Giulia Panozzo

How to show the impact of your SEO changes with Causal Impact

- In-house Director of Customer Acquisition
- SEO, Test & Learns and Neuromarketing
- Founder of Neuroscientive (research and consultancy)

Agenda:

1. What does Causal Impact do?
2. Why should you care?
3. How can it help your strategy?
4. Demo: how to run an analysis with Causal Impact
5. Discussion: Statistics VS the world

What does Causal Impact do?

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Example: Title change

‘Let’s add a price point to the title!’

https://www.example.com › ... › Dresses

Little Black Dresses | Example.com

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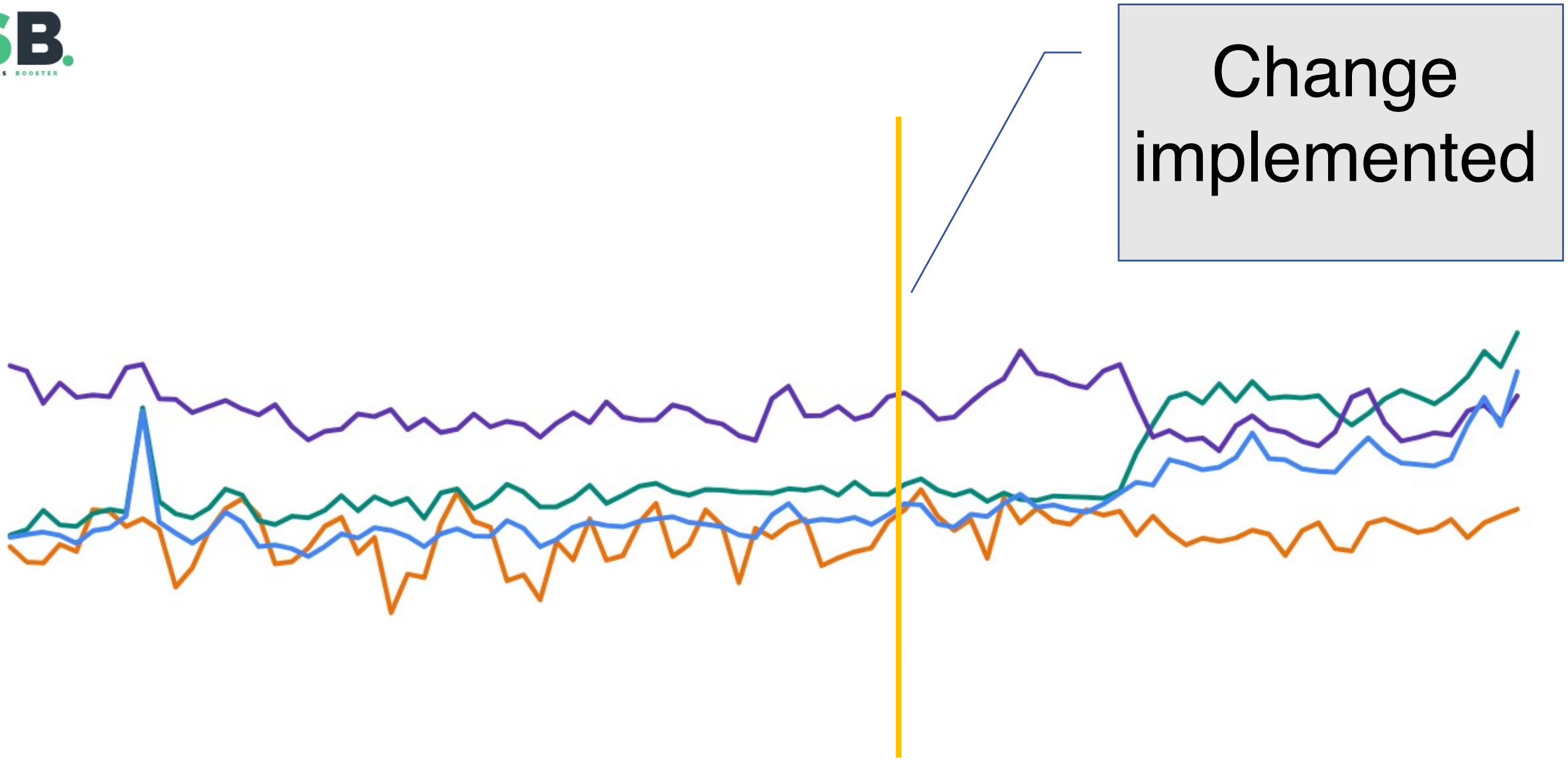
‘Let’s add a price point to the title!’

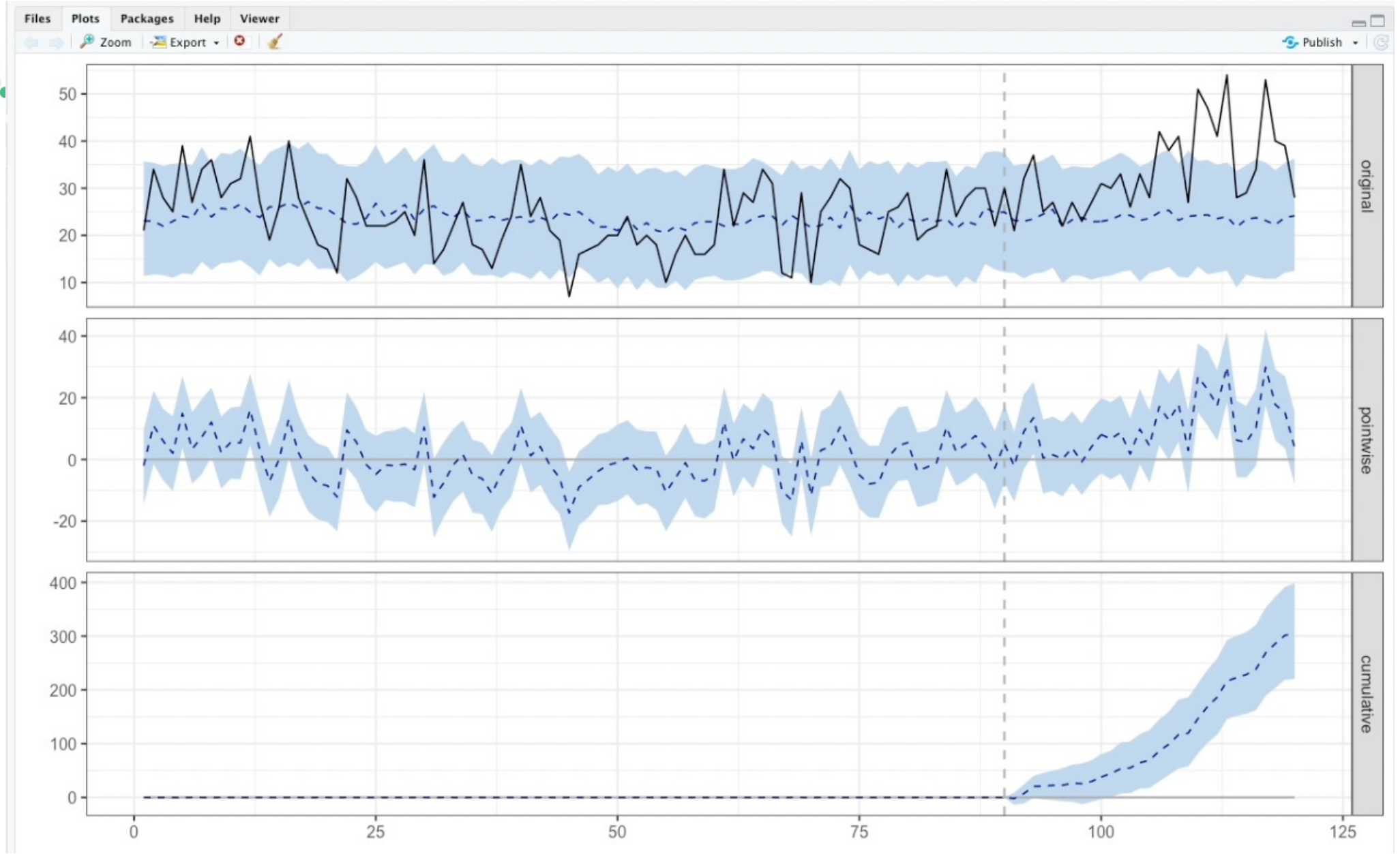
https://www.example.com › ... › Dresses

Little Black Dresses from £15 | Example.com


Change implemented

Date	Clicks	Impressions	CTR	Position
25/06/2022	84	5428	1.55%	5.58
24/06/2022	79	5033	1.57%	5.82
23/06/2022	84	5523	1.52%	5.6
22/06/2022	107	5644	1.90%	5.08
21/06/2022	107	5479	1.95%	4.9
20/06/2022	129	5619	2.30%	4.62
19/06/2022	124	5371	2.31%	4.56
18/06/2022	102	5654	1.80%	4.71
17/06/2022	98	5377	1.82%	5.13

