



# AUDIENCE MEASUREMENT 6.0



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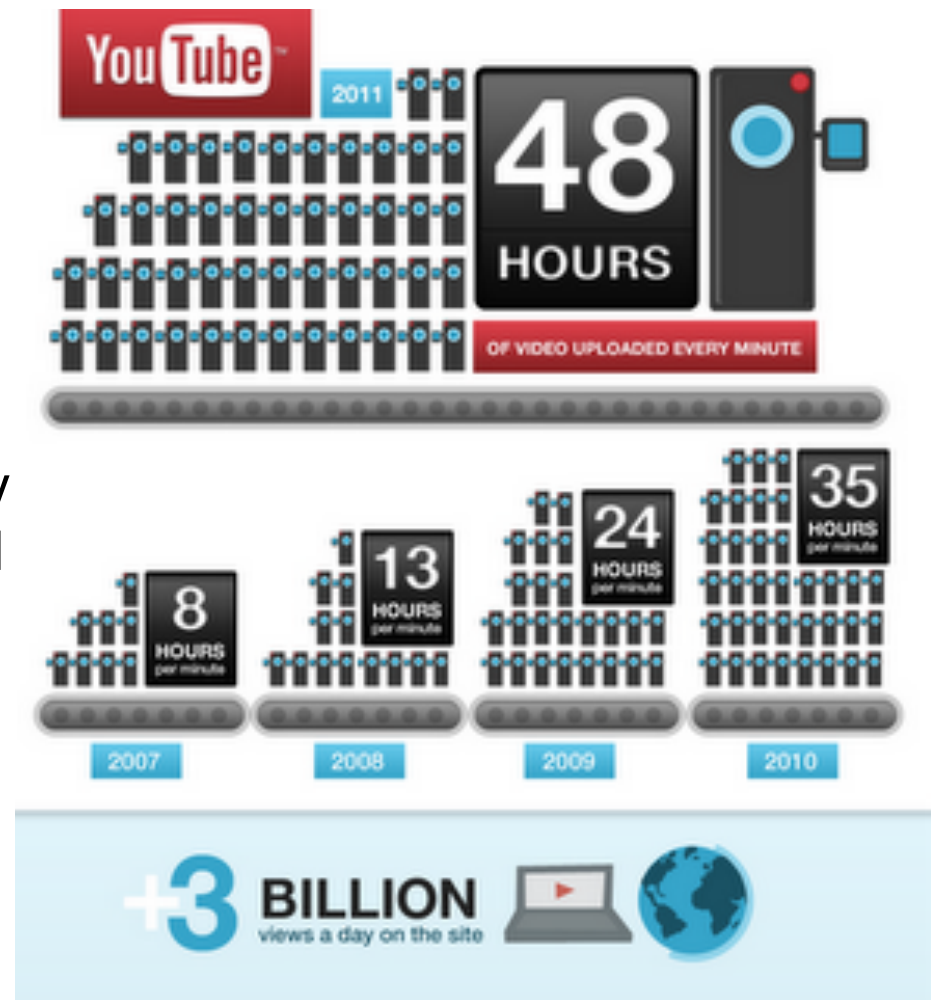


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# Background

- YouTube launched in May 2005
- Grown to the world's most popular online video community
  - 3 billion watches every day
  - 48 hours of video uploaded every minute
  - 2 billion monetized views every week



