If You Don't Have Anything Nice to Say, Please Say Something: Increasing Honesty In Airbnb Reviews

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Trust and Reputation as the Backbone of Airbnb


airbnb
Sign Up
Log In
Help
List Your Space
WELCOME HOME
Rent unique places to stay from local hosts in 190 countries.
How It Works
Where do you want to go?
Check In
Check Out
1 Guest
Search
Explore the World
See where people are traveling, all around the world.


airbnb
San Francisco, CA, United States
Browse
Sign Up
Log In
Help
List Your Space
Search When I Move the Map
Angel Island State Park
Golden Gate National Recreation Area
Alcatraz Island
Treasure Island
Golden Gate
North Beach
Telegraph Hill
Presidio
Pacific Heights
Chinatown
Sea Cliff
Richmond District
Tenderloin
de Young Museum
AT&T Park
Haight-Ashbury
Golden Gate Park
Cole Valley
The Castro
Mission District
Dogpatch
Twin Peaks
Sunset District
Diamond Heights
Bernal Heights
Glen Park
Balboa Park
Hunters Poin
Lake Merced Park
Merced Heights
Outer Mission
Crocker-Amazon
Visitacion Valley
Candlestick P
Daly City
Colma
San Bruno Mountain State Park
Brisbane
Language and Currency
Dates
Check In
Check Out
1 Guest
Room Type
Entire Place
Private Room
Shared Room
Price Range
$10
$1000+
More Filters
1000+ Rentals · San Francis
$107
$69
Private Garden Artist Space
Entire home/apt · 118 reviews · Mission District, San Franc...
Perfectly located Castro
Private room · 226 reviews · The Castro, San Francisco

Reviews on Airbnb

212 Reviews ★★★★★

Summary				
	Accuracy	★★★★★	Location	★★★★★
	Communication	★★★★★	Check In	★★★★★
	Cleanliness	★★★★★	Value	★★★★★

Reviews From Hosts

Tod

As an experienced AirBnB host, Kepa was the perfect guest. From a logistical perspective, she communicated clearly about the details of her arrival and departure and asked good questions before arriving to ensure a good visit. We ended up chatting quite a bit -- I was happy to show her around the property as she had a great appreciation for my garden.

March 2012

Allison

Kepa is wonderful and super super easy. Airbnb called me directly to book the nights for her. I would recommend her as a guest to anyone. She's awesome.

March 2012

Reviews From Guests

Adrian

We had a wonderful time staying with Kepa. She made us very welcome and gave us lots of help with parking our hire car in the right place. Would highly recommend!

September 2014 — Potrero Hill Garden Suite

Cheryl

We enjoyed our stay at the cabana. Although it was only for one night and we didn't get a chance to meet Kepa, she made every effort to accommodate our needs. The cabana itself is charming, comfortable and private. We were also able to walk to dinner and didn't need to use our car at all during our stay. We'd definitely stay here again!

September 2014 — Potrero Hill Garden Cabana

Truncating the trust formation process

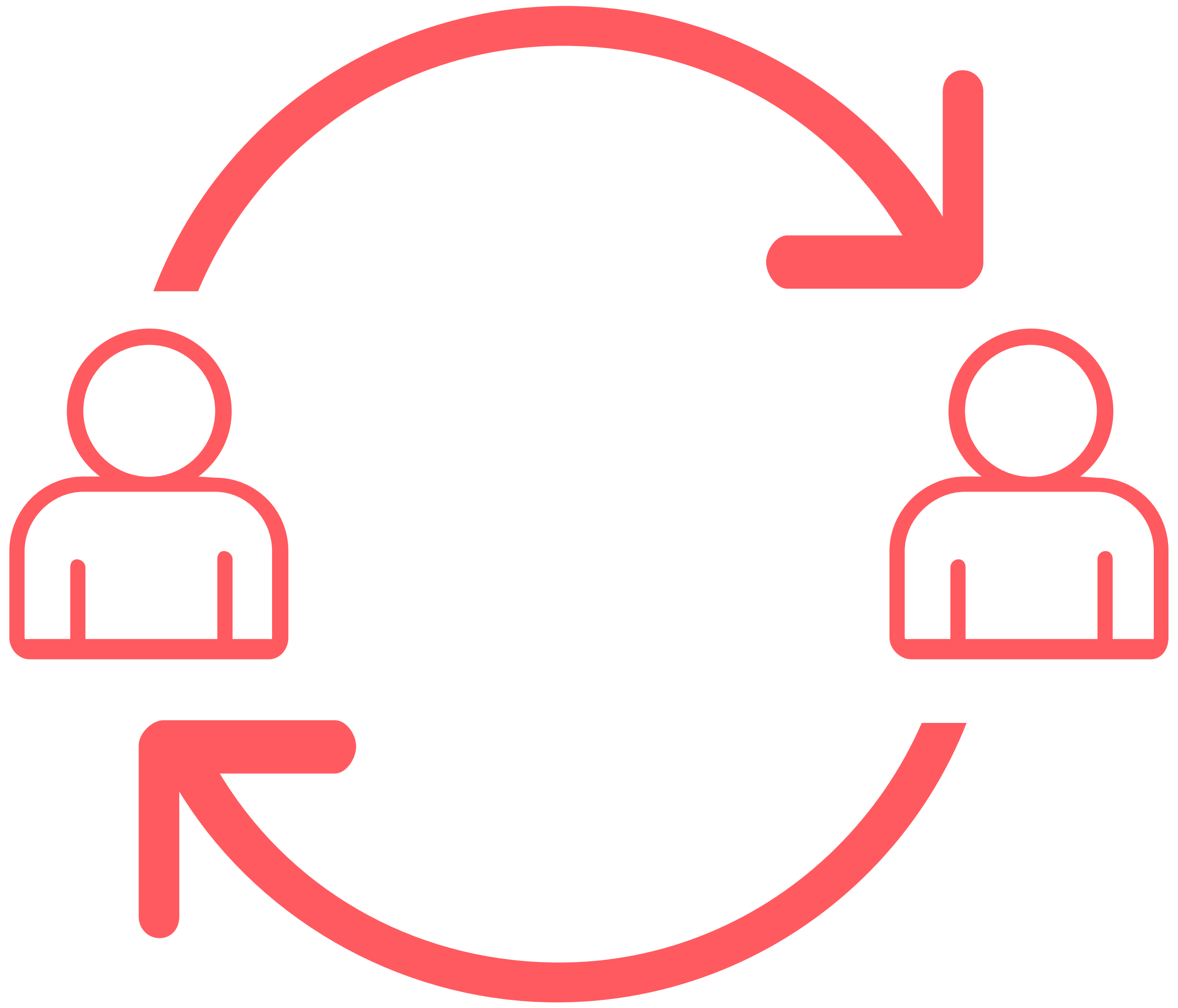
"Nice to meet you"

"You're welcome to stay at our place"