Pre-implementation data + Post-implementation data


Files
Plots
Packages
Help
Viewer
Zoom
Export
Publish
original
pointwise
cumulative
50
40
30
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-20
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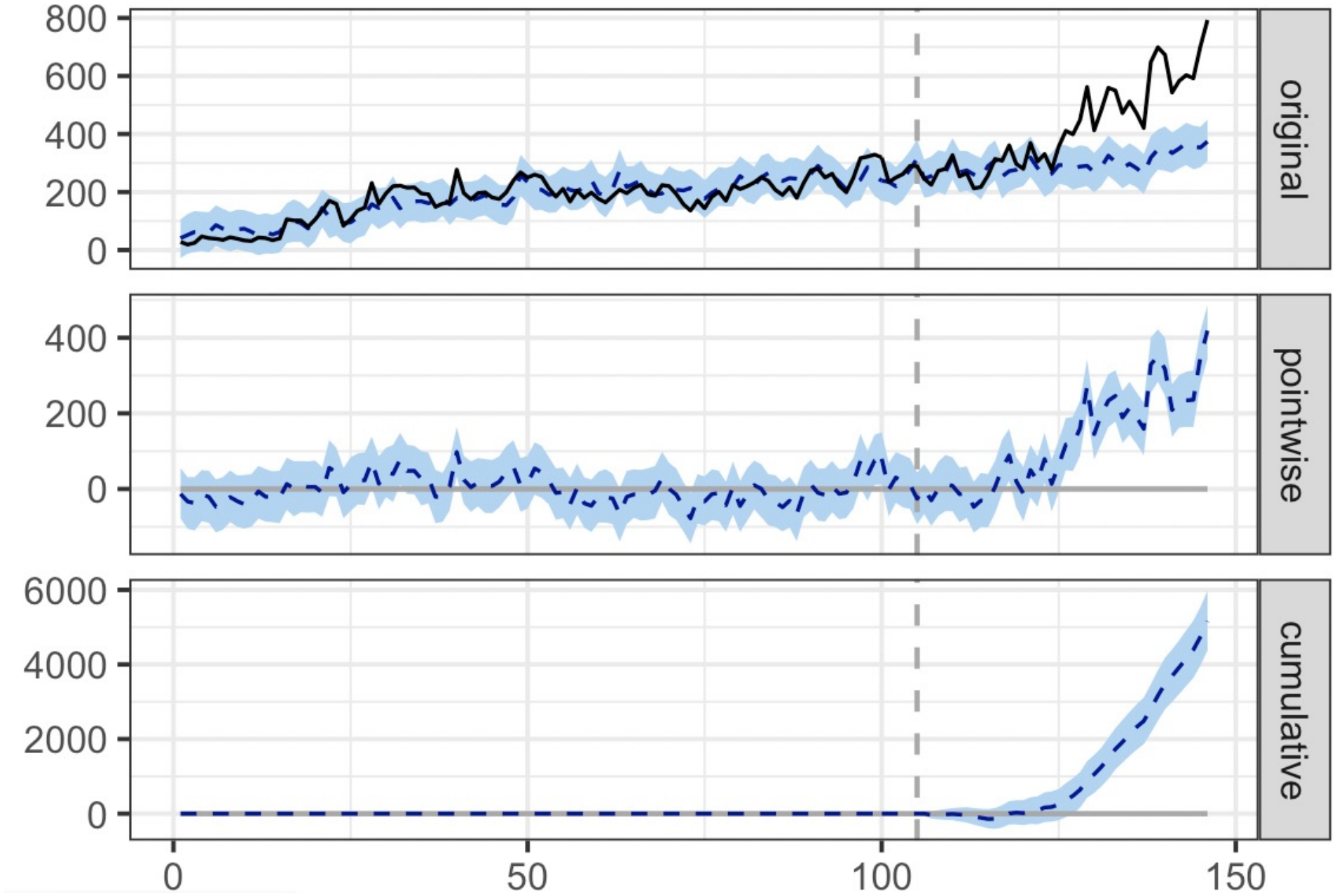
100
0
0
25
50
75
100
125


800
600
400
200
0
original
400
200
0
pointwise
6000
4000
2000
0
cumulative
0
50
100
150

The above results are given in terms of absolute numbers. In relative terms, the response variable showed an increase of +43%. The 95% interval of this percentage is [+30%, +56%].

The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability p = 0.001). This means the causal effect can be considered statistically significant.

Why should you care about Causal Impact (and Statistics?)

Giulia Panozzo - @SequinsNSearch

Because Testing is Hard!

Giulia Panozzo @SequinsNsearch · Jun 21

#SEO pals: What do you find to be the most challenging part of running a #test?


Choose test group
40%
Analyse/Trust results
40%
Apply findings at scale
20%

Choose test group(s)	13%
Analyse/Trust results	38%
Apply findings at scale	25%
Other (let me know below!)	25%

LinkedIn

Ash New (He/Him) • 1st

Senior SEO Manager - Mobile | Virgin Media O2

Resource, Costs & Business Buy In.

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‘Let’s add a price point to the title!’

https://www.example.com › ... › Dresses

Little Black Dresses | Example.com

‘Let’s add a price point to the title!’

https://www.example.com › ... › Dresses

Little Black Dresses from £15 | Example.com

‘But will this help bring more traffic in?’

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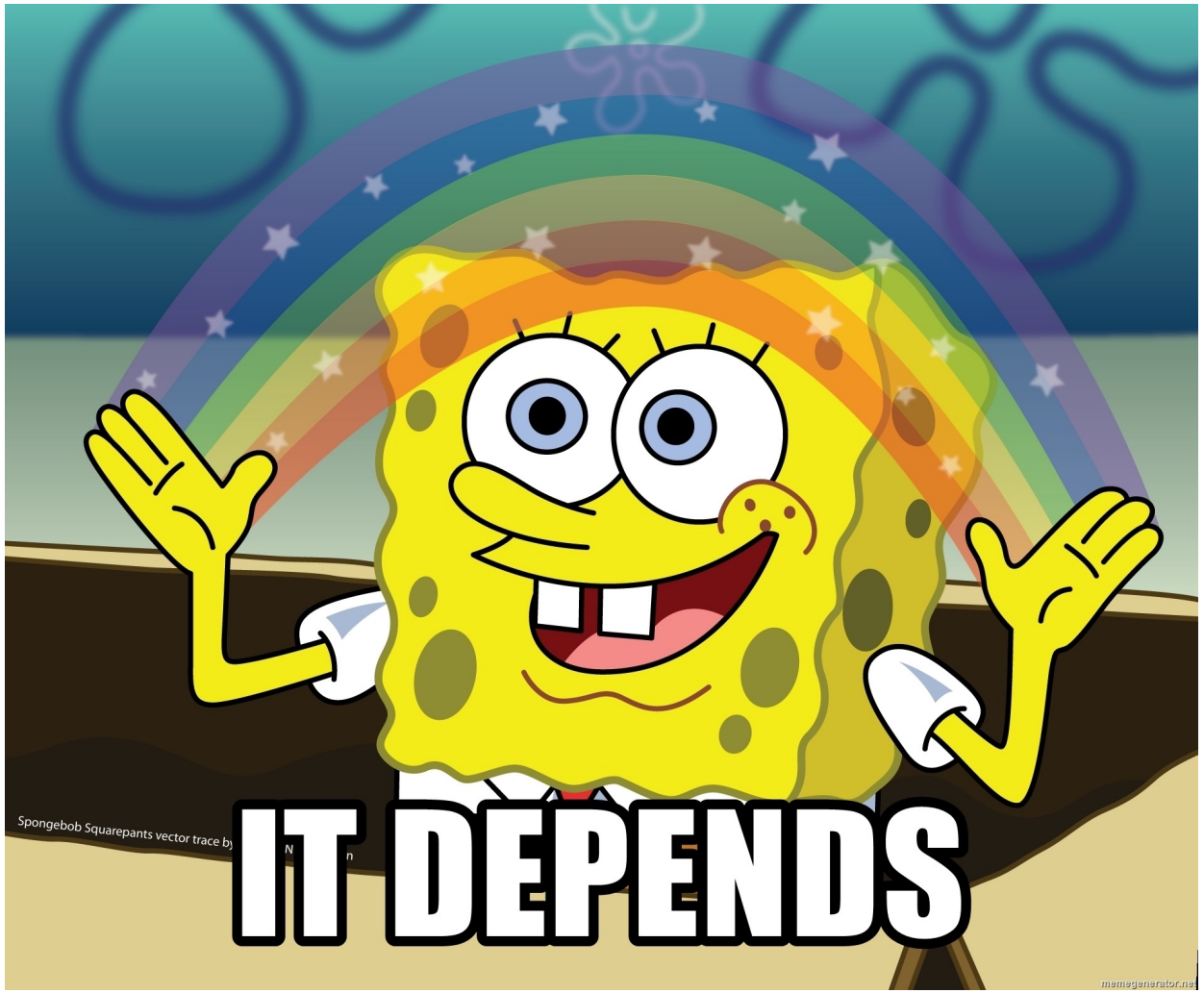
‘Well…’



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However, with Causal Impact…

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Causal Impact gives you the confidence to leverage statistically significant results and drive changes at scale

‘But will this help bring more traffic in?’