# Problem

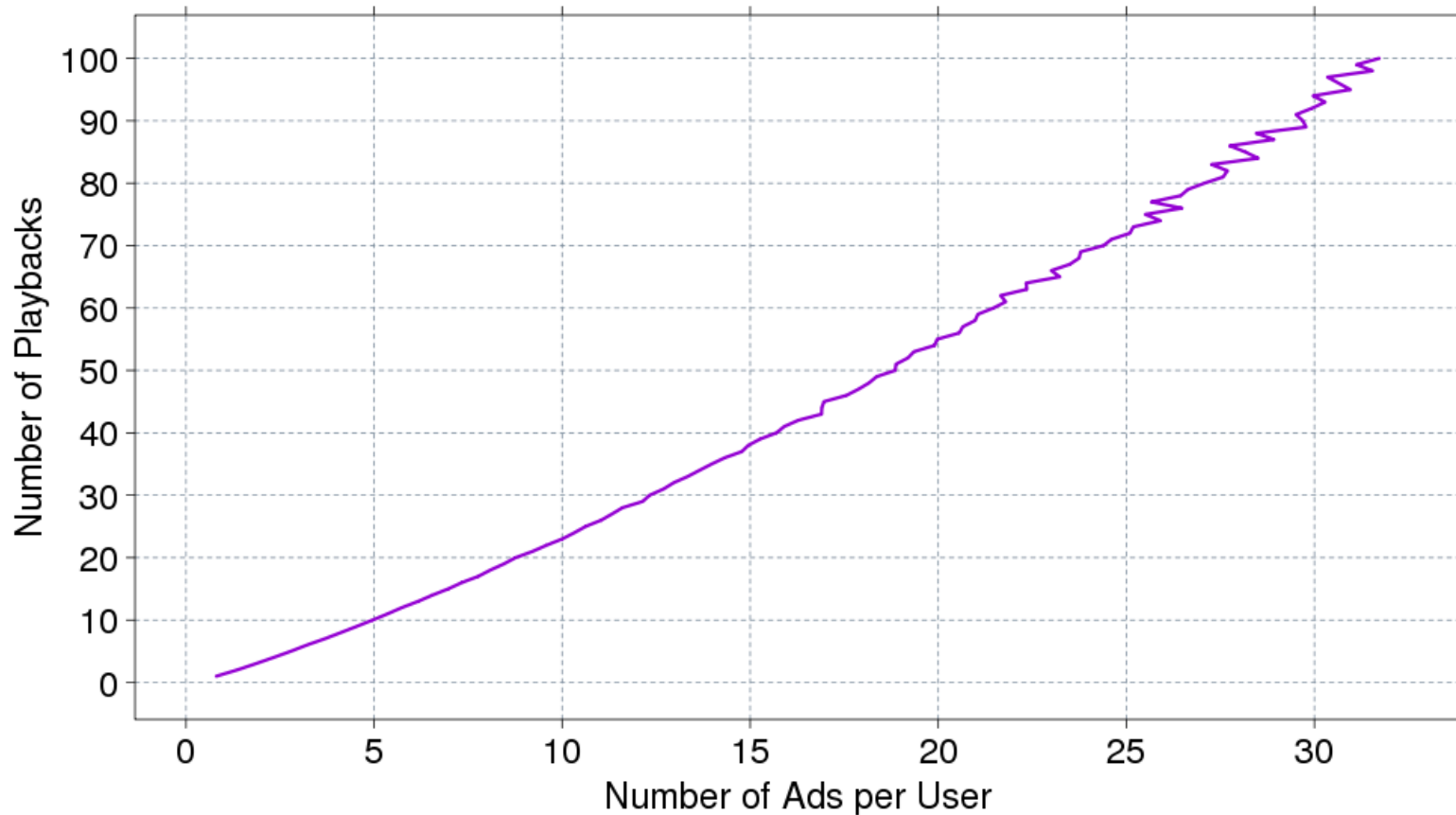
- Deriving causation from passive data is challenging
  - Observational studies are subject to selection bias
  - Segmenting groups of users for statistical comparisons is difficult and error prone
- Large scale randomized experiments provide a powerful alternative
  - Run on live traffic
  - Allow for causal inferences
  - Smallest experiments yield about 200K unique cookies per day

# Example

- Question: How do ads on YouTube impact usage?
  - Do ads cause viewers to use the site less?
- Naïve approach: Look for correlation between ad viewing and time on site
  - Do users who see lots of ads use YouTube less?