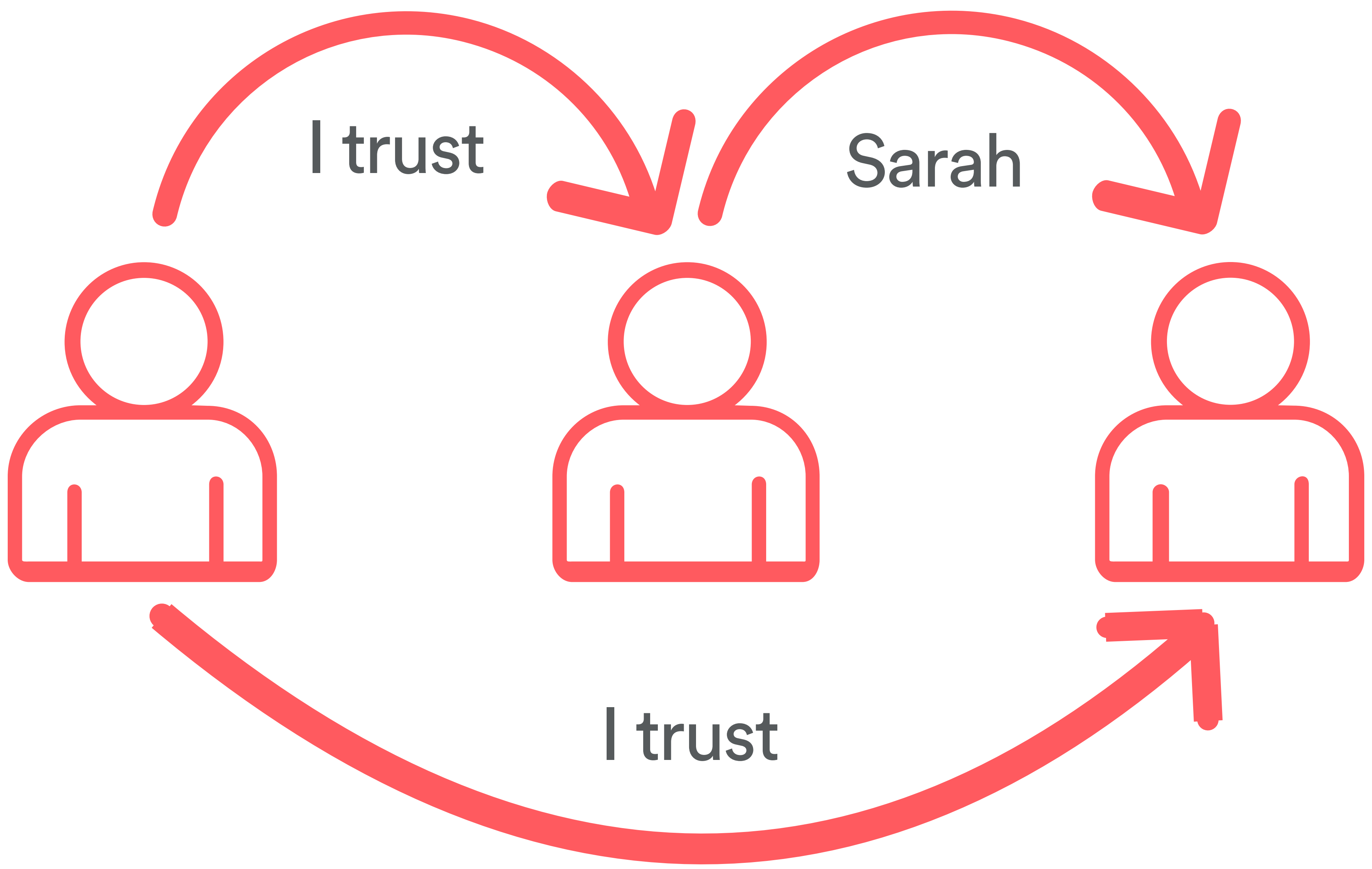
1 Year?

2 Years?

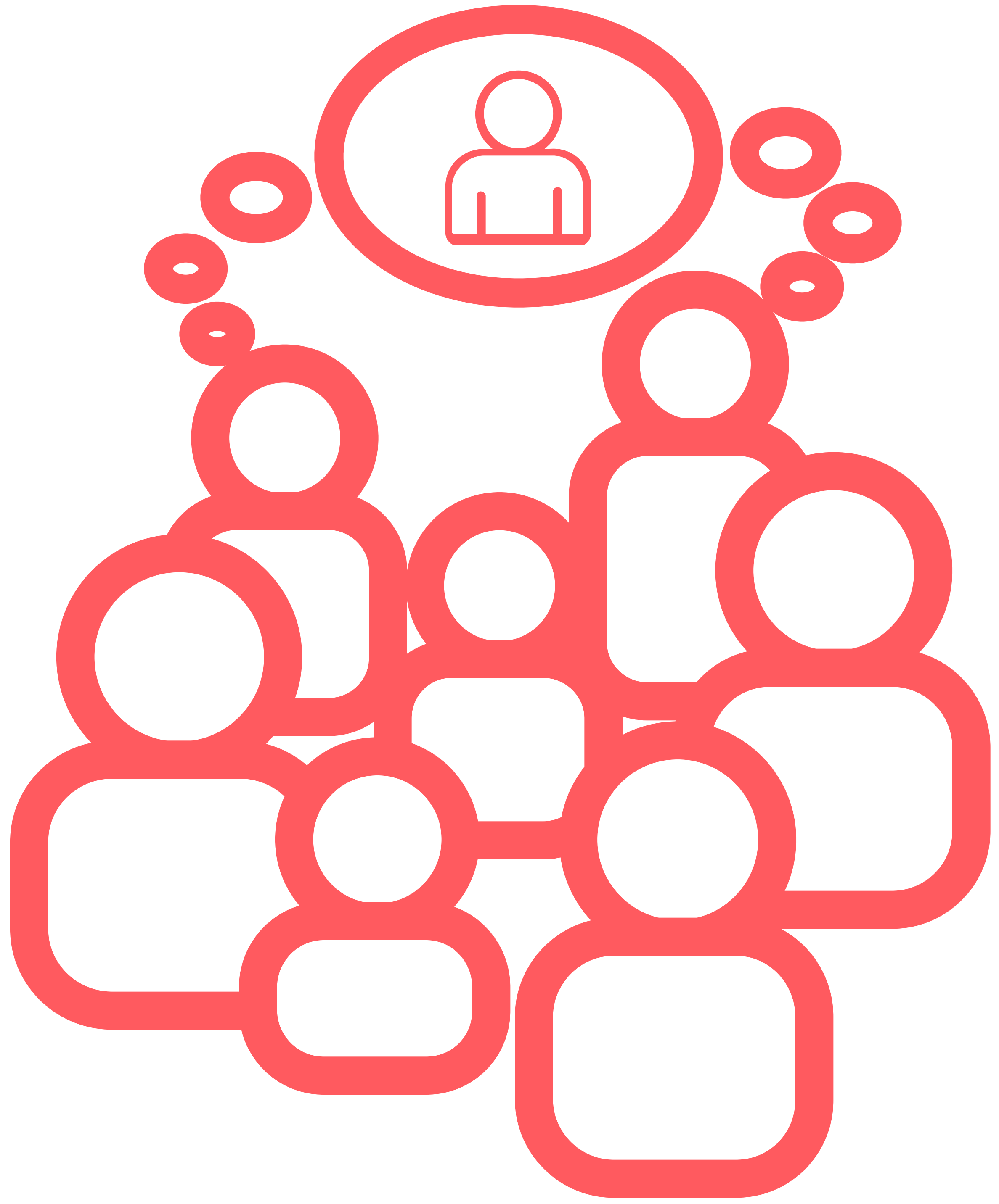
4 hours, max



“Trust”