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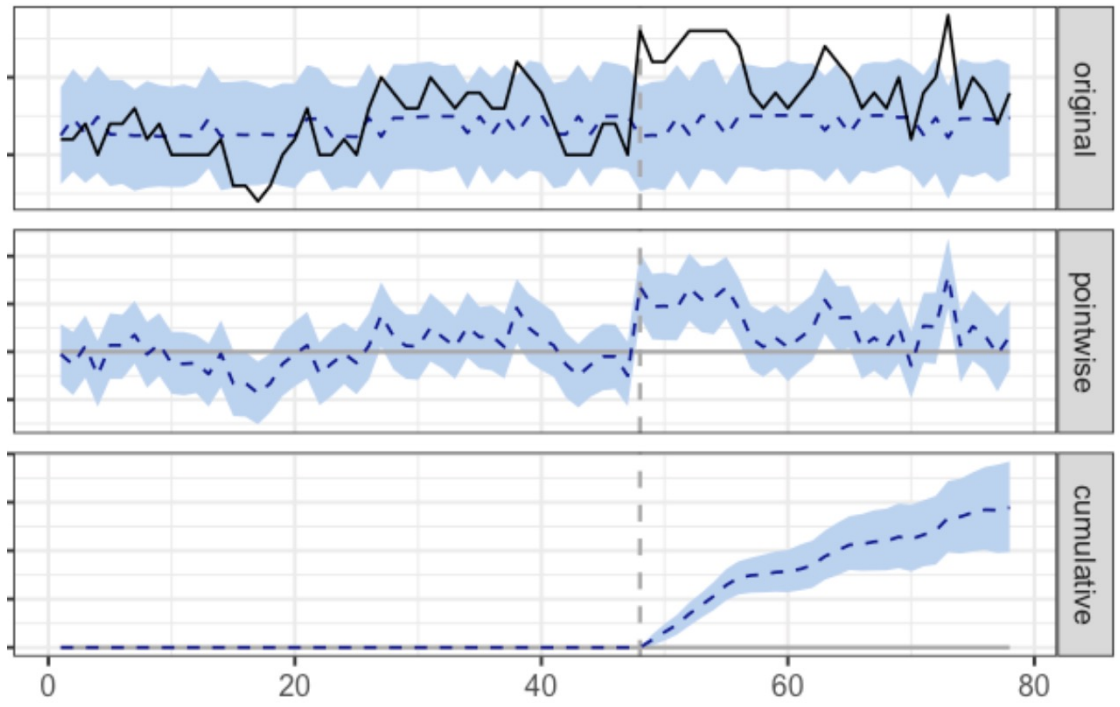
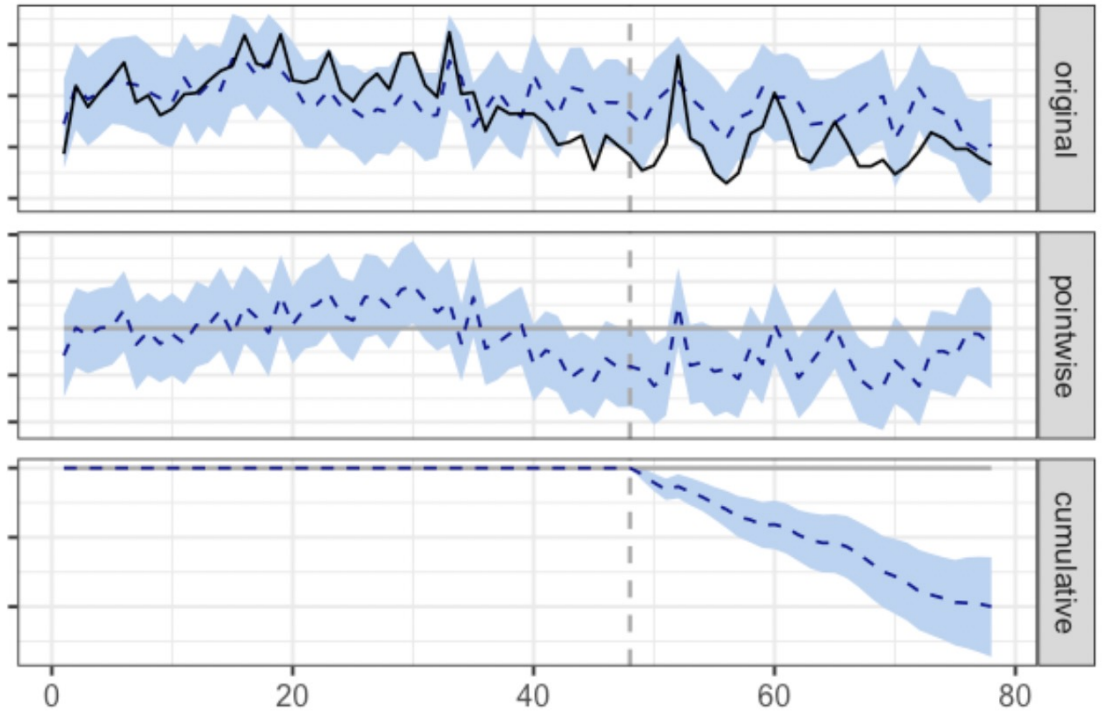


(Most likely)
YES



(Most likely)
NO

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You can use Causal Impact on a number of domains, not only on SEO tests!

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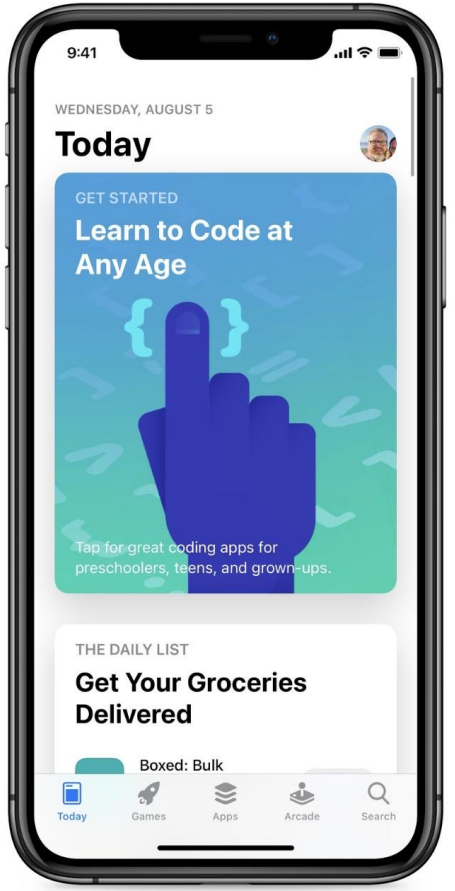
Impact of feature changes on app installs

Causal Impact for App Store Analysis

William Martin
University College London, United Kingdom
w.martin@ucl.ac.uk



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Impact of influencer campaigns

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Impact of offline events and campaigns

Adele

From Wikipedia, the free encyclopedia

And almost any time series data

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If you run Causal Impact on R Studio, it's free and open-source

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seoClarity™

SplitSignal

SearchPilot

When you find a cool new expensive tool and have to get your boss approval

RStudio®

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What is it really – and how can it help your strategy?

