

# SPILOVER EFFECTS OF VIRTUAL TOURS ON TOURISM IN CHINA DURING THE PANDEMIC AGE

Author & Presenter: Jiaqi (Tristan) Liu, Ruiqi (Selena) Ge

Supervisor: Professor Jiding Zhang

New York University Shanghai

06/21/2023



# Agenda

- **Introduction**
  - Methodology
  - Result - Math Modeling
  - Result - Data Analysis
  - Discussion
  - Conclusion

# 1. Introduction

Lena Belle – does the popularity of her videos make people more willing to go to Disney?

Yes! I really want to see her with my own eyes!

Maybe no... Video is enough as Lena Belle in reality has no difference with what I see in videos...

So... Does the spillover effect of Lena Belle influence the tourist number of Disney?



# 1. Introduction

Similarly, does the spillover effect of online videos influence people's desire of going to the destination?



上海纽约大学  
NYU SHANGHAI



# Agenda

- Introduction
- **Methodology**
- Result - Math Modeling
- Result - Data Analysis
- Discussion
- Conclusion

## 2. Methodology



Math modeling – Bayes Theorem

Data analysis – 6 cities, government reports & data collection, R

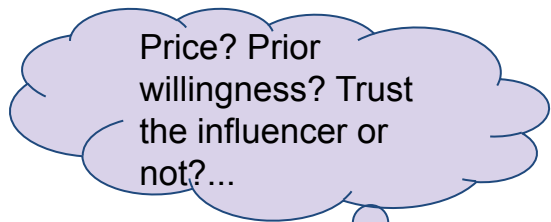




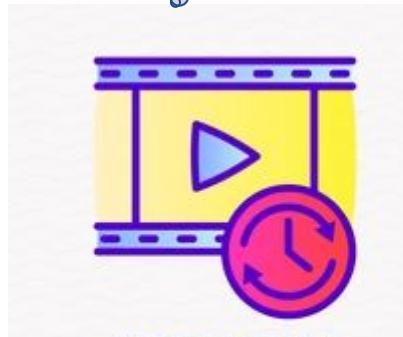
# Agenda

- Introduction
- Methodology
- **Result - Math Modeling**
  - Result - Data Analysis
  - Discussion
  - Conclusion

# 3.1 Hypothesis



**Viewer**



**Influencer**

(Probably)



**Affiliator of the influencer**

Assume that viewers will detect the affiliation level of the video.



# 3.1 Hypothesis



H1

People who have seen travel videos are **more likely** to make the decision to travel than those who have not.

H2

**[Precise level]** The initial level of precision of the influencer's prior belief on the destination( $y$ ) will **positively** impact the viewer's decision.