# Results using retrospective data

## Playbacks as a Function of Ads per User



More ads lead to more playbacks? Or more playbacks lead to more ads?

# What went wrong?

- Naïve analysis suffers from length-biased selection
  - Long sessions are more likely to have ads
  - Known issue in statistical sampling since at least 1969
- These issues are very common in practice
  - Thread length in textiles
  - Patient visit duration in hospitals
  - Vegetarians in business meetings

# Better Methods

- Using cookies to divide the population of YouTube visitors
  - Expose some of the population to a new treatment (e.g. new ad format, withholding ads, throttling ad coverage)
  - Keep an equal sized sample of the population as a control
- Measure comparisons between the two groups to determine if the the experiment changes user behavior:
  - More watches on YouTube
  - Longer session length
  - Reduced in-stream ad abandonment

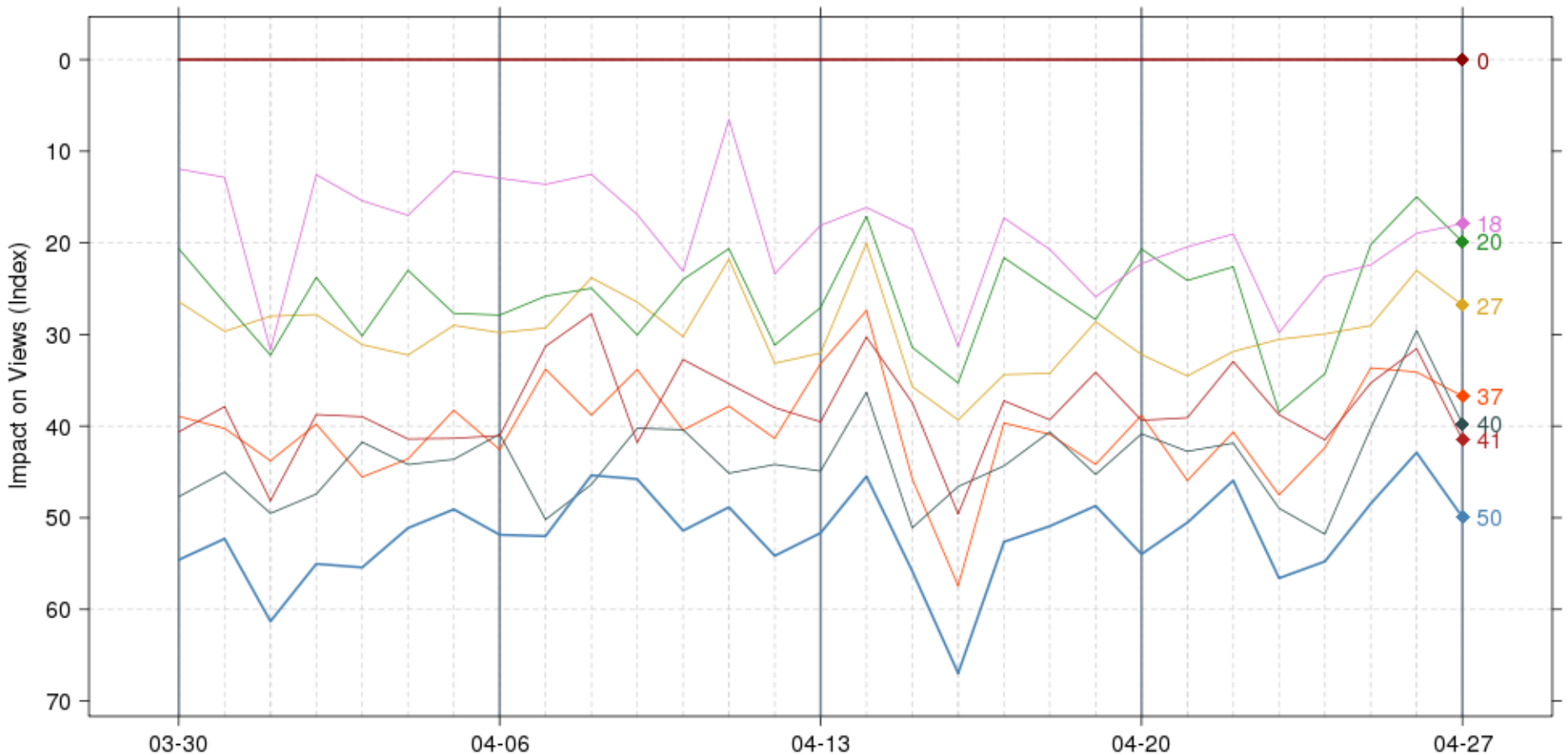
# Holdback experiments

- YouTube ad formats
  - In-stream video ads
  - Overlay ads
  - Mid-page companion units (MPUs)
- Holdback experiments
  - 6 experiments holding back combinations of the 3 ad formats
  - 1 additional experiment to holdback all ads
  - 1 additional experiment for the status quo (control)
  - Each experiment run on 0.1% of YouTube traffic
- Compare playbacks per visitor among the 8 groups