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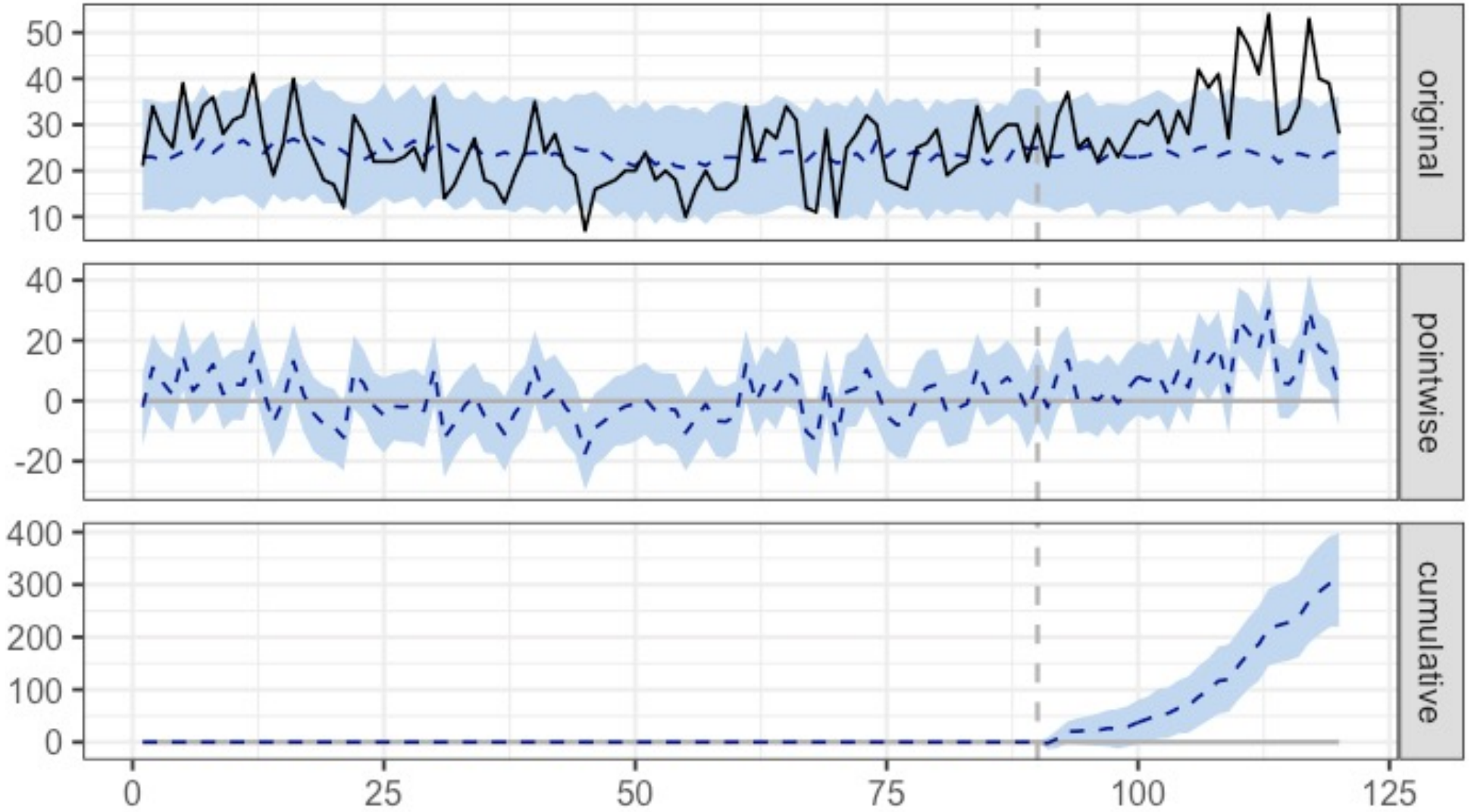
What is Causal Impact?



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Powerful package to analyse data and infer the cumulative impact of a change in a time series

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Based on BSTS (Bayesian Structural Time Series) statistical model

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Uses past data to predict the outcome in the absence of the treatment (the counterfactual)

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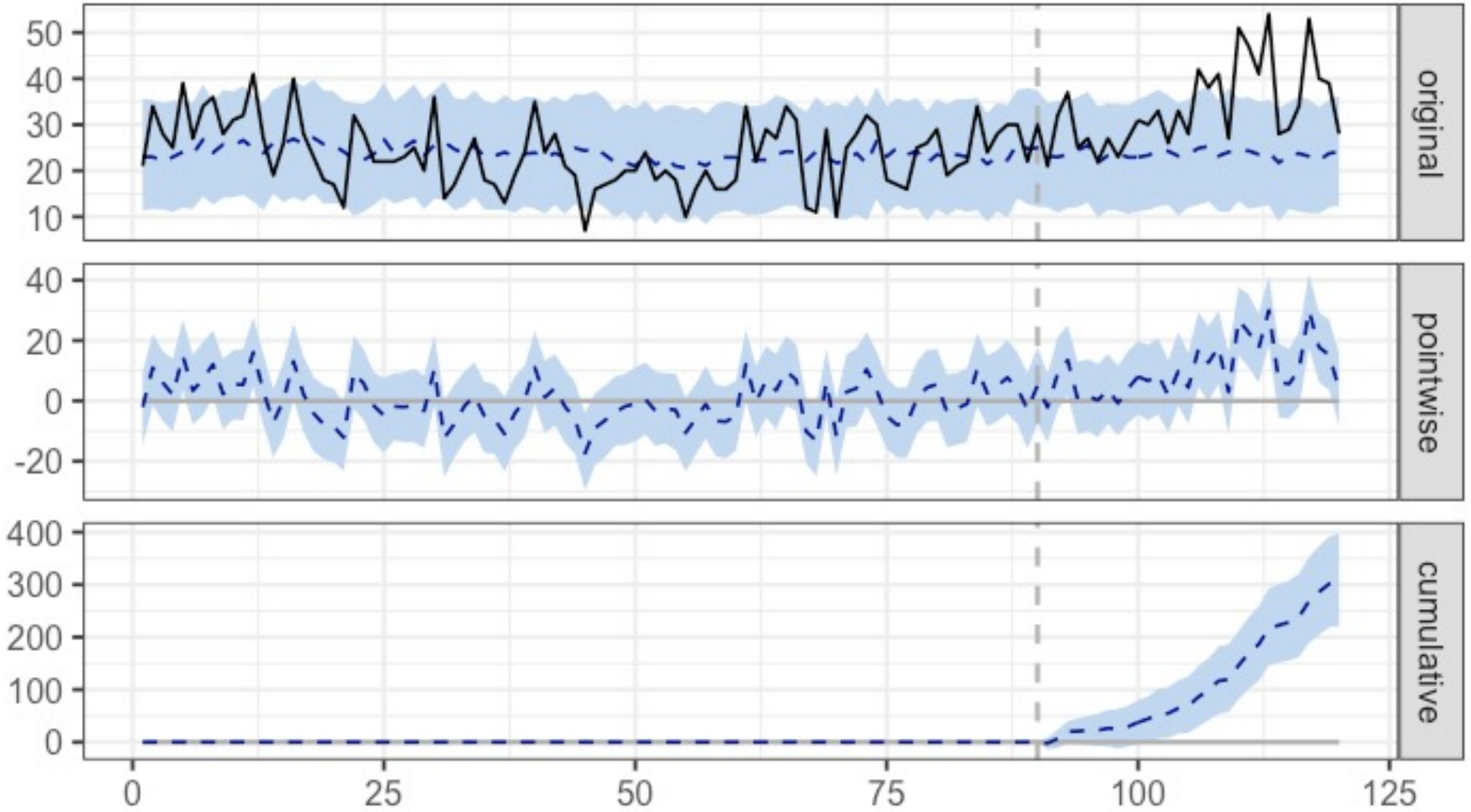
Defines the impact by measuring the deviation of the actual VS predicted outcome

What is Causal Impact?



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How can it help us in marketing?

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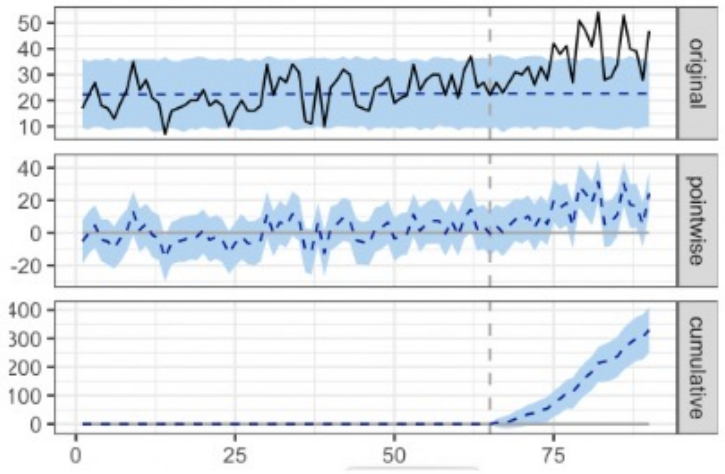
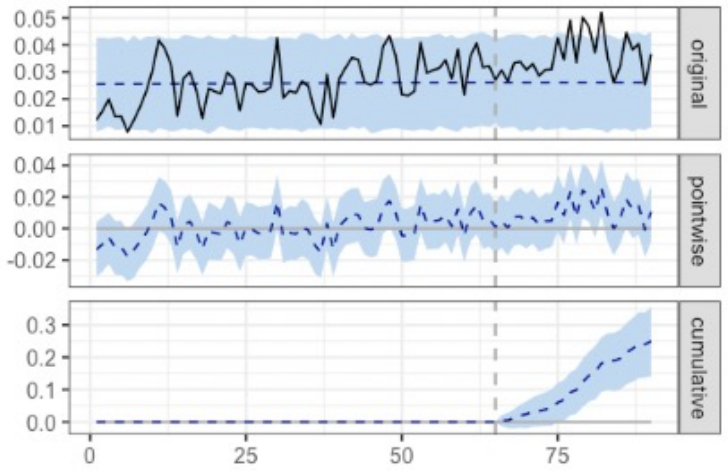
How can it help us in marketing?