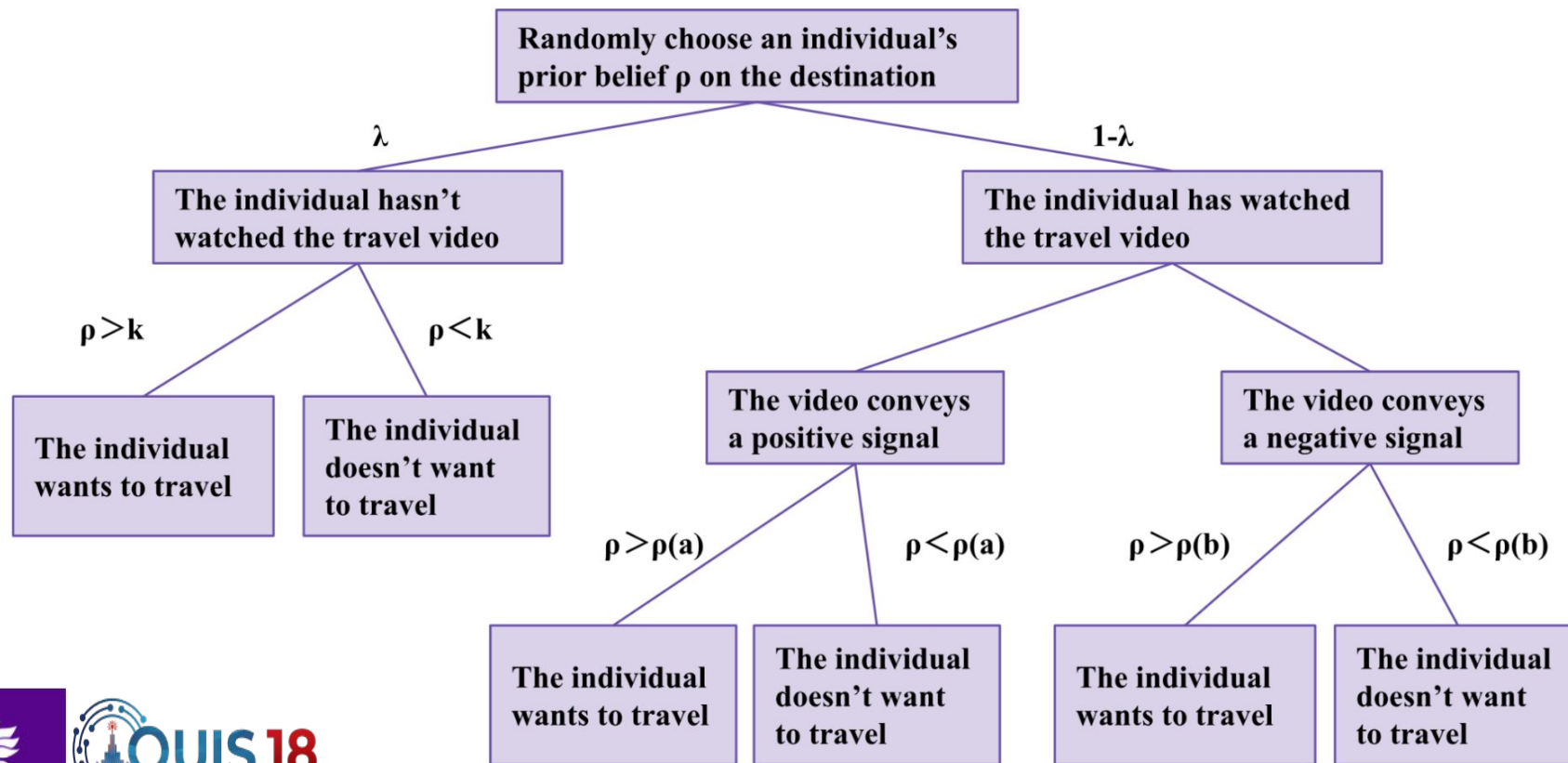
H3

**[Affiliation level]** The amount of positive distortion to the signal due to influencer's affiliation level( $a$ ) will **negatively** impact the viewer's decision.

H4

**[Utility level]** The ratio of price/utility of going to the destination justified by the viewer( $k$ ) will **negatively** impact the viewer's decision.

## 3.2 Tree diagram of math modeling



# 3.3 Derivation Process

(a) If the individual hasn't seen the travel video, he/she will travel to the destination iff  $\rho > p/v$ , i.e.  $\rho > k$

(b) If the individual has seen the travel video, the probability of wanting to travel to the destination becomes:  $P(T | G)$  and  $P(T | B)$

