_{FE} + \varepsilon.$$

I(*Invested*) takes a value of one if the startup team was chosen by the accelerator, and zero otherwise. All pitch feature variables are standardized into a zero-mean variable with a standard deviation of one. Visual variables are constructed by Microsoft Azure APIs. Vocal and verbal variables are identical to those in Table 3. Pitch Factor is constructed by the same method as in Table 3. All regressions include Accelerator FE. Control variables include founders' education background (whether they have a Master's or a PhD degree, whether they attended an elite university, defined as the U.S. News & World Report's Top 10), founders' prior work experience (whether they have prior entrepreneurship experience, whether they ever held a senior position in prior employment), team size, and video resolution. Standard errors clustered at the accelerator-year level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

**Table A.11. Features in Pitches and Investment Decisions: Robustness Checks**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Dependent Var: I(*Invested*) | | | |
| Pitch-Factor | 0.028*** | 0.026** | 0.016*** | 0.027*** |
| | (0.010) | (0.010) | (0.006) | (0.007) |
| Observations | 1,139 | 1,139 | 1,139 | 1,139 |
| Specification | OLS | OLS | Logit | Logit |
| $R^2$/Pseudo $R^2$ | 0.151 | 0.181 | 0.402 | 0.261 |
| Accelerator FE | Y | Y | | Y |
| Startup/Team Controls | | Y | Y | Y |
| Accelerator-Year FE | | | Y | |
| Industry FE | | | | Y |

*Notes.* Logit regressions, marginal effect. The analysis is obtained using the following model:

$$I(Invested) = \alpha + \beta \cdot X + \delta_{FE} + \varepsilon.$$

I(*Invested*) takes a value of one if the startup team was chosen by the accelerator, and zero otherwise. All pitch feature variables are standardized into a zero-mean variable with a standard deviation of one. All variables are identical to those in Table 3. Control variables include founders' education background (whether they have a Master's or a PhD degree, whether they attended an elite university, defined as the U.S. News & World Report's Top 10), founders' prior work experience (whether they have prior entrepreneurship experience, whether they ever held a senior position in prior employment), team size, and video resolution. Standard errors clustered at the accelerator-year level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

**Table A.12. Gender Breakdown by Industry**

| | Men-Only | Women-Only | Mixed-Gender |
|---|---|---|---|
| Communication Service | 4.83 | 7.10 | 4.81 |
| Consumer Discretionary | 20.57 | 21.94 | 15.19 |
| Consumer Staples | 2.50 | 6.13 | 2.59 |
| Energy | 0.36 | 0.65 | 0.00 |
| Financials | 5.19 | 5.16 | 4.07 |
| Health Care | 6.62 | 8.06 | 10.00 |
| Industrials | 7.69 | 8.39 | 9.63 |
| Information Technology | 48.12 | 37.42 | 50.00 |
| Materials | 0.18 | 0.65 | 0.00 |
| Real Estate | 1.97 | 0.97 | 1.48 |
| Unclear | 1.97 | 3.55 | 2.22 |
| Total Observation | 559 | 310 | 270 |
| Total % | 100.00 | 100.00 | 100.00 |

*Notes:* This table provides industry (GICS) distributions of collected videos across different team gender compositions.

**Table A.13. Oster Test of Investment Decisions With Content Controls**

| $R^2_{max} = \min(2.2R^2_c, 1)$ | | | | | | |
|---|---|---|---|---|---|---|
| $\delta = 1$ | | | $\delta = 2$ | | | $\delta$ s.t. $\beta_{adj} = 0$ |
| $\beta_{adj}$ | Identified Set | Reject Null? | $\beta_{adj}$ | Identified Set | Reject Null? | |
| 0.022 | [0.022,0.023] | Y | 0.020 | [0.020,0.023] | Y | 10.31 |

| $R^2_{max} = \min(3R^2_c, 1)$ | | | | | | |
|---|---|---|---|---|---|---|
| $\delta = 1$ | | | $\delta = 2$ | | | $\delta$ s.t. $\beta_{adj} = 0$ |
| $\beta_{adj}$ | Identified Set | Reject Null? | $\beta_{adj}$ | Identified Set | Reject Null? | |
| 0.021 | [0.021,0.023] | Y | 0.018 | [0.018,0.023] | Y | 6.252 |