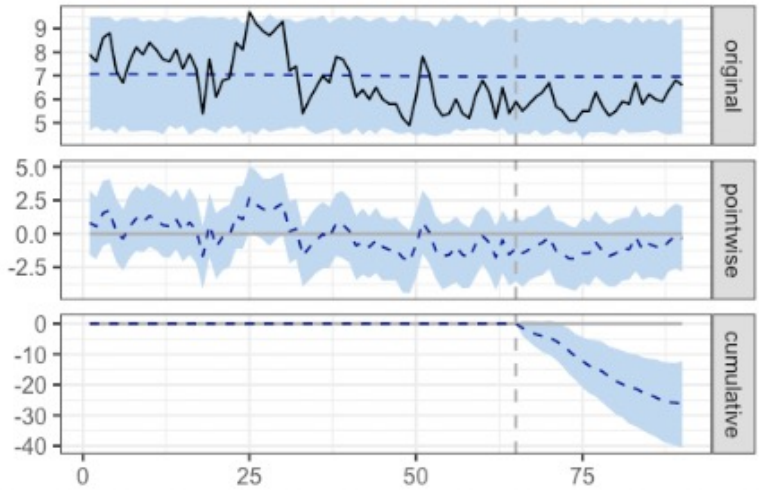
Clicks: +58%



CTR: +38%



Position: -15%



*Example of a clear **winner** from a title tag change*

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It can validate proposed strategy changes in case of any doubts

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It’s great to clearly show stakeholders the impact of our team’s work

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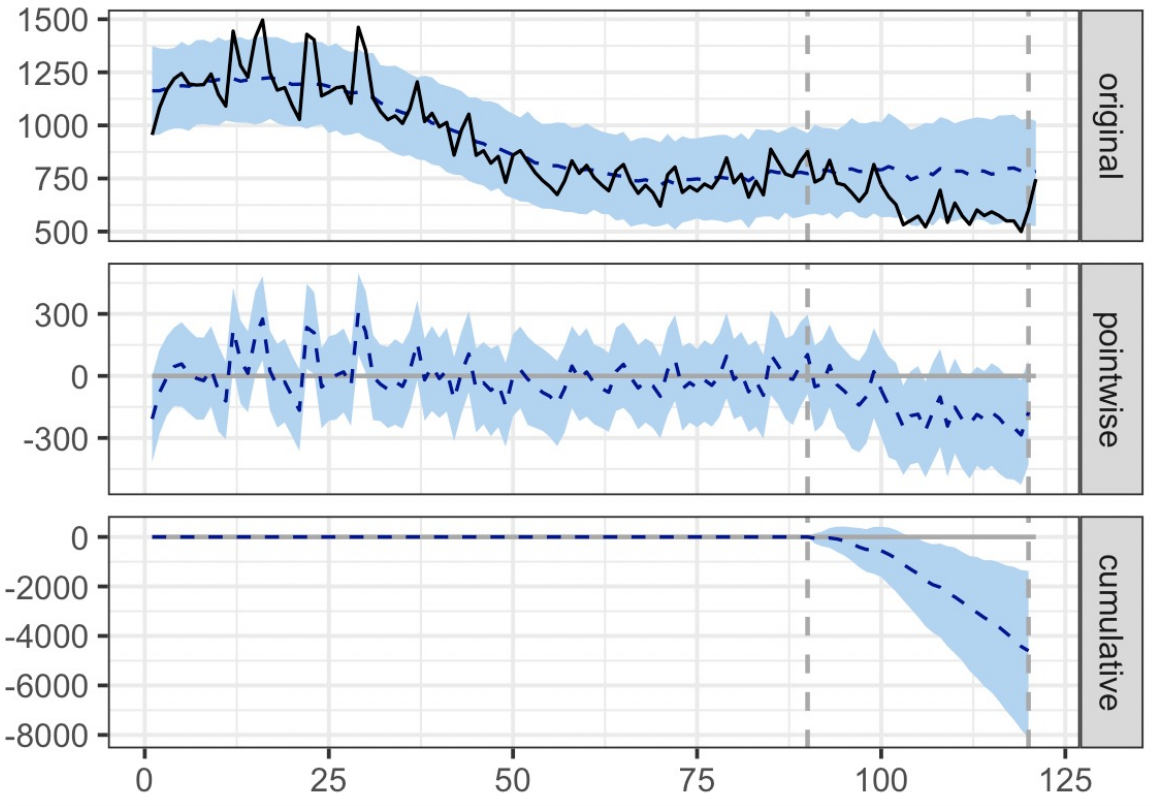
It can help forecast the direction of changes at scale and help
make a case for more resources

How can it help us in marketing?



*Example of a clear **loser** from a title tag change*

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By clearly identifying a winner or loser, we can understand what works and doesn't work for our audience