- >  $\lambda$ : The probability that an individual hasn't seen the travel video before
- >  $\rho$ : The probability that the individual wants to travel to the destination based on his/her prior belief.  $p \in [0, 1]$
- > T: The event that the individual wants to travel to the destination. On prior belief:  $P(T) = p$
- > F: The event that the individual doesn't want to travel to the destination. On prior belief:  $P(F) = 1 - p$
- > a: The amount of positive distortion to the signal due to the influencer's affiliation level.  $a \in [0, 1]$
- >  $\gamma$ : The initial level of precision of the influencer's prior belief on the destination. Assume that an independent influencer should have a similar prior belief with the individual, i.e.  $\gamma > 0.5$   
 $P(g | T, a) = \gamma + a(1 - \gamma)$ ,  $P(g | F, a) = a\gamma + (1 - \gamma)$
- > g: The event that the influencer justifies the destination worth a visit.
- > b: The event that the influencer doesn't justify the destination worth a visit.
- > G: The event that the video conveys a positive signal to the audience
- > B: The event that the video conveys a negative signal to the audience  
 Assume that  $P(G | g) = P(B | b) = 1$ , which means the audience will precisely receive the signal that the influencer wants to convey
- > p: The price of going to the destination
- > v: The utility of going to the destination justified by the individual
- > k: The ratio of  $p/v$

$$P(T | G) = \frac{P(G | T) * P(T)}{P(G | T) * P(T) + P(G | F) * P(F)} = \frac{[\gamma + a(1 - \gamma)] \rho}{[\gamma + a(1 - \gamma)] \rho + [1 - \gamma + a\gamma](1 - \rho)}$$

$$P(T | B) = \frac{P(B | T) * P(T)}{P(B | T) * P(T) + P(B | F) * P(F)} = \frac{(1 - \gamma) \rho}{(1 - \gamma) \rho + \gamma(1 - \rho)}$$

→ If the video conveys a positive signal, the individual will travel to the destination iff  $P(T | G) > k$ , i.e.  $\rho > \rho(a)$ , where

$$\rho(a) = \frac{k(1 - \gamma(1 - a))}{(1 - k)(\gamma + a(1 - \gamma)) + k(1 - \gamma(1 - a))}$$

→ If the video conveys a negative signal, the individual will travel to the destination iff  $P(T | B) > k$ , i.e.  $\rho > \rho(b)$ , where

$$\rho(b) = \frac{k\gamma}{(1 - k)(1 - \gamma) + k\gamma}$$



# 3.3 Derivation Process



→ If the video conveys a positive signal, the individual will travel to the destination iff  $P(T | G) > k$ , i.e.  $p > p(a)$ , where