“Transferred Trust”



“Reputation”

Functions of a Healthy Reputation System

- Healthy reputation systems reduce the need for brand
- They help new users to intuitively determine quality of inventory
- They help developers and data scientists develop features and programs

"That was Airbnb's real innovation — a platform of 'trust' — where everyone could not only see everyone else's identity but also rate them as good, bad or indifferent hosts or guests. This meant everyone using the system would pretty quickly develop a relevant 'reputation' visible to everyone else in the system."

Thomas Friedman

"And Now for a Bit of Good News...," The New York Times, July 19, 2014

"How Airbnb and Lyft Finally Got Americans to Trust Each Other"

WIRED

April, 2014

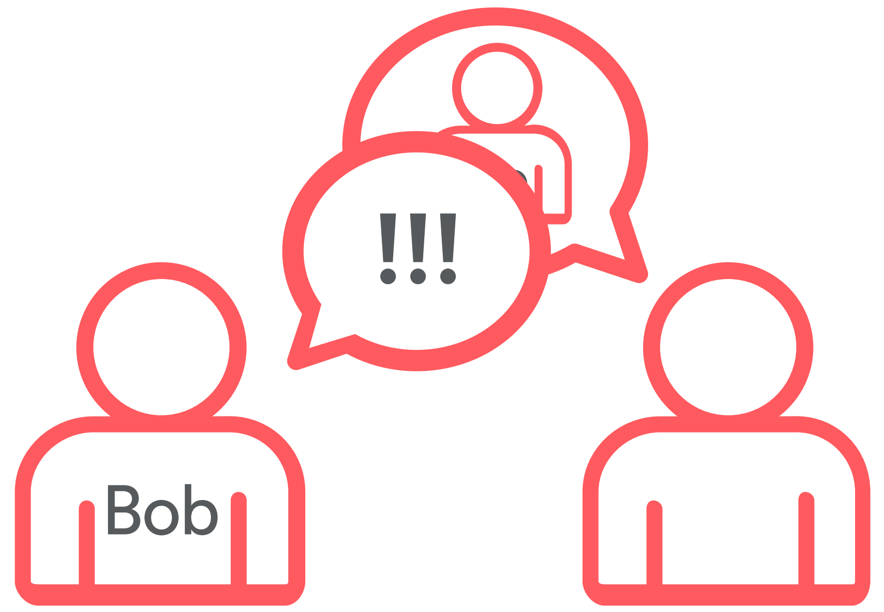
Why Honesty Matters: Garbage In, Garbage Out

The reputation system mechanics I’ve described thus far rely on accurate measures of quality in individual reviews. Otherwise, they don’t work well.

However...

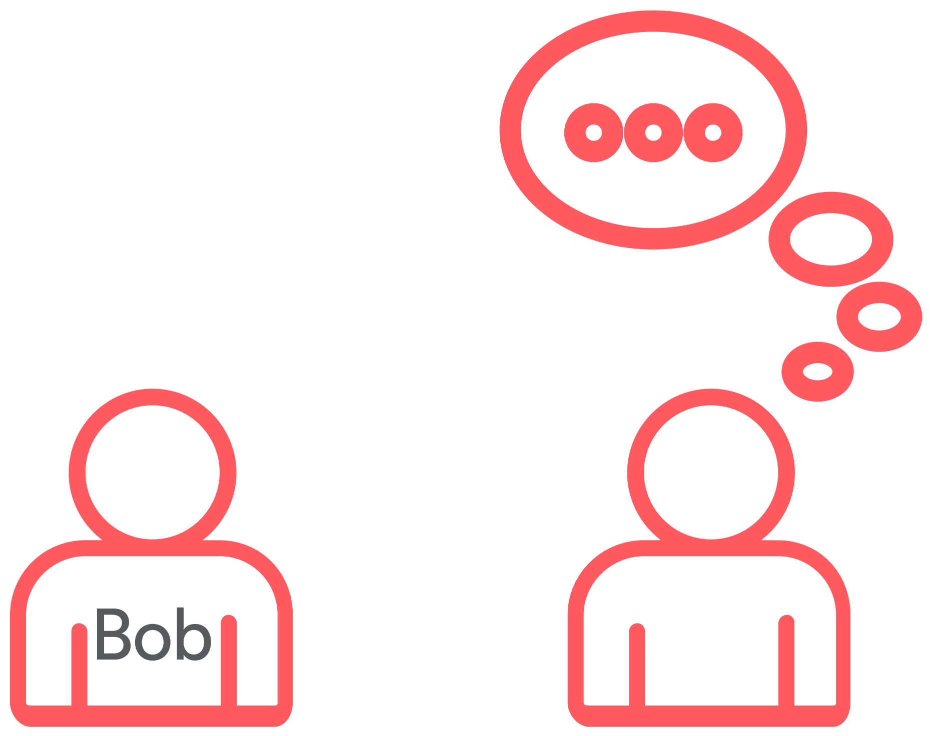
The ratings in most reputation systems are overly positive, and suffer from some amount of non-response bias