Demo: how to run a Causal Impact analysis

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1. Download R Studio

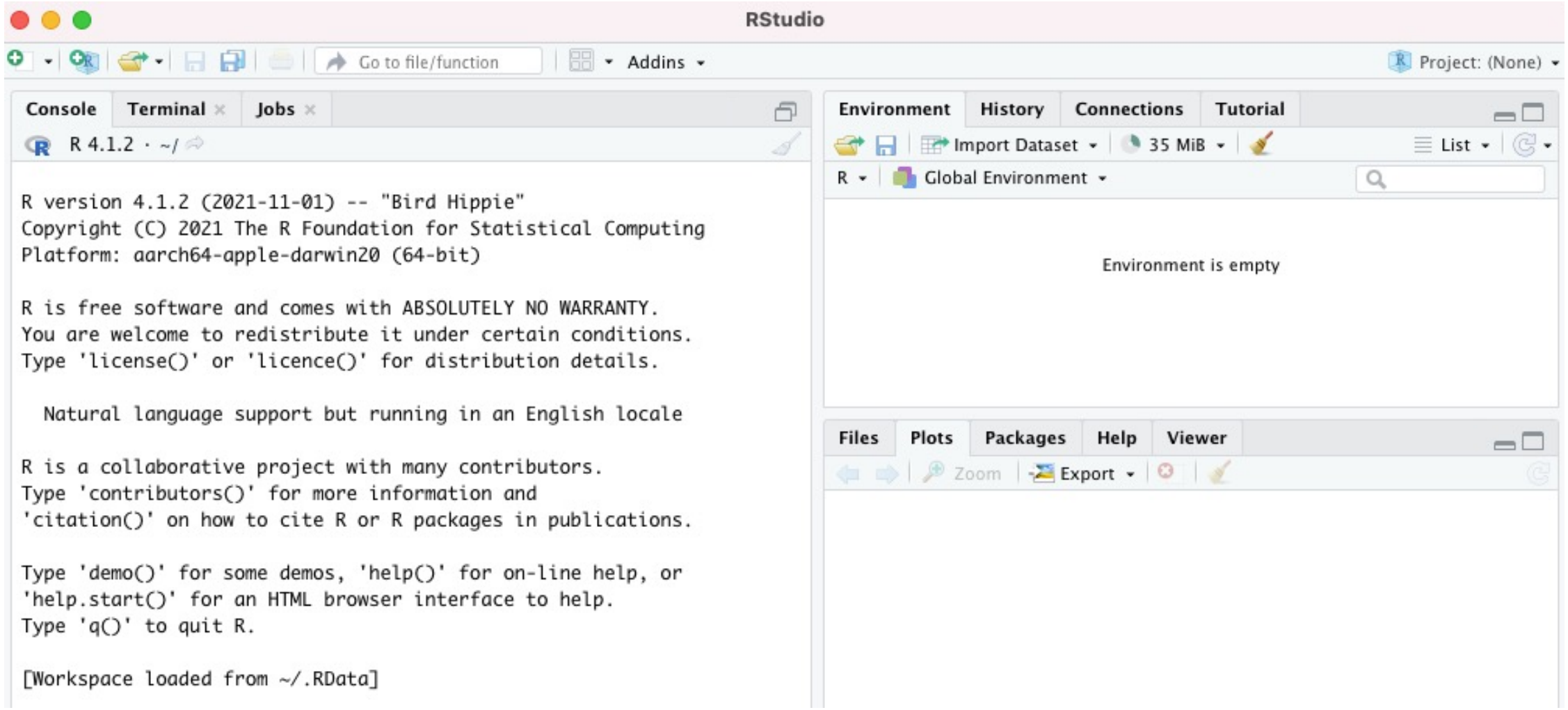
Download R first

https://cran.r-project.org/

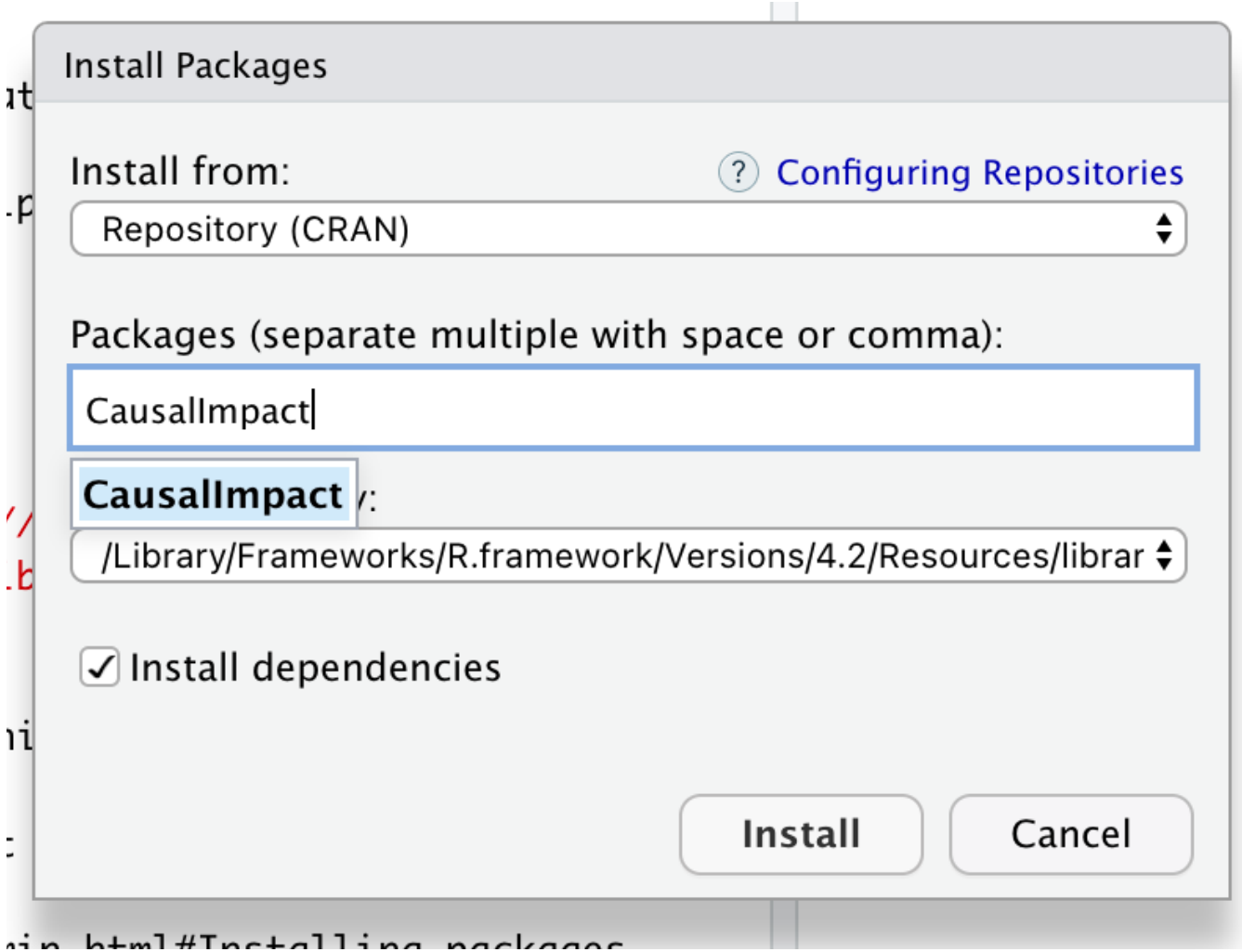
Download RStudio

https://www.rstudio.com/products/rstudio/download/

1. Download R Studio



1.1 Install Causal Impact



2. Prepare the data

Date	Clicks	Impressions	CTR	Position
25/06/2022	84	5428	1.55%	5.58
24/06/2022	79	5033	1.57%	5.82
23/06/2022	84	5523	1.52%	5.6
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19/06/2022	124	5371	2.31%	4.56
18/06/2022	102	5654	1.80%	4.71
17/06/2022	98	5377	1.82%	5.13

2. Prepare the data

date	clicks_test	clicks_control1	clicks_control2
01/01/2022	21	37	40
02/01/2022	34	43	49
03/01/2022	28	35	51
04/01/2022	25	49	58
05/01/2022	39	54	51
06/01/2022	27	48	48
07/01/2022	34	67	36
08/01/2022	36	58	59
09/01/2022	28	61	40

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The first column is always your test group.

Other columns can be used as control groups if they are a good fit

The pre-period should be at least twice as long as the post-period, to allow the model to plot the actual VS predicted outcome

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Any column with 0 should be either removed or corrected

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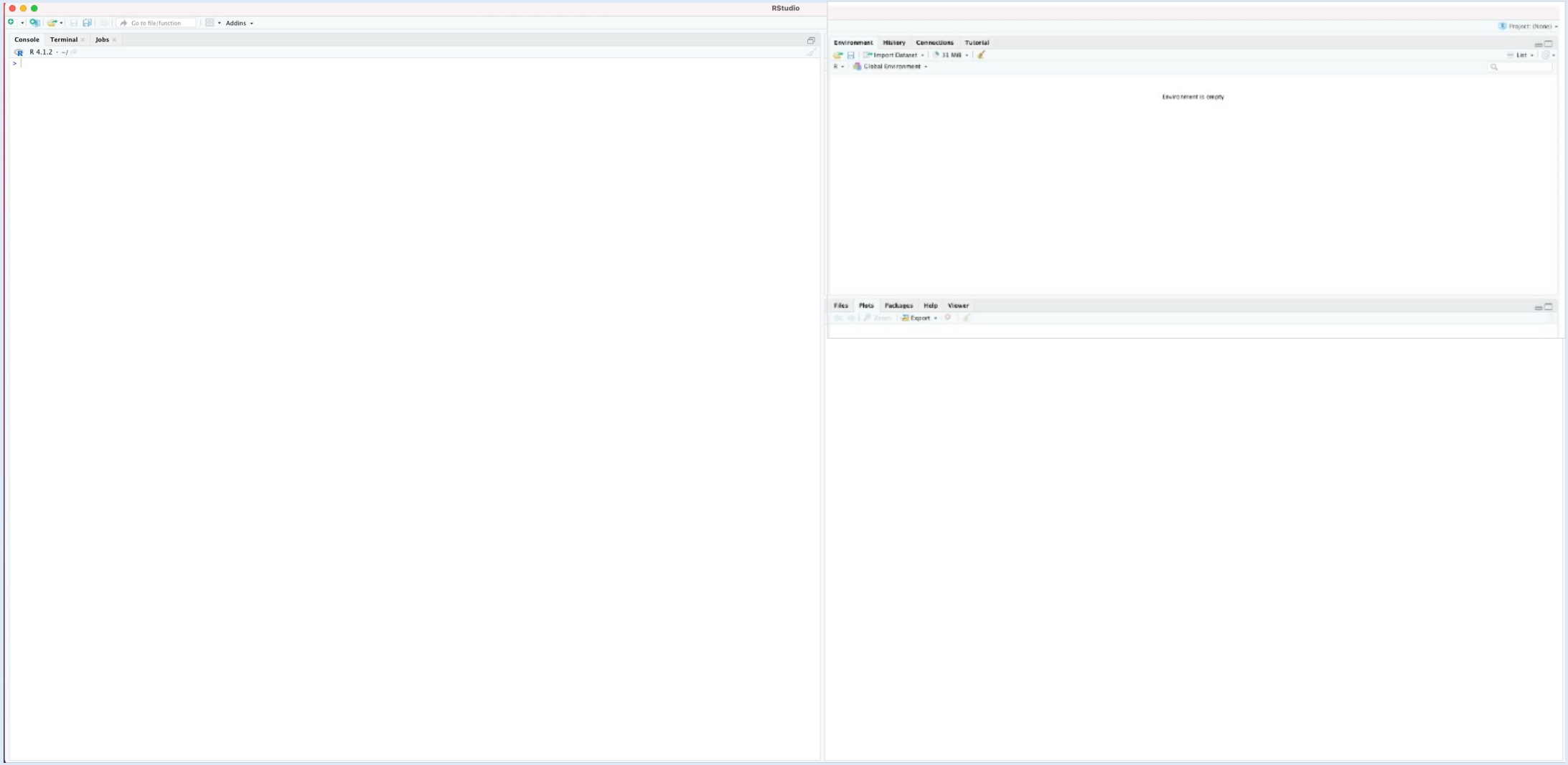
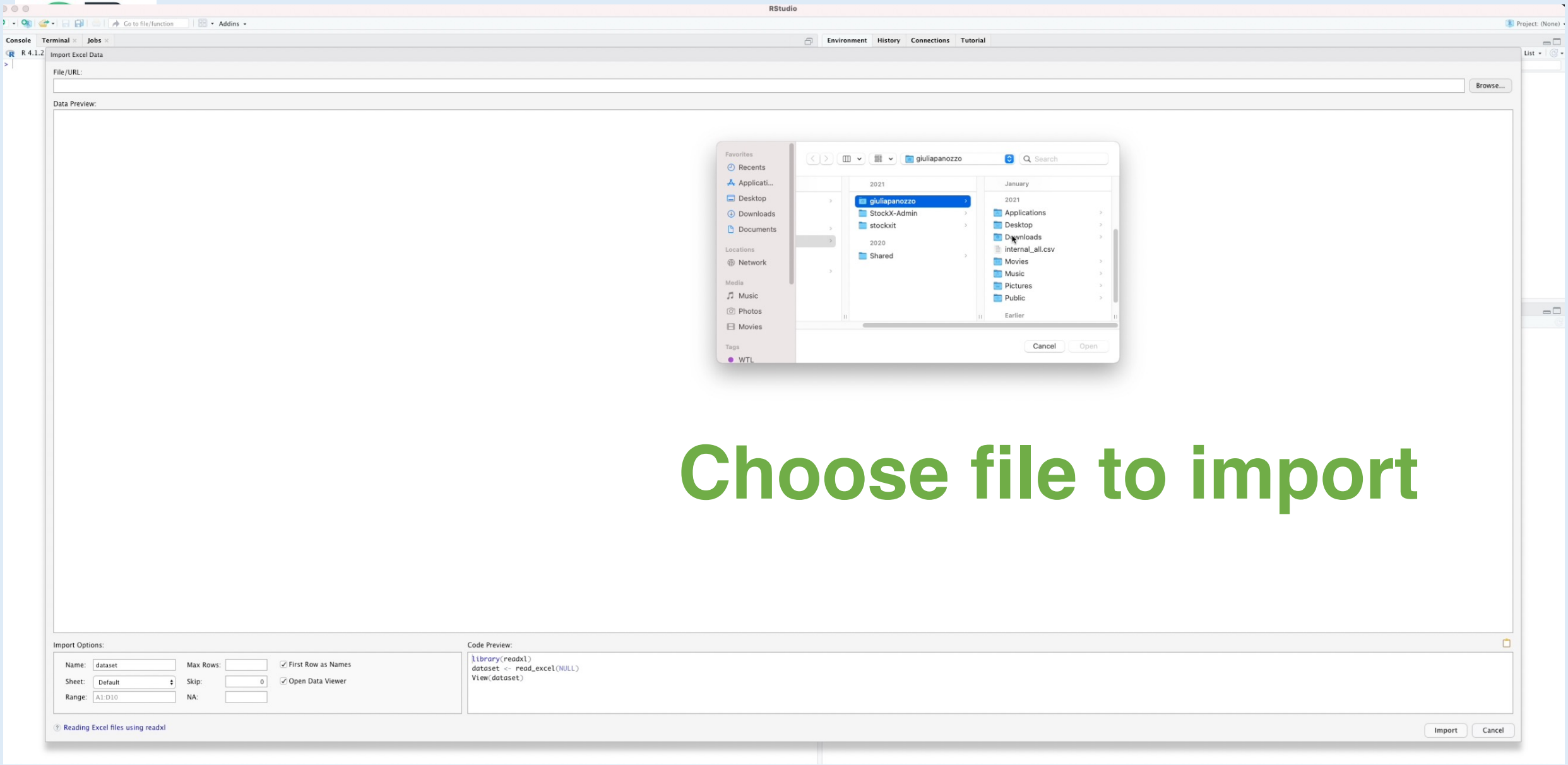
Multiple 0s