| $R^2_{max} = 1$ | | | | | | |
|---|---|---|---|---|---|---|
| $\delta = 1$ | | | $\delta = 2$ | | | $\delta$ s.t. $\beta_{adj} = 0$ |
| $\beta_{adj}$ | Identified Set | Reject Null? | $\beta_{adj}$ | Identified Set | Reject Null? | |
| 0.018 | [0.018,0.023] | Y | 0.012 | [0.012,0.023] | Y | 3.311 |

*Notes.* This table tests the role of omitted and unobservable control variables in explaining the relation between the Pitch Factor and the venture investment decision, using the test designed in Oster (2019). To implement, we estimate a linear model of

$$I(Invested) = \alpha + \beta \cdot X + \delta_{FE} + \varepsilon,$$

first with content control variables only through which we obtain $\beta_u$ and $R^2_u$, and then with the added startup/team control variable, through which we obtain $\beta_c$ and $R^2_c$. The set of startup/team control variables is identical to that in Table 3.

For any given test parameter combination $\delta$ and $R^2_{max}$, Oster (2019) defines the bias-adjusted coefficient, denoted as $\beta_{adj}$ that is determined by parameters $\delta$ and $R^2_{max}$, to be closely approximated by (strictly equal to when $\delta = 1$)

$$\beta_{adj} \approx \beta_c - \delta \frac{(\beta_u - \beta_c)(R^2_{max} - R^2_c)}{R^2_c - R^2_u}.$$

With this adjusted coefficient $\beta_{adj}$, the recommended identified set is the interval between $\beta_{adj}$ and $\beta_c$. In the table, we report the adjusted $\beta$ and identified set for different combinations of parameters, and we also report whether the identified set rejects the null of $\beta = 0$ and the $\delta$ value to make certain $R^2_{max}$ reach zero.

# G. Experiment: Summary Statistics and Sample

**Table A.13. Summary Statistics of Subjects in Experiments**

| | N | Mean | STD | 25% | 50% | 75% |
|---|---|---|---|---|---|---|
| Age | 102 | 28.35 | 3.31 | 25.00 | 28.00 | 31.00 |
| Man | 102 | 0.60 | 0.49 | 0.00 | 1.00 | 1.00 |
| Woman | 102 | 0.40 | 0.49 | 0.00 | 0.00 | 1.00 |
| White | 102 | 0.45 | 0.50 | 0.00 | 0.00 | 1.00 |
| Black or African American | 102 | 0.03 | 0.17 | 0.00 | 0.00 | 0.00 |
| Asian | 102 | 0.42 | 0.50 | 0.00 | 0.00 | 1.00 |
| Hispanic or Latino | 102 | 0.05 | 0.22 | 0.00 | 0.00 | 0.00 |
| Mixed Race | 102 | 0.03 | 0.17 | 0.00 | 0.00 | 0.00 |
| Other Race | 102 | 0.02 | 0.14 | 0.00 | 0.00 | 0.00 |

*Notes.* This table provides descriptive statistics of demographic information of subjects in our experiment sample. The demographic information is collected during the experiment. For each variable, we report the number of observations, mean, standard deviation, and 25th, 50th, and 75th percentiles.