$$p(a) = \frac{k(1-\gamma(1-a))}{(1-k)(\gamma+a(1-\gamma)) + k(1-\gamma(1-a))}$$

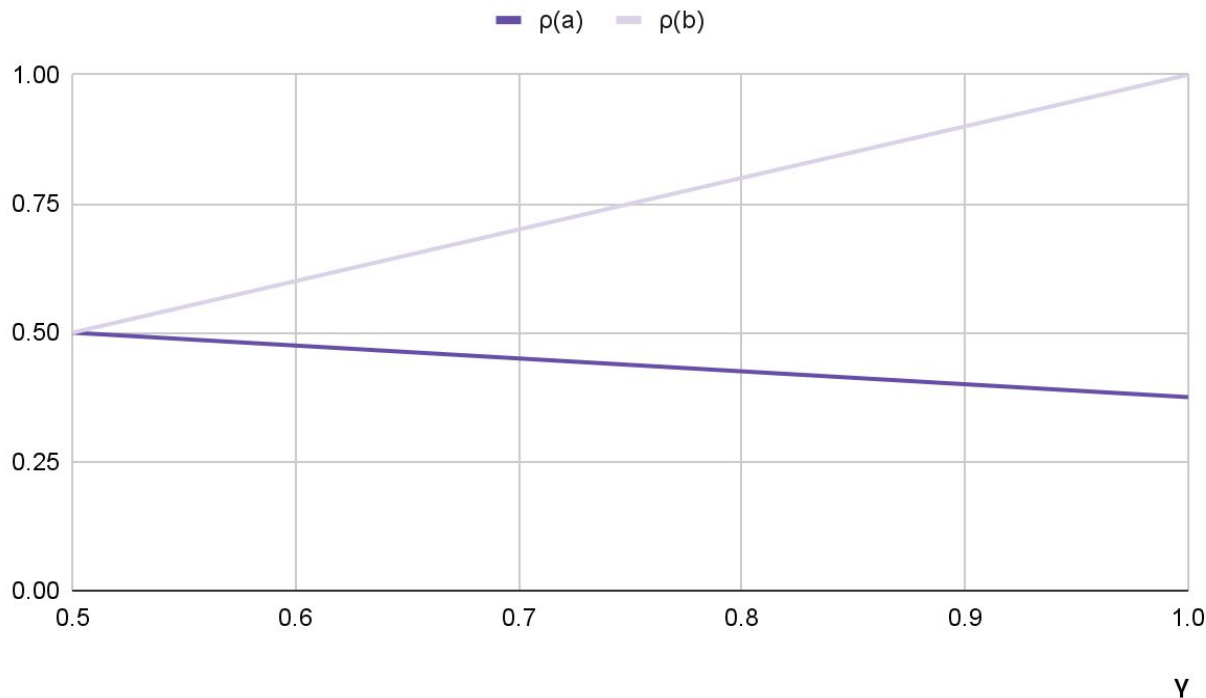


→ If the video conveys a negative signal, the individual will travel to the destination iff  $P(T | B) > k$ , i.e.  $p > p(b)$ , where

$$p(b) = \frac{k\gamma}{(1-k)(1-\gamma) + k\gamma}$$

## 3.4 Factors Correlation

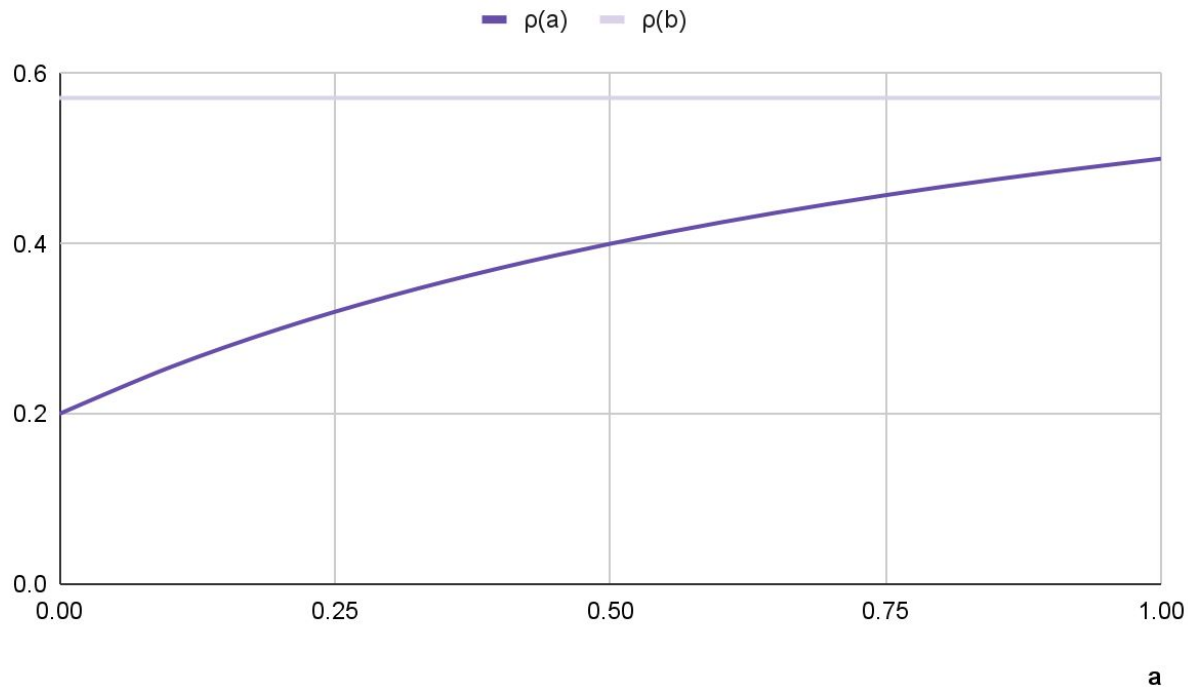
(1) Fix  $a = 0.6$ ,  $k = 0.5$ , observe the change in  $\gamma$ ,  $\gamma \in (0.5, 1]$