VS

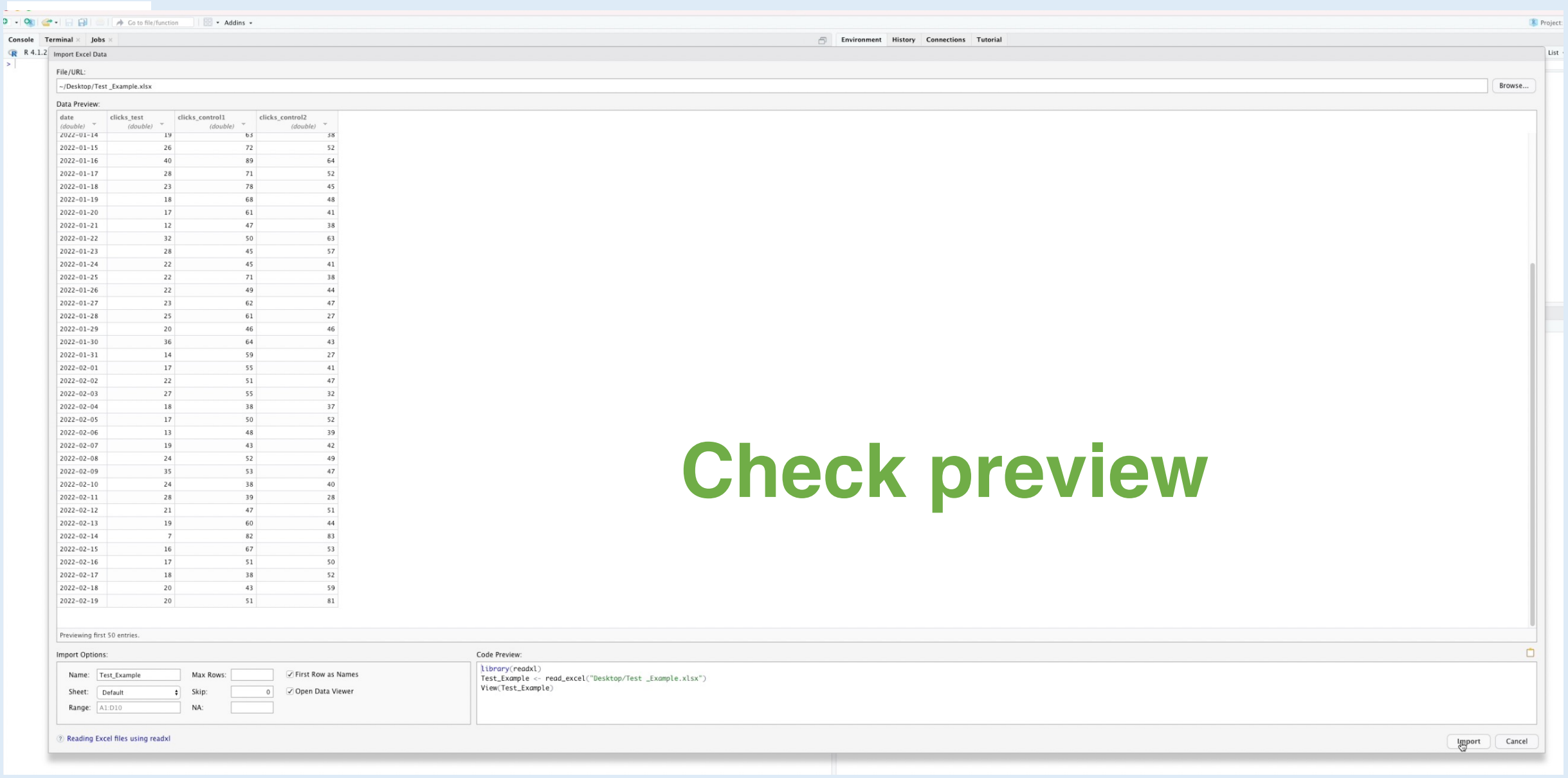
Isolated 0 in data set

3. Run the script!





Choose file to import



Check preview

Test_Example

Filter

	clicks_test	clicks_control1	clicks_control2
1	21	37	40
2	34	43	49
3	28	35	51
4	25	49	58
5	39	54	51
6	27	48	48
7	34	67	36
8	36	58	59
9	28	61	40
10	31	58	39
11	32	67	37
12	41	59	47
13	27	47	44
14	19	63	38
15	26	72	52
16	40	89	64
17	28	71	52
18	23	78	45
19	18	68	48
20	17	61	41
21	12	47	38
22	32	50	63