Potential Sources of Bias



Bias 1: Retaliation

Bias 2: Induced Reciprocity



Bias 3: Discomfort

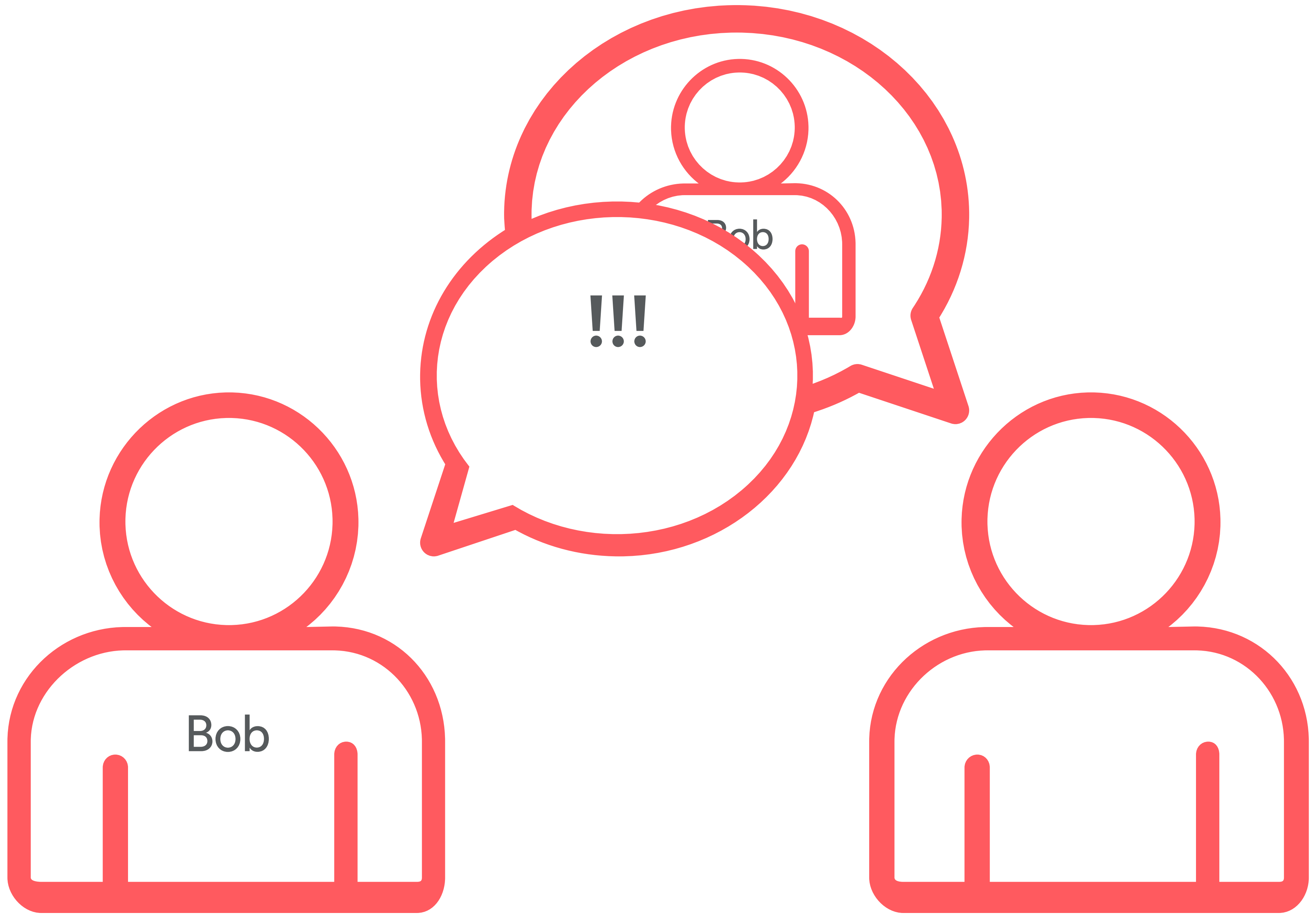
We identified this as an issue at Airbnb, and our data science team started thinking about ways to fix it.

Here’s What We’ve Done So Far

The Review Flow
(*pre*-July 2014)

Example: host submits first

Tackling Bias 1 & Bias 2



Simultaneous Reveal

Reviews Have Changed

Your host will only see your review once they have left you one, too, or when the review period ends (14 days after checkout). An honest review helps improve the experience for future travelers and the host. See our review guidelines.