The initial level of precision of the influencer's prior belief on the destination( $\gamma$ )

## 3.4 Factors Correlation

(2) Fix  $k = 0.5$ ,  $\gamma = 0.8$ , observe the change in  $a$ ,  $a \in [0, 1]$

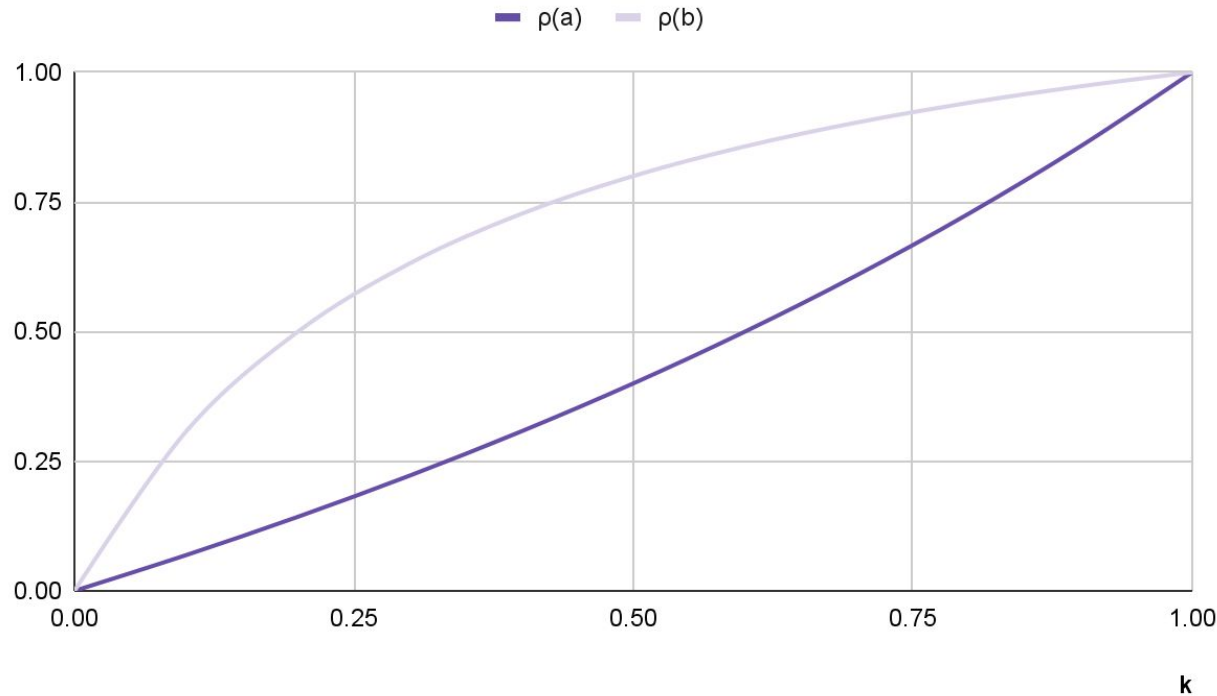


The amount of positive distortion to the signal due to influencer's affiliation level(**a**)



## 3.4 Factors Correlation

(3) Fix  $a = 0.5$ ,  $\gamma = 0.8$ , observe the change in  $k$ ,  $k \in [0, 1]$



The ratio of price/utility of going to the destination justified by the viewer( $k$ )



# Agenda

- Introduction
- Methodology
- Result - Math Modeling
- **Result - Data Analysis**
- Discussion
- Conclusion

# 4.1 Data

6 cities – Beijing, Shanghai, Guangzhou, Sanya, Hangzhou, Chongqing

2 types of datas – government reports about tourism numbers & data collected about number of videos uploaded and numbers of plays (about 12,000 pieces of data)