**Table A.14. Summary Statistics of Unstandardized Features in Experiments**

| | N | Mean | STD | 25% | 50% | 75% |
|---|---|---|---|---|---|---|
| *Visual (Facial)* | | | | | | |
| Visual-Positive | 62 | 0.18 | 0.17 | 0.06 | 0.13 | 0.30 |
| Visual-Negative | 62 | 0.17 | 0.18 | 0.05 | 0.10 | 0.24 |
| Visual-Beauty | 62 | 0.59 | 0.09 | 0.52 | 0.60 | 0.64 |
| *Vocal (Audio)* | | | | | | |
| Vocal-Positive | 62 | 0.08 | 0.04 | 0.04 | 0.07 | 0.09 |
| Vocal-Negative | 62 | 0.02 | 0.01 | 0.01 | 0.01 | 0.02 |
| Vocal-Arousal | 62 | 0.35 | 0.35 | 0.09 | 0.23 | 0.67 |
| Vocal-Valence | 62 | 0.28 | 0.26 | 0.08 | 0.22 | 0.49 |
| *Verbal (Text)* | | | | | | |
| Verbal-Positive | 62 | 0.02 | 0.01 | 0.01 | 0.01 | 0.02 |
| Verbal-Negative | 62 | 0.01 | 0.01 | 0.00 | 0.01 | 0.02 |
| Verbal-Warmth | 62 | 0.02 | 0.02 | 0.01 | 0.02 | 0.02 |
| Verbal-Ability | 62 | 0.03 | 0.03 | 0.01 | 0.03 | 0.04 |

*Notes.* This table provides descriptive statistics of pitch features. For each variable, we report the number of observations, mean, standard deviation, and 25th, 50th, and 75th percentiles. Variables are categorized into vocal, video, and verbal.

## Table A.15. Summary Statistics of Video Pitches in Experiments

| | N | Mean | STD | 25% | 50% | 75% |
|---|---|---|---|---|---|---|
| Duration (second) | 62 | 61.76 | 4.88 | 58.00 | 61.00 | 66.00 |
| Video Size (MB) | 62 | 12.79 | 10.22 | 4.55 | 9.10 | 17.06 |
| Number of Words | 62 | 174.74 | 39.34 | 149.00 | 176.00 | 199.00 |
| Number of Sentences | 62 | 11.65 | 3.53 | 9.00 | 11.50 | 13.00 |
| Number of Views | 62 | 2,742.06 | 14,558.83 | 65.00 | 149.50 | 327.00 |
| Number of Likes | 62 | 3.03 | 7.53 | 0.00 | 0.00 | 2.00 |
| Number of Dislikes | 62 | 0.24 | 0.97 | 0.00 | 0.00 | 0.00 |

*Notes.* This table provides descriptive statistics of basic information of the pitch videos. For each variable, we report the number of observations, mean, standard deviation, and 25th, 50th, and 75th percentiles.

## Table A.16. Summary Statistics of Startups in Experiments (as of July 2019)

| | N | Mean | STD | 25% | 50% | 75% |
|---|---|---|---|---|---|---|
| Invested by Accelerator | 62 | 0.44 | 0.50 | 0.00 | 0.00 | 1.00 |
| Firm Age | 62 | 3.44 | 1.71 | 2.00 | 3.00 | 5.00 |
| Number of Employees | 32 | 26.56 | 70.81 | 5.00 | 5.00 | 30.00 |
| Startup Alive | 32 | 0.91 | 0.30 | 1.00 | 1.00 | 1.00 |
| Raised VC | 32 | 0.53 | 0.51 | 0.00 | 1.00 | 1.00 |
| Total Funding Amount ($000) | 32 | 12,685 | 47,022 | 0.00 | 148 | 2,700 |

*Notes.* This table provides descriptive statistics of characteristics of startups all measured as of July 2019 from Crunchbase and PitchBook. For each variable, we report the number of observations, mean, standard deviation, and 25th, 50th, and 75th percentiles.