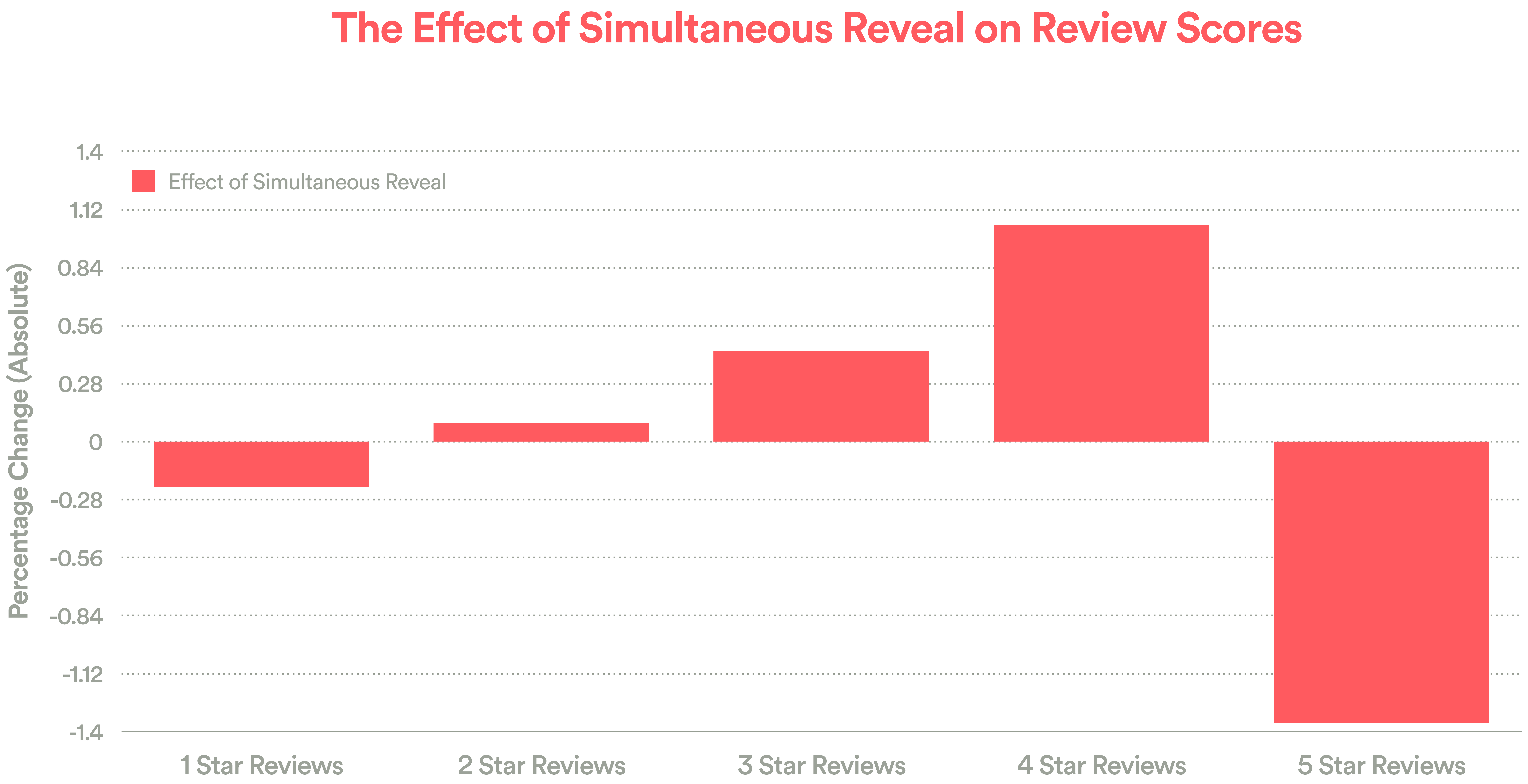
Get Started

Simultaneous Reveal Review Flow

Example: host submits first

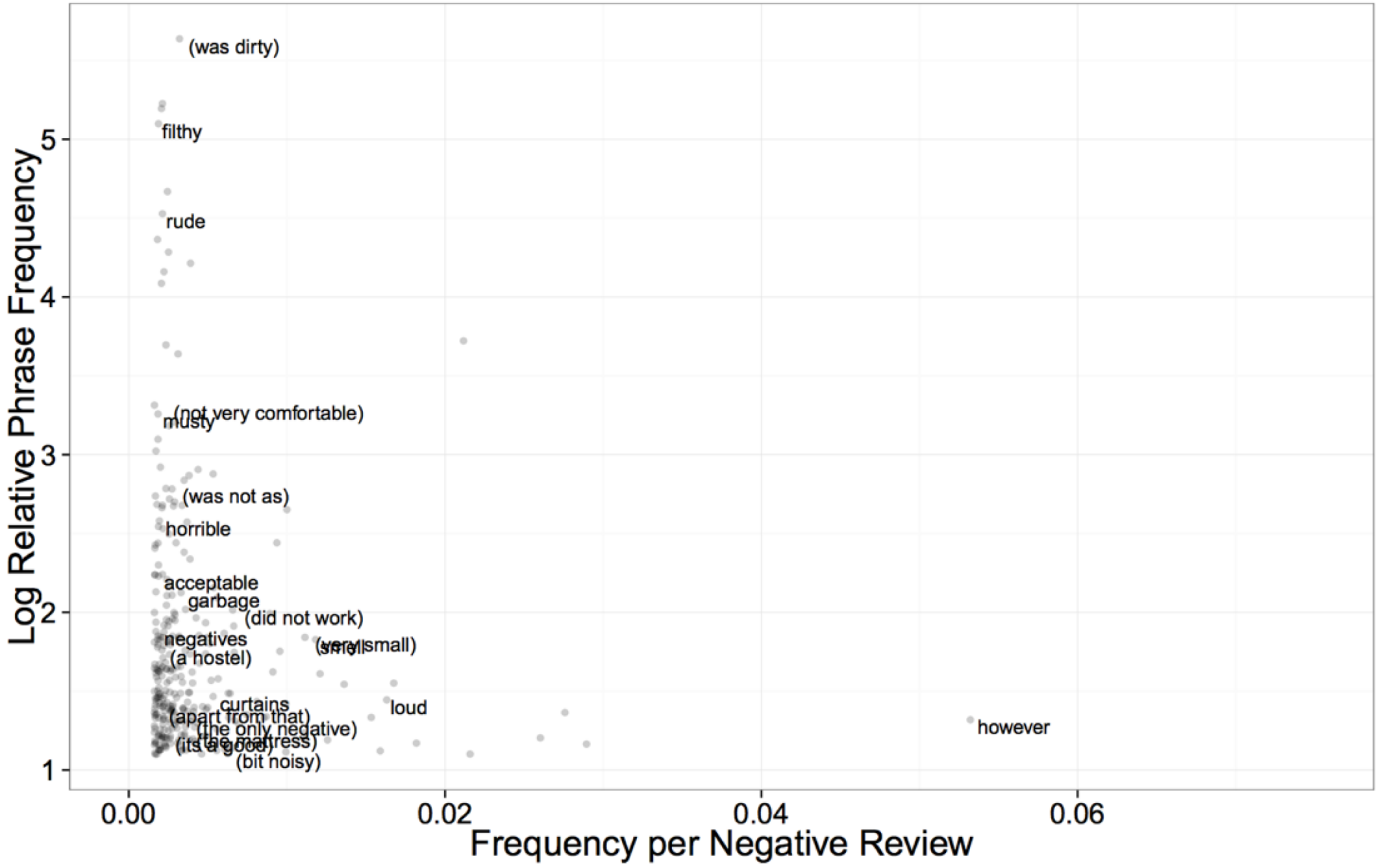
The Effect of Simultaneous Reveal on Review Rates

	Host Reviews Guest	Guest Reviews Host
Control	73%	65%
Simultaneous Reveal	79%	68%


The Effect of Simultaneous Reveal on Review Scores
Effect of Simultaneous Reveal
Percentage Change (Absolute)
1.4
1.12
0.84
0.56
0.28
0
-0.28
-0.56
-0.84
-1.12
-1.4
1 Star Reviews
2 Star Reviews
3 Star Reviews
4 Star Reviews
5 Star Reviews

Crude Measures of Sentiment in Review Text

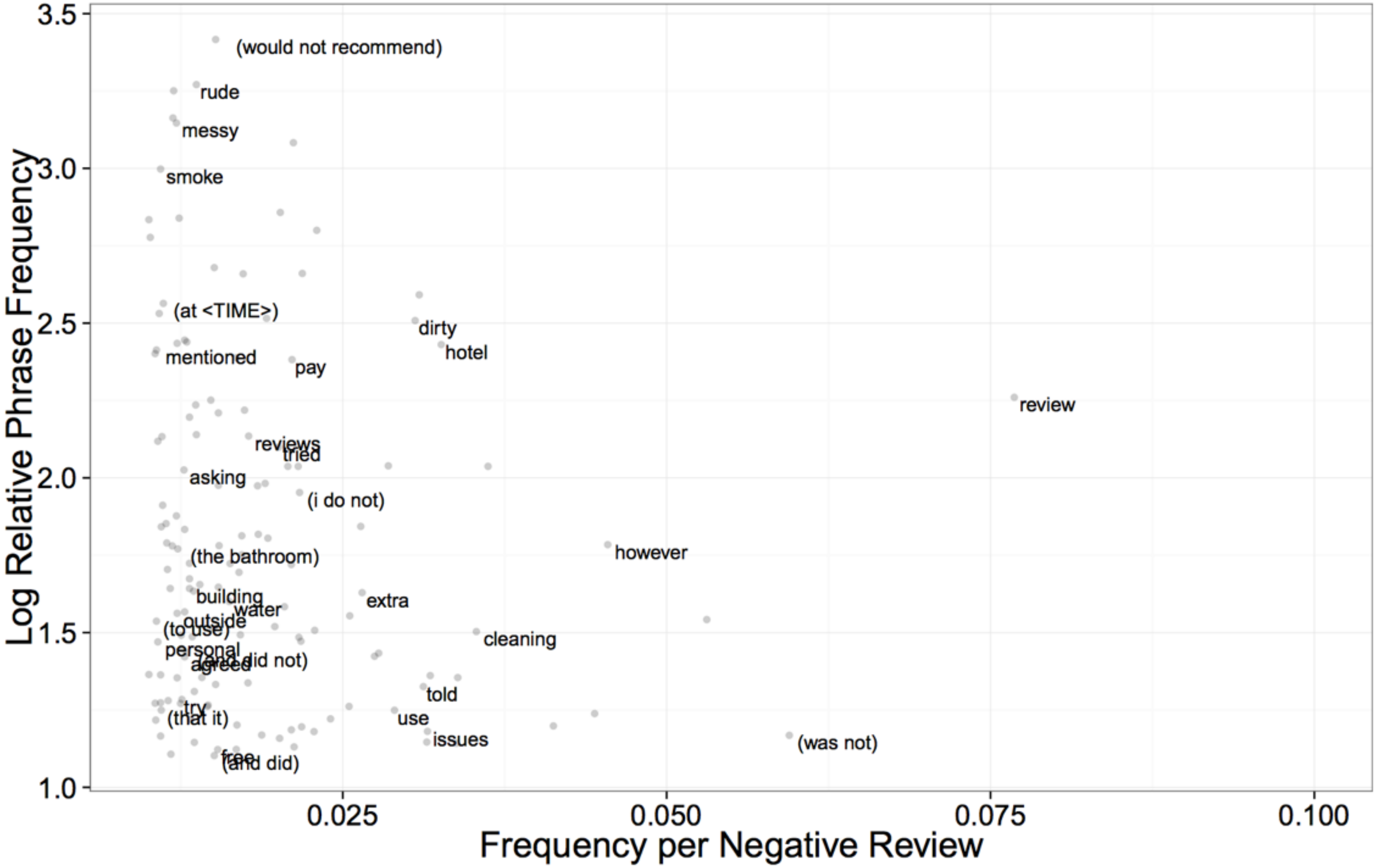
Fig. A1: Distribution of negative phrases in guest reviews of listings.