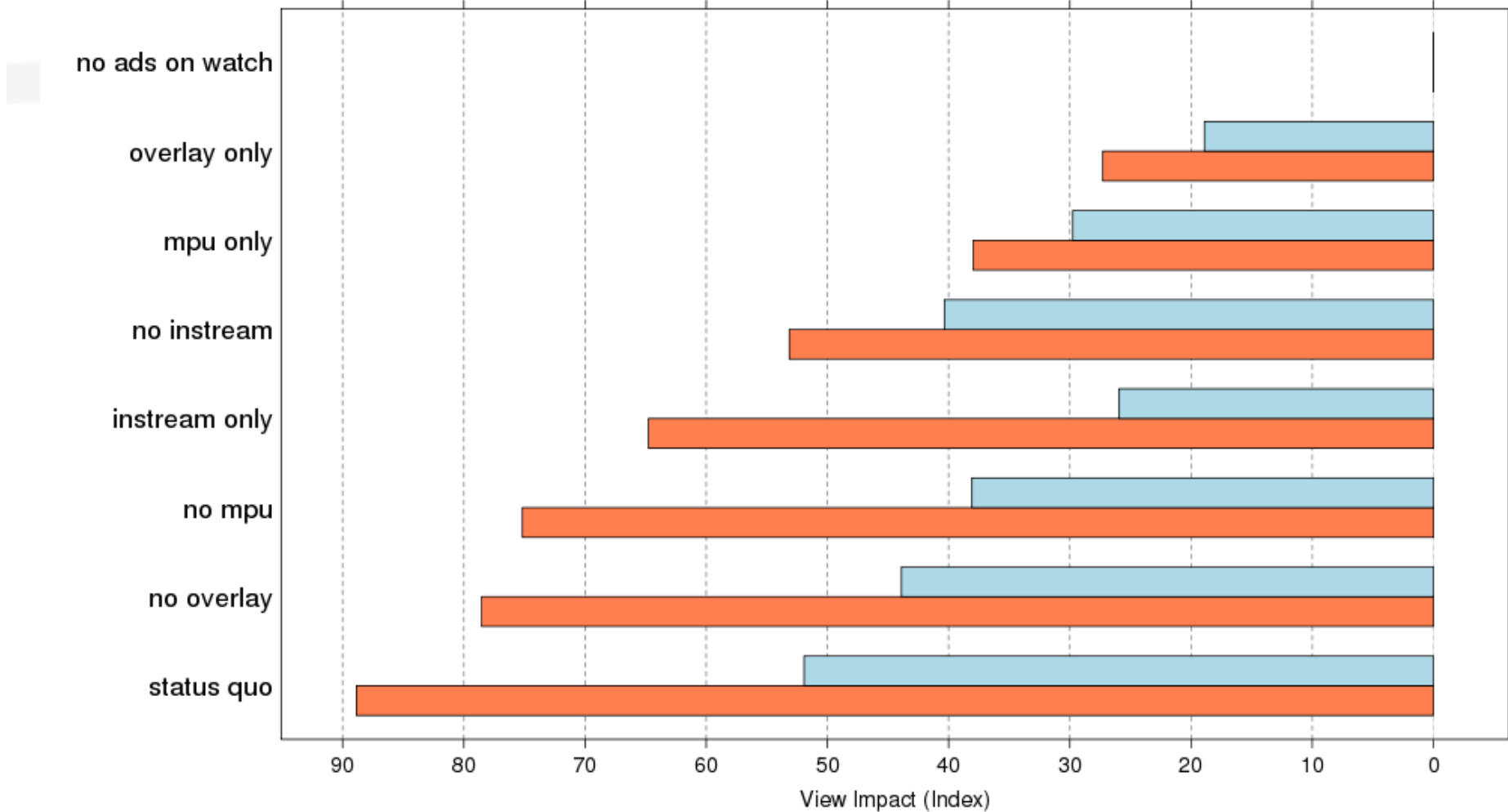
# Watch impact by experiment

no ads on watch — no instream — no mpu — overlay only —  
 status quo — no overlay — instream only — mpu only