Time span – 2018 to 2022, quarterly

2020年1季度		
	游客接待量	增长%
游客总量 (万人次)	1781.0	-72.6
国内游客 (万人次)	1764.4	-72.6
外省来京游客 (万人次)	1113.0	-71.0
市民在京游客 (万人次)	651.4	-75.0
入境游客 (万人次)	16.6	-76.2
旅游收入		
	总收入 (亿元)	增长%
总收入 (亿元)	345.0	-72.1
国内旅游收入 (亿元)	328.7	-71.9
外省来京收入 (亿元)	316.7	-70.3
市民在京收入 (亿元)	12.0	-88.5
国际旅游外汇收入 (亿美元)	2.3	-75.7
国际旅游收入折合人民币 (亿元)	16.3	-74.9

注：游客总量=国内游客+入境游客

国内游客=外省（区、市）来京游客+市民在京游客

国内旅游收入=外省（区、市）来京收入+市民在京收入

国际旅游收入折合人民币=国际旅游外汇收入×当期汇率

旅游总收入=国内旅游收入+国际旅游收入折合人民币

2/1

北京	2018Q1	784099	113	62599000
北京	2018Q2	818137	77	82122000
北京	2018Q3	2063678	120	90290000
北京	2018Q4	1221162	126	75924000
北京	2019Q1	3408742	236	65103000
北京	2019Q2	3804924	199	94590000
北京	2019Q3	2703936	229	85053000
北京	2019Q4	3918724	217	77352000
北京	2020Q1	3089924	128	17810000
北京	2020Q2	533896	75	38453000
北京	2020Q3	2234863	91	57679000
北京	2020Q4	2312420	174	69923000
北京	2021Q1	11231191	83	52349000
北京	2021Q2	3687513	195	78394000
北京	2021Q3	2530995	234	67694000
北京	2021Q4	1247973	176	56691000
北京	2022Q1	1586471	127	52843000
北京	2022Q2	1905574	139	26821000
北京	2022Q3	3268618	241	66955000
北京	2022Q4	1260660	119	35689000



# 4.1 Data

Video platform – Bilibili (one of the most popular video platforms in China)

Run regressions on both datas – do the trend of data collected match the trend of government reports?



## 4.2 Regression Model

Regression model to analyze the correlation between the number of tourists and the number of videos uploaded as well as the number of plays quarterly:

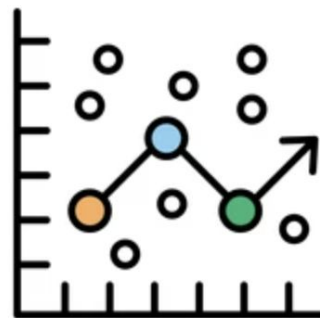
$$NumTourist = \beta_1 NumPlays + \beta_2 NumUploads + \alpha_i + \gamma_t + \eta AfterCOVID + \epsilon_{it}$$

For  $\alpha_i$  and  $\gamma_t$ , we use dummy variable as fixed effects:

$$\alpha_i = I(Beijing) + I(Hangzhou) + \dots + I(Sanya)$$

$$\gamma_t = I(2018Q1) + I(2018Q2) + \dots + I(2022Q4)$$

Then we ran the model in R.

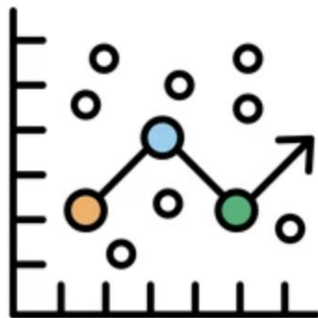


## 4.2 Regression Outcome

For nearly all quarters, the  $\alpha_i$ ,  $\gamma_t$ , and  $\eta$  are derived with a slightly positive number.

For  $\beta_1$  and  $\beta_2$ , numbers fluctuated at about 0.