"Relative phrase frequency" refers to the ratio with which the phrase occurs in reviews with a rating of less than 5 stars.

Crude Measures of Sentiment in Review Text

Fig. A2: Distribution of negative phrases in host reviews of guests.



“Relative phrase frequency” refers to the ratio with which the phrase occurs in reviews with a non-recommendation.

Effect of Host Reviews on Guest Reviews

Table IV: Retaliation and Induced Reciprocity - Guest

	Does Not Recommend	Overall Rating < 5	Negative Sentiment
	(1)	(2)	(3)
Treatment	0.002	0.029***	0.032***
	(0.002)	(0.006)	(0.005)
Host Negative Sentiment	0.671***	0.690***	0.383**
	(0.128)	(0.122)	(0.159)
Host Does Not Recommend	0.134	0.055	0.254*
	(0.094)	(0.109)	(0.132)
Treatment * Host Negative Sentiment	−0.631***	−0.719***	−0.454**
	(0.159)	(0.177)	(0.208)
Treatment * Host Does Not Recommend	−0.012	0.279*	0.003
	(0.122)	(0.153)	(0.173)
Guest, Trip, and Listing Char.	Yes	Yes	Yes
Observations	18,207	18,207	18,207

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Guests respond to negative text with negative reviews

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Guests induced to leave positive reviews by positive host reviews

Host Strategic Considerations

Table 9: Fear of Retaliation - Host

	Reviews First	Does Not Recommend (First)	Neg. Sentiment (First)	
	(1)	(2)	(3)	(4)
Treatment	0.028***	0.001*	0.002*	−0.001
	(0.003)	(0.001)	(0.001)	(0.001)
Does Not Recommend				0.616***
				(0.010)
Treatment * Does Not Recommend				0.121***
				(0.012)
Guest, Trip, and Listing Characteristics	Yes	Yes	Yes	Yes
Observations	120,230	61,720	31,975	31,975

The regressions in columns (2) - (4) are estimated only for cases when the host reviews first. "Treatment" refers to the simultaneous reveal experiment. *p<0.10, ** p<0.05, *** p<0.01

Host Strategic Considerations

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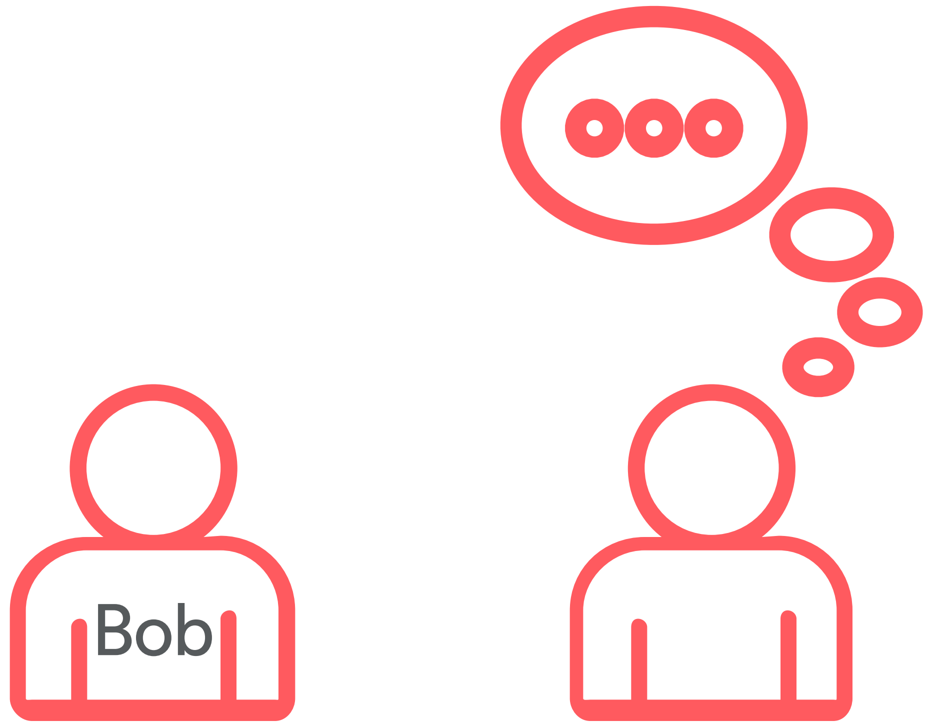
Treatment	0.028***	0.001*	0.002*	−0.001
	(0.003)	(0.001)	(0.001)	(0.001)
Does Not Recommend				0.616***
				(0.010)
Treatment * Does Not Recommend				0.121***
				(0.012)
Guest, Trip, and Listing Characteristics	Yes		Yes	Yes
Observations	120,230		31,975	31,975

Hosts are strategic and omit non-positive feedback from text

The regressions in columns (2) - (4) are estimated only for cases when the host reviews first. "Treatment" refers to the simultaneous reveal experiment. *p<0.10, ** p<0.05, *** p<0.01

Tackling Bias 3



Bias 3: Discomfort

Incentivized Reviews

Hi Varun,

We noticed that you didn't leave a review for your stay with Patrick at Incredible Cottage. Reviews enable others to make informed decisions and help build the Airbnb community. Leave a review by December 29, 2009 and you'll get $25 off your next trip*.