# Watch impact in the U.S.

US Global



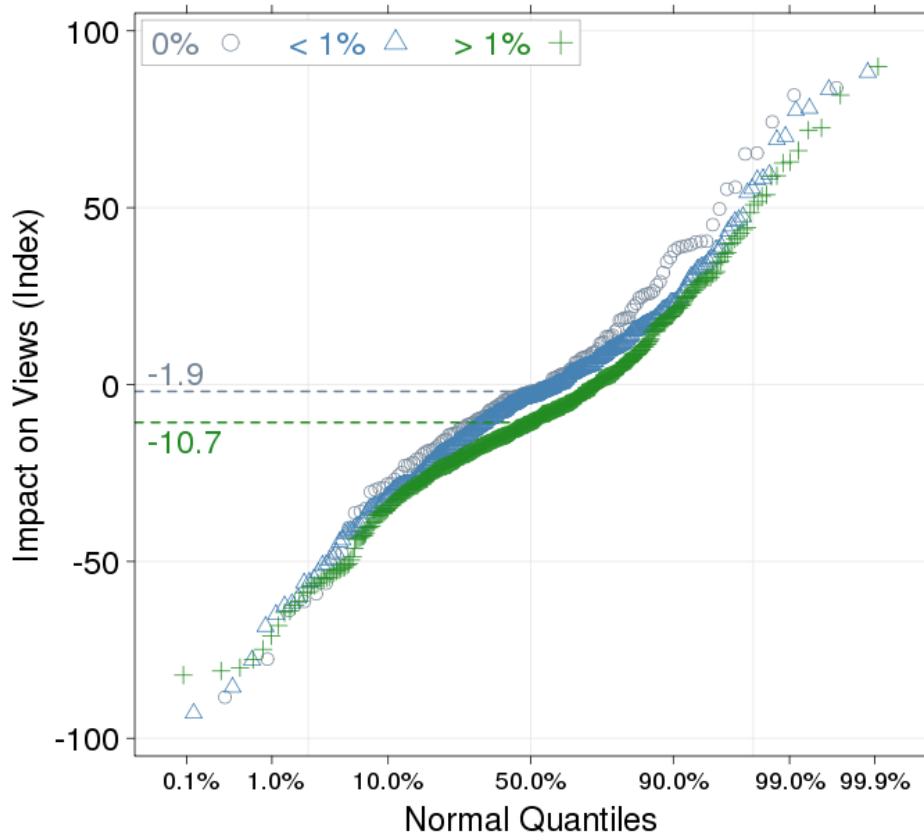
# Further analysis: Impact of advertising on partners