.....why?







# Agenda

- Introduction
- Method
- Result - Math Modeling
- Result - Data Analysis
- **Discussion**
- Conclusion

# 5.1 Discussion of Math Modeling

1.  $\rho(b)$  dominates  $\rho(a)$ : People will always be more likely to make travel decisions after watching videos conveying positive signal than negative ones regardless of the three factors

1.1. Theoretical Proof

1.2. Numerical Proof

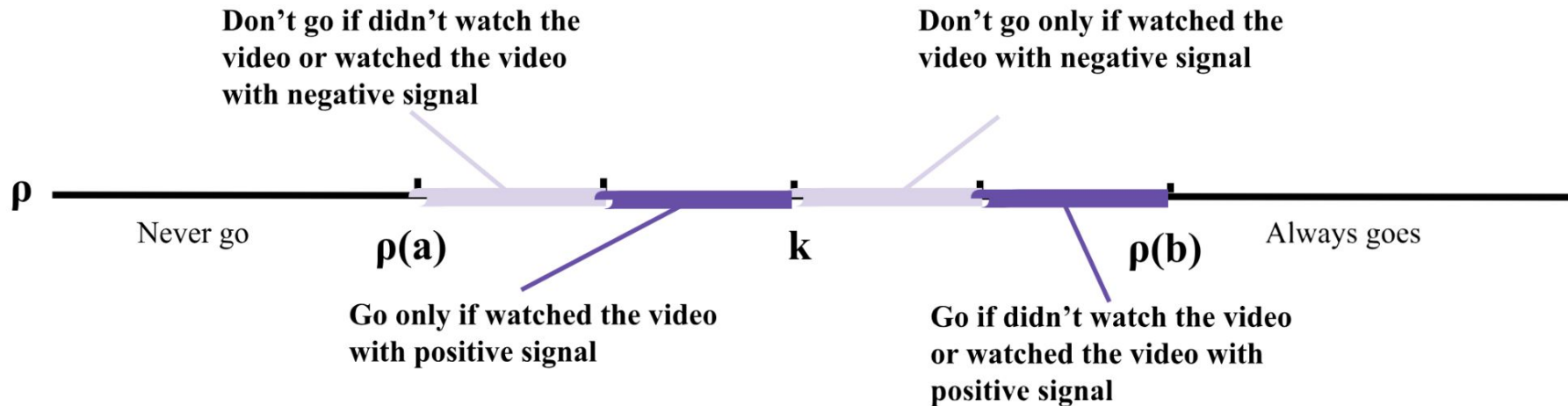
2.

Factors	Good Signal	Bad Signal
Precision Level ( $\gamma$ )	Depend on affiliation level. If $a$ is high, negatively correlated with viewer's decision; If $a$ is low, positively correlated.	Negatively correlated.
Affiliation Level ( $a$ )	Negatively correlated	\
Utility Level ( $k$ )	Negatively correlated	Negatively correlated



# 5.1 Discussion of Math Modeling

Assume that  $p$  is uniformly distributed, then:



## 5.2 Discussion of data analysis

Why the result not so significant?

- Other events need to be considered:  
Political reasons, big events ...

- Other online video platforms need to be considered:  
Online live videos, and online promotional sales...

- The time gap between people perceive the video and they go to travel need to be reconsidered:  
We set the time gap to be six months, but how to prove that?





# Agenda

- Introduction
- Methodology
- Result
- Discussion
- **Conclusion**

## 6. Conclusion

Theoretically, the ideal result of our hypothesis can be deduced from the mathematical model. With the impact of short videos conveying different sentiment signals, people will be segmented into different clusters with different willingness to travel, and most people will tend to have a higher travel desire in view of affiliation. However, the regression result doesn't have a clear result, which probably attributes to some other factors that can influence real-world tourism numbers, like Olympic Winter Games and others. We are now trying to find a better way to quantify more variables, and hoping to find more relevances.







# Thank you!