**Table A.17. Summary Statistics of Teams in Experiments**

| | N | Mean | STD | 25% | 50% | 75% |
|---|---|---|---|---|---|---|
| Number of People | 62 | 2.10 | 1.20 | 1.00 | 2.00 | 3.00 |
| Single-Member | 62 | 0.34 | 0.48 | 0.00 | 0.00 | 1.00 |
| Multi-Member | 62 | 0.66 | 0.48 | 0.00 | 1.00 | 1.00 |
| Men-Only | 62 | 0.52 | 0.50 | 0.00 | 1.00 | 1.00 |
| Women-Only | 62 | 0.32 | 0.47 | 0.00 | 0.00 | 1.00 |
| Mixed Gender | 62 | 0.16 | 0.37 | 0.00 | 0.00 | 0.00 |
| Has LinkedIn | 62 | 0.73 | 0.45 | 0.00 | 1.00 | 1.00 |
| Prior Senior Position | 45 | 0.82 | 0.39 | 1.00 | 1.00 | 1.00 |
| Prior Startup Experience | 45 | 0.58 | 0.50 | 0.00 | 1.00 | 1.00 |
| Elite University | 45 | 0.13 | 0.34 | 0.00 | 0.00 | 0.00 |
| Master Degree | 45 | 0.33 | 0.48 | 0.00 | 0.00 | 1.00 |
| PhD Degree | 45 | 0.13 | 0.34 | 0.00 | 0.00 | 0.00 |

*Notes.* This table provides descriptive statistics of the startup teams. Team member background information is collected from LinkedIn. For each variable, we report the number of observations, mean, standard deviation, and 25th, 50th, and 75th percentiles.

**Table A.18. Summary Statistics of Beliefs and Investment Decisions in Experiments**

| | N | Mean | STD | 25% | 50% | 75% |
|---|---|---|---|---|---|---|
| *Belief* ($\mu$) | | | | | | |
| Baseline P($invested$) | 952 | 0.20 | 0.17 | 0.08 | 0.15 | 0.29 |
| Baseline P($alive\|invested$) | 952 | 0.25 | 0.15 | 0.12 | 0.20 | 0.32 |
| I($invested$) | 952 | 0.46 | 0.50 | 0.00 | 0.00 | 1.00 |
| P($alive\|invested$) | 952 | 0.31 | 0.23 | 0.14 | 0.26 | 0.45 |
| P($alive\|not\ invested$) | 952 | 0.17 | 0.18 | 0.05 | 0.10 | 0.24 |
| P($success\|invested$) | 952 | 0.13 | 0.18 | 0.02 | 0.05 | 0.17 |
| *Precision of Belief* ($\sigma$) | | | | | | |
| Baseline P($invested$) | 952 | 3.30 | 0.79 | 3.00 | 3.00 | 4.00 |
| Baseline P($alive\|invested$) | 952 | 3.24 | 0.69 | 3.00 | 3.00 | 4.00 |
| I($invested$) | 952 | 2.60 | 0.90 | 2.00 | 3.00 | 3.00 |
| P($alive\|invested$) | 952 | 2.74 | 0.85 | 2.00 | 3.00 | 3.00 |
| P($alive\|not\ invested$) | 952 | 2.74 | 0.86 | 2.00 | 3.00 | 3.00 |
| P($success\|invested$) | 952 | 2.73 | 0.88 | 2.00 | 3.00 | 3.00 |

*Notes.* This table provides descriptive statistics of beliefs and investment decisions elicited in the experiment. For each variable, we report the number of observations, mean, standard deviation, and 25th, 50th, and 75th percentiles.

Yale University

## Consent Form

Hi, this is a survey designed by the research team of Song Ma (Assistant Professor of Finance at Yale School of Management). We are conducting research to examine the relation between entrepreneurs' performance in video pitching and their outcomes in obtaining venture investment.

We are inviting you to participate in this study by completing this short survey. This survey will take you around 20 minutes. The results of the survey will be used for research purposes only. All of your responses will be held in confidence.

**This survey is also a required assignment of MGT 897 - Entrepreneurial Finance.** You will get a base point of 5 as long as you finished this survey. In addition to your base point, we will award you bonus credits. The bonus credit (up to 3 points) is determined by how well you did in the survey (e.g., you choose to invest in an entrepreneur team that later became more successful.)

Would you like to participate in the study?

- ○ Yes
- ○ No

## Basic Information Section

What is your Yale NetID?

What is your year of birth? (e.g., 1990)

Which program do you currently entroll at Yale University?

- Undergraduate
- Master at Yale SOM (e.g., MBA, EMBA, MAM, and MMS)
- PhD
- Other

Which year are you in the current program at Yale University?

- First year
- Second year
- Third year and above

Choose one or more races that you consider yourself to be:

- White
- Asian
- Black or African American
- Hispanic or Latino
- Other

What is your gender?