- Partners control how many in-stream ads are shown on their content
- We can measure the partner-level impact from showing in-stream ads using the in-stream holdback experiment
  - Partners who show an in-stream on at least 1% of their views see a 5% decrease in watches
  - Approximately 1 view is lost for every 3 in-streams shown

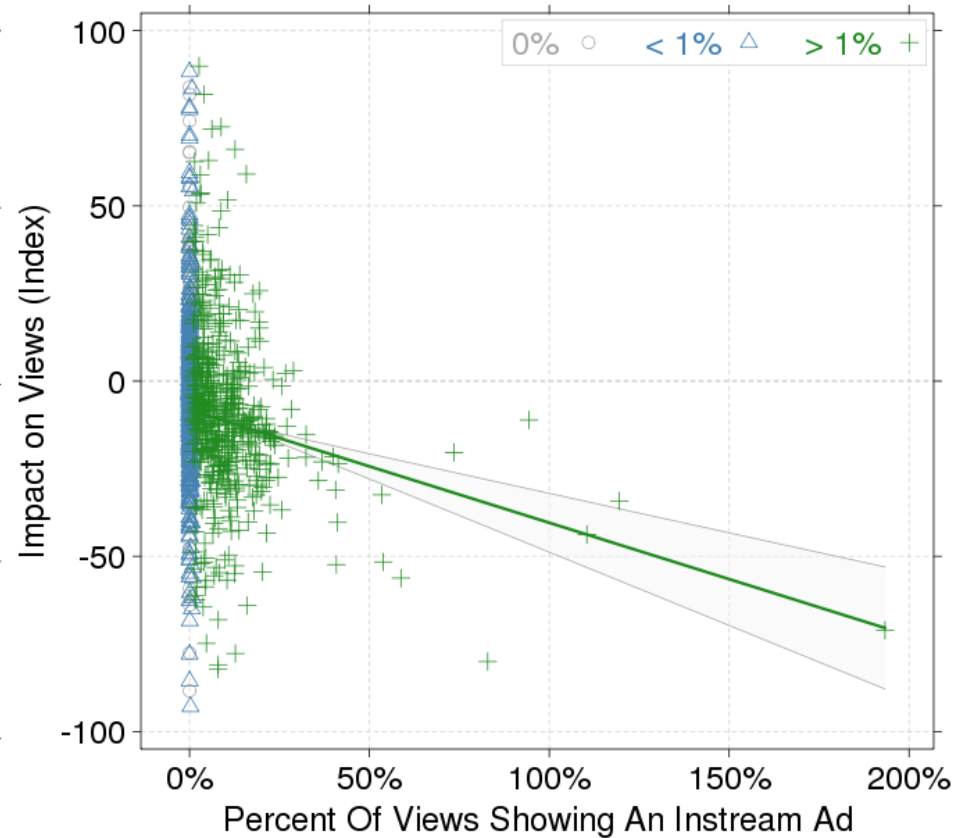
Experiments provide necessary metrics partners can use to make decisions

# Partner impact of instream ads

## Partner Level Impact On Views From Instream Holdback



## Partner Level Impact On Views From Instream Coverage



# Conclusions

- Retrospective analysis can be misleading
  - Direction of causation can be difficult to determine
- Randomized experiments can help
  - Provide causal connections rather than correlations
- Online media is uniquely suited to the experimental approach
  - Live traffic can be segmented at random
  - Changes in user behavior can be measured precisely

# Next Steps

- Understand advertiser impact
  - Recent experiments focus on user and partner impact
  - New experiments should explore advertiser hypotheses as well
- Broaden our scope
  - Effectiveness of different ad formats
  - Relevant advertising to reduce ad impact

# Thank You!

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