Review Patrick - Get $25

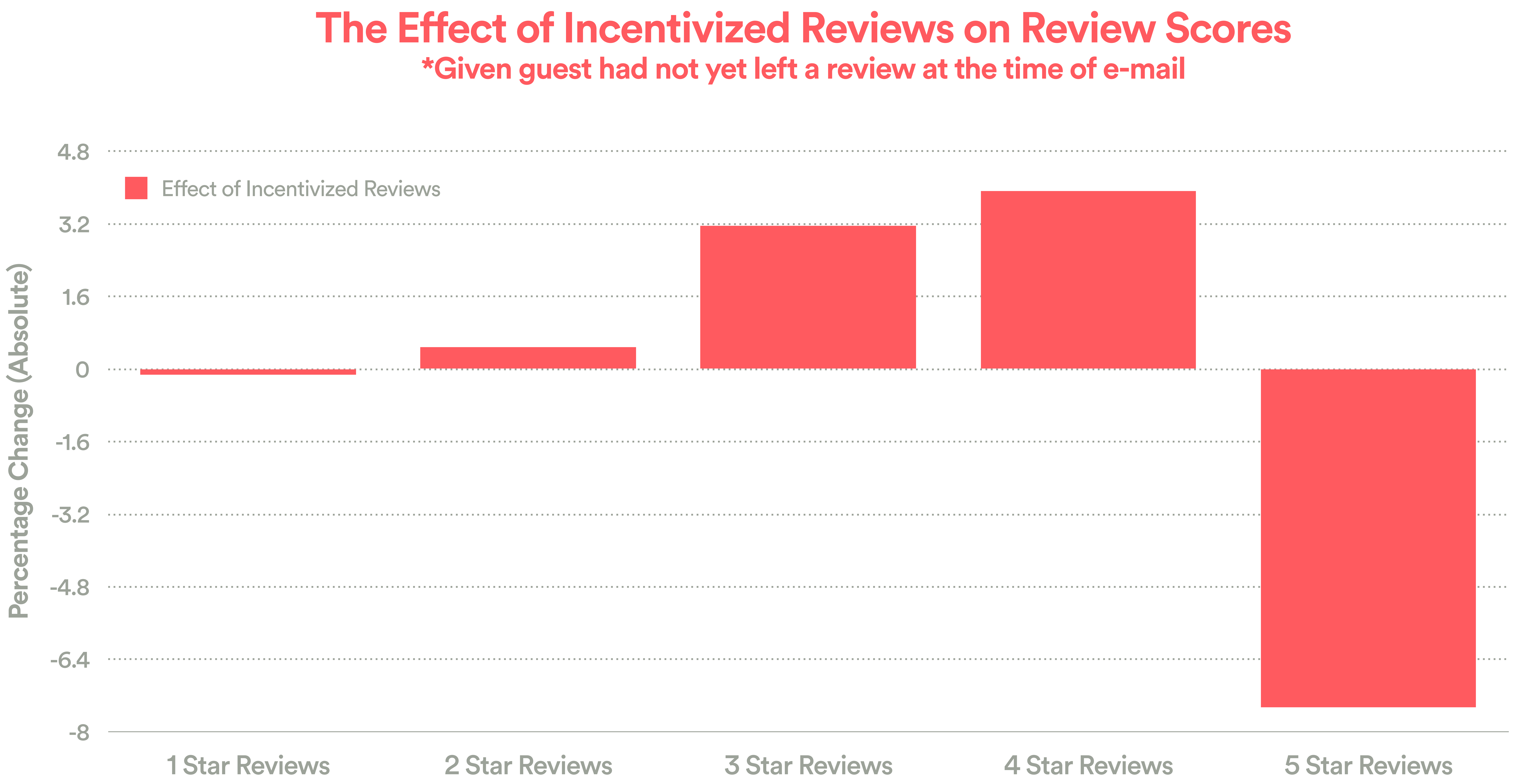
Incentivized Reviews Review Flow

Example: host submits first

The Effect of Incentivized Reviews on Review Rates*

***Given guest had not yet left a review at the time of e-mail**

	Guest Reviews Host
Control	23%
Incentivized Reviews	39%



The Effect of Incentivized Reviews on Review Scores
*Given guest had not yet left a review at the time of e-mail
Effect of Incentivized Reviews
Percentage Change (Absolute)
4.8
3.2
1.6
0
-1.6
-3.2
-4.8
-6.4
-8
1 Star Reviews
2 Star Reviews
3 Star Reviews
4 Star Reviews
5 Star Reviews

Other Observed Effects

- Increase in ‘negative’ words conditional on rating
- Guests leave private suggestions for improvement to hosts at a greater rate
- People leave reviews faster

How We’re Improving our Existing Findings with NLP
(Ongoing Work)

Our previous method of measuring sentiment in reviews was crude, and might not be as exact as we'd hope. How might we use natural language processing to improve on our results?

Challenge

- Want to develop a classifier that determines whether a review (or review fragment) is negative or positive
- What do we use as labels? We want to measure variations in sentiment controlling for star rating, so star ratings may not be the best
- Hard to use existing sentiment corpora, since Airbnb is a specialized context