- Male
- Female

○ Other

Which of the following categories best describes your previous occupation? (Choose at least one and no more than four)

- ☐ Student
- ☐ Asset Management and Banking
- ☐ Consulting
- ☐ Education
- ☐ Energy/Healthcare/Manufacturing
- ☐ Entrepreneur
- ☐ Technology
- ☐ Venture Capital and Private Equity
- ☐ No Full-time Work Experience
- ☐ Other

**Benchmark Belief Section**

**On average**, **what percentage** of startups do you think can successfully raise Series A financing from VC conditional on trying?

| | 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Percentage of Obtaining Fundings | | | | | | | | | | | |

How confident are you with your answers to the question about the probability of obtaining the investment that your were just asked?

○ Extremely confident
○ Very confident
○ Somewhat confident
○ Not very confident
○ Not at all confident

If a startup has already been invested by a venture capital, what do you think is the **average** successful rate of a startup to survive in the following three years?

| | 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Probability of Surviving | | | | | | | | | | | |

How confident are you with your answers to the question about the surviving probability that your were just asked?

- Extremely confident
- Very confident
- Somewhat confident
- Not very confident
- Not at all confident

**Video Pitch Experiment Introduction**

Now, imagine that you are a venture investor. **You are going to decide whether to invest in a given startup after watching its one-minute video pitch.** If you decide to invest in this startup, the contract will be the same – you will invest $150K in this startup team for 7% share of the company.

In the following part of the survey, you are going to watch 10 video pitches and decide whether to invest in these startups.

***Note: The submission button for each page will appear only after the video is watched and all questions are answered. If the submission button does not***

***appear even after all questions are answered, please wait several seconds and do not reload the web page. (Reloading will only reset the your answers.)***

### Video Pitch lY3hoi1eizM (Example)

**These page timer metrics will not be displayed to the recipient.**

First Click: *0 seconds*

Last Click: *0 seconds*

Page Submit: *0 seconds*

Click Count: *0 clicks*


**Please watch the video. All survey questions are related to this video. (The submission button will appear after the video is played and questions are answered.)**

If you were an investor, are you willing to invest $150K in this startup team for 7% share of the company?

- Yes
- No

How confident are you with your answers to the question about the investment decision that your were just asked?

- Extremely confident
- Very confident
- Somewhat confident
- Not very confident
- Not at all confident

If this startup **was able to raise Series A financing from VC**, what is the probability that you think this startup will still be alive (including being acquired) three years later?

| | 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Probability of Surviving | | | | | | | | | | | |

How confident are you with your answers to the question about the surviving probability that your were just asked?

- Extremely confident
- Very confident
- Somewhat confident
- Not very confident
- Not at all confident

If this startup **was not chosen by a VC**, what is the probability that you think this startup will still be alive (including being acquired) three years later?

| | 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Probability of Surviving | | | | | | | | | | | |

How confident are you with your answers to the question about the surviving probability that your were just asked?

- Extremely confident
- Very confident
- Somewhat confident
- Not very confident
- Not at all confident

What is the probability that you think this startup will become a huge success (e.g., a Unicorn)?

| | 0 | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Probability of Huge Success | | | | | | | | | | | |

How confident are you with your answers to the question about the huge success probability that your were just asked?

- Extremely confident
- Very confident
- Somewhat confident

Not very confident

Not at all confident

What are the most important factors in your decision of whether to invest in **this startup**?

| | Extremely important | Very important | Somewhat important | Not very important | Not at all important |
|---|---|---|---|---|---|
| Team's pitching traits (e.g., facial expression, passionate voice, beauty) | | | | | |
| Team's general ability | | | | | |
| Team's general sociability | | | | | |
| Products, business model, industry, and market | | | | | |
| Team's previous industry experience | | | | | |
| Team's previous entrepreneurial experience | | | | | |
| Team's education background | | | | | |

**Ending**

This is the end of the survey. Thanks for your valuable time.

If you have any additional comments about this survey, please provide them below. (Optional)

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