Showing 1 to 22 of 120 entries, 3 total columns

Set pre and post periods

Console Terminal Jobs

R 4.1.2 · ~/

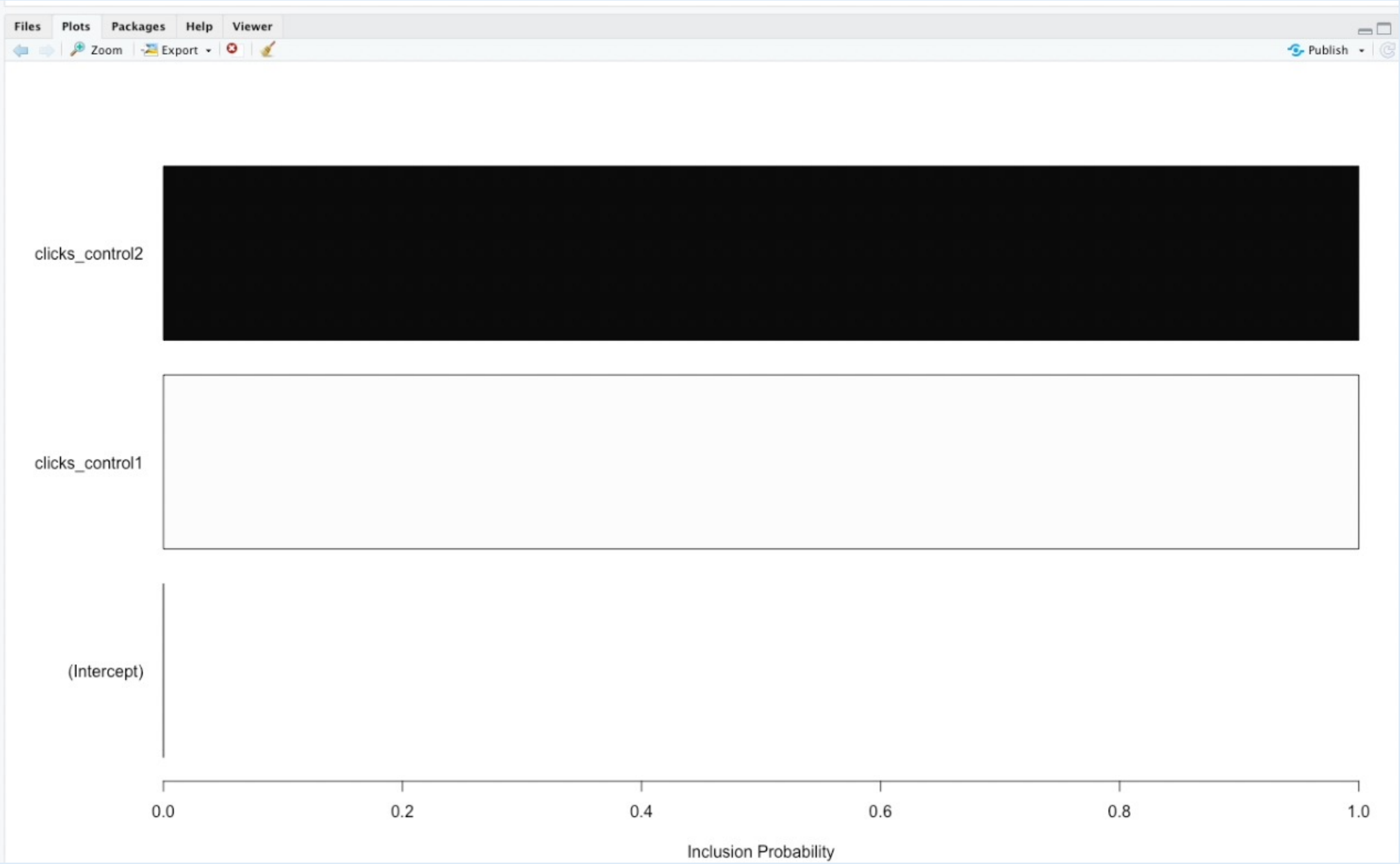
```
> library(readxl)
> Test_Example <- read_excel("Desktop/Test _Example.xlsx")
> View(Test_Example)
> pre.period<-c(1,90)
> post.period<-c(91,120)
> Test_Example$date<-NULL
> impact<-CausalImpact::CausalImpact(Test_Example,pre.period,post.period)
```


Files
Plots
Packages
Help
Viewer
Zoom
Export
Publish
original
pointwise
cumulative
It’s a winner!

Console Terminal Jobs

R 4.1.2 · ~/

```
> impact<-CausalImpact::CausalImpact(Test_Example,pre.period,post.period)
> plot(impact)
> summary(impact)
Posterior inference {CausalImpact}

                         Average      Cumulative
Actual                   34           1014
Prediction (s.d.)        24 (1.5)     709 (45.4)
95% CI                   [21, 26]     [615, 793]

Absolute effect (s.d.)   10 (1.5)     305 (45.4)
95% CI                   [7.4, 13]    [220.6, 399]

Relative effect (s.d.)   43% (6.4%)   43% (6.4%)
95% CI                   [31%, 56%]   [31%, 56%]

Posterior tail-area probability p:   0.001
Posterior prob. of a causal effect:  99.8996%

For more details, type: summary(impact, "report")

> summary(impact,"report")
Analysis report {CausalImpact}


During the post-intervention period, the response variable had an average value of approx. 33.80. By contrast, in the absence of an intervention, we would have expected an average response of 23.62. The
 95% interval of this counterfactual prediction is [20.51, 26.45]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response var
iable. This effect is 10.18 with a 95% interval of [7.35, 13.29]. For a discussion of the significance of this effect, see below.

Summing up the individual data points during the post-intervention period (which can only sometimes be meaningfully interpreted), the response variable had an overall value of 1.01K. By contrast, had th
e intervention not taken place, we would have expected a sum of 0.71K. The 95% interval of this prediction is [0.62K, 0.79K].

The above results are given in terms of absolute numbers. In relative terms, the response variable showed an increase of +43%. The 95% interval of this percentage is [+31%, +56%].

This means that the positive effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations. It should be noted, however, that the question of
 whether this increase also bears substantive significance can only be answered by comparing the absolute effect (10.18) to the original goal of the underlying intervention.

The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability p = 0.001). This means the causal effect can be considered statistically significant.
> plot(impact$model$bsts.model, "coefficient")
>
```


Files
Plots
Packages
Help
Viewer
Zoom
Export
Publish
clicks_control2
clicks_control1
(Intercept)
0.0
0.2
0.4
0.6
0.8
1.0
Inclusion Probability

Now give it a go!

```
#---Start by setting your pre and post period. Pre-period should be twice as long as your post period. Replace the numbers in parentheses with
your relevant timeframes.
pre.period<-c(1,90)
post.period<-c(91,120)
#---Now take out the date column: replace 'Test_Example' with the name of your document.
Test_Example$date<-NULL
#---Awesome! Your test group is now in the first column. Define the impact on your dataset, replacing 'Test_Example' with the name of your
document.
impact<-CausalImpact::CausalImpact(Test_Example,pre.period,post.period)
#---Time to see the magic in action! Copy and paste one row at the time below.
plot(impact)
#---this will show the impact of the change on a graph.
summary(impact)
#---this will indicate exactly how significant (or not) the change is, in percentage.
summary(impact,"report")
#---this will give you an extensive summary of the prediction and the outcome.
plot(impact$model$bsts.model, "coefficient")
#---this will show you all of of the control groups that were considered a good fit as covariants.
```

Access this script here

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What I've learned from (several) trials and errors…

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The date column should always be removed when using this script

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Column titles can error out if they contain special characters, spaces, capitalised letters

Start small, then expand your datasets with additional controls and features once you're comfortable with the script

Statistics VS real world

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“Statistics can be made to prove anything – **even the truth**.”

(Noel Moynihan)

1. External events can impact your data

Google algo updates

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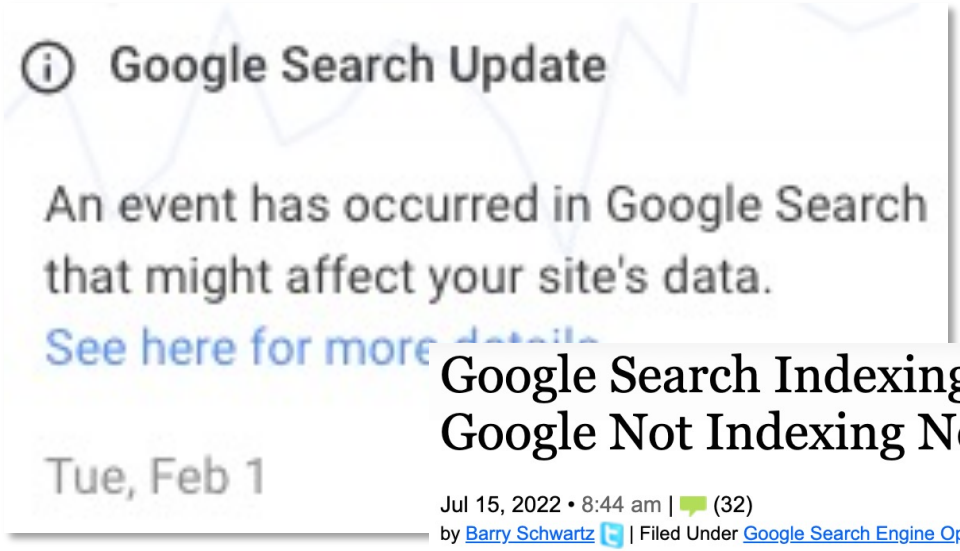

Tools tracking failures

Engineering releases

Jira

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