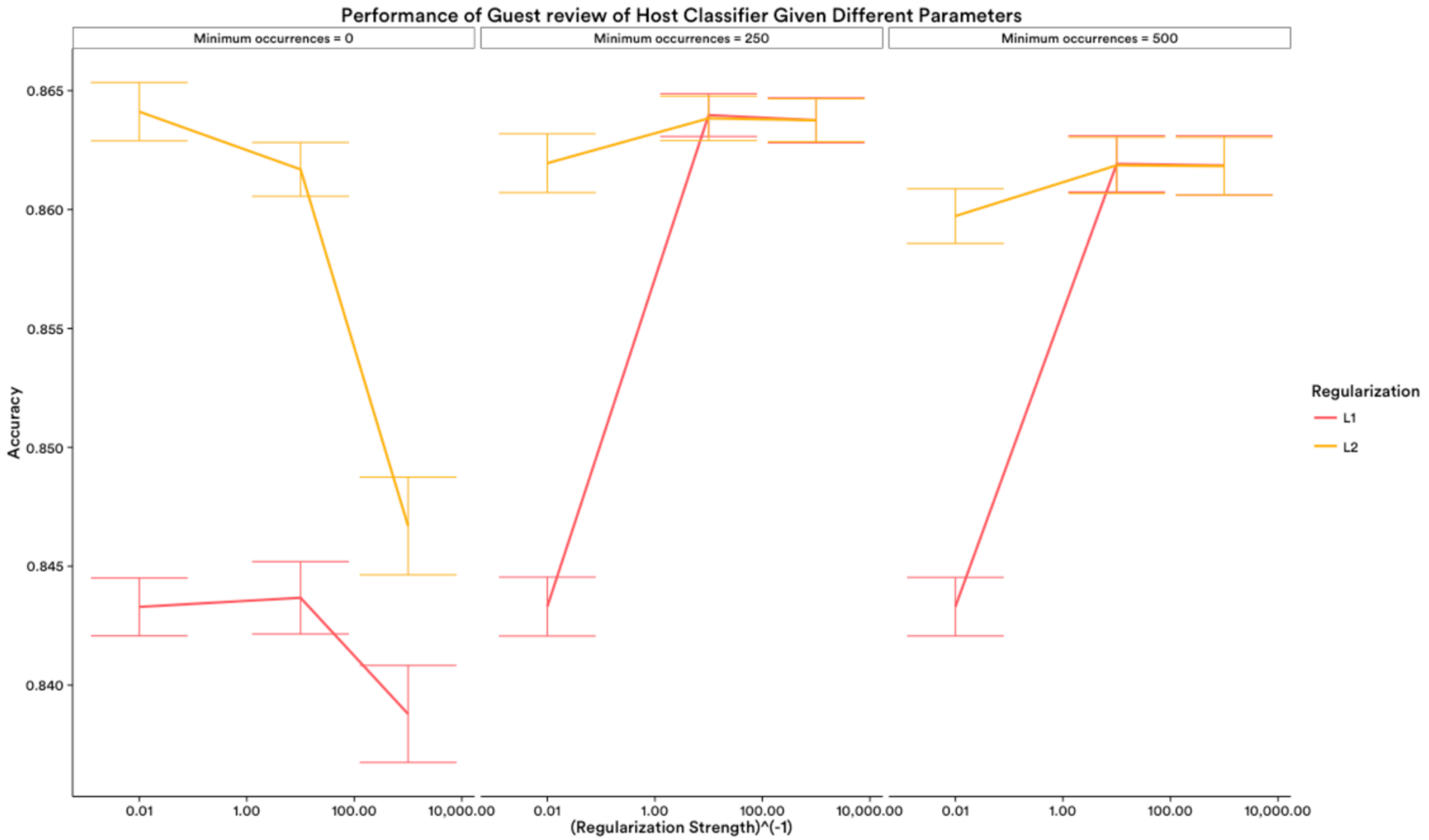
Solution

- Train a logistic-regression based classifier, using a dictionary of n-grams as our features
- Train on only 5-star reviews and 1/2-star reviews, to achieve good segmentation between positive and negative sentiment
- Evaluate this model on our data, and observe changes in sentiment over time (and due to our experiment)

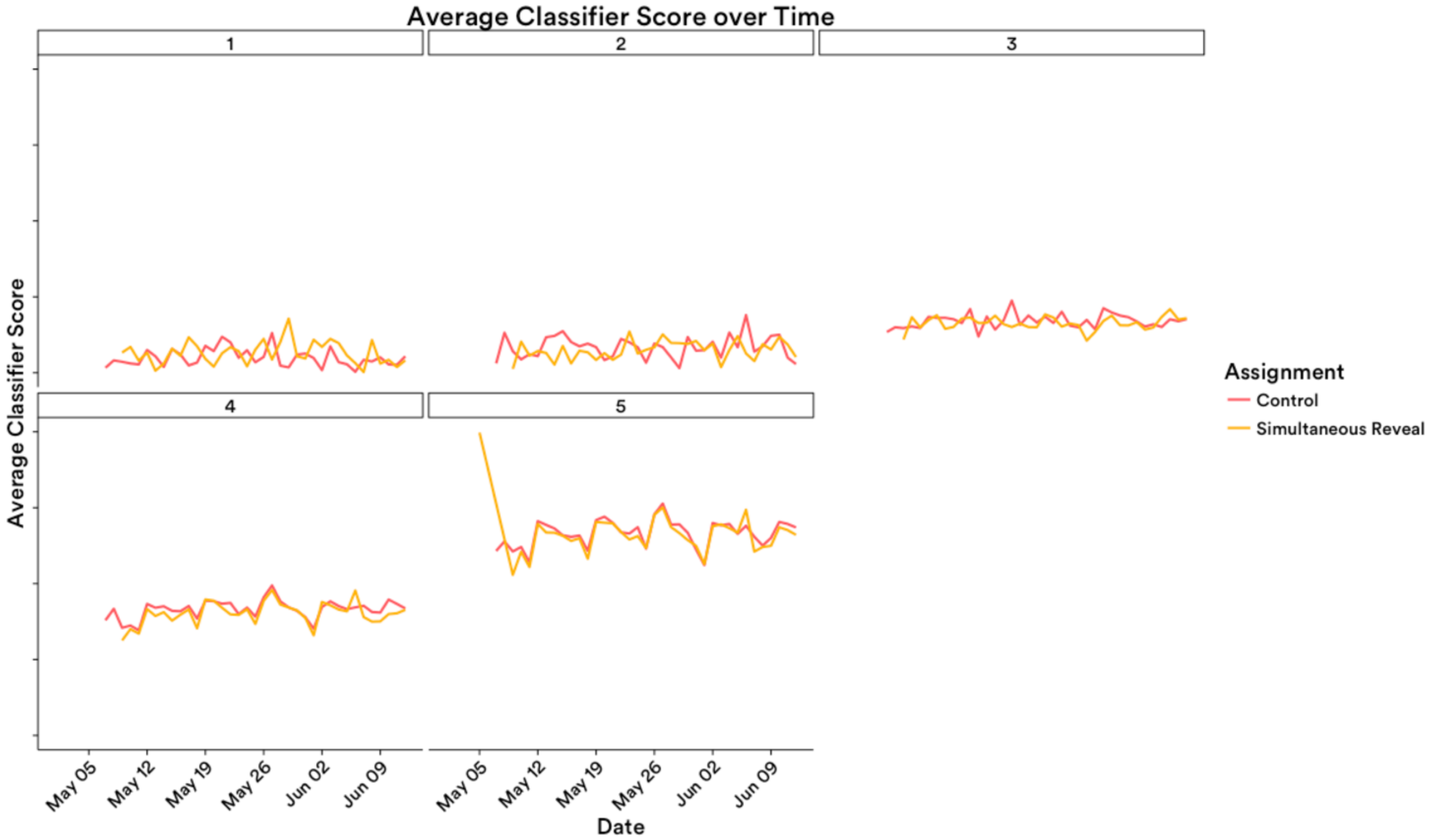
Model is successful at classifying positive and negative reviews, with interesting results

- ~85% accuracy using 10-fold cross validation
- Verification that some meaningful n-grams in Airbnb reviews may not appear as positive/negative in existing sentiment corpora
    - e.g., “third” is a word with strong negative weight. Likely corresponds to listings on the third floor, or 3-person capacity listings with only one bed.

Model Performance is not dependent on model parameters



We see differences in sentiment between the simultaneous reveal control and treatment



We see differences in sentiment between the simultaneous reveal control and treatment

	1 Star Review	2 Star Review	3 Star Review	4 Star Review	5 Star Review
Difference in average classifier score	-1.7%	-3.6%	-3.2%	-5.7%	+29.4%

Next steps: Plug this new output from our classifier into our old regressions, and see how our results differ

High Level Learnings

What We Observed

- There is a bias in the observed reviews distribution due to non-response
- Hosts and guests act strategically
- Intrinsic reasons for reviewing (or not reviewing) are important
- Changes in review process can reduce the magnitude of these biases

What We’re Continuing to Work On

- Becoming more and more sophisticated around how we study review text and sentiment
- Quantifying the magnitude of bias in reviews and getting at the ‘true’, underlying distribution of experiences
- Coming up with even more new ways to increase review honesty

Questions?

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P.S. We're hiring!
https://www.airbnb.com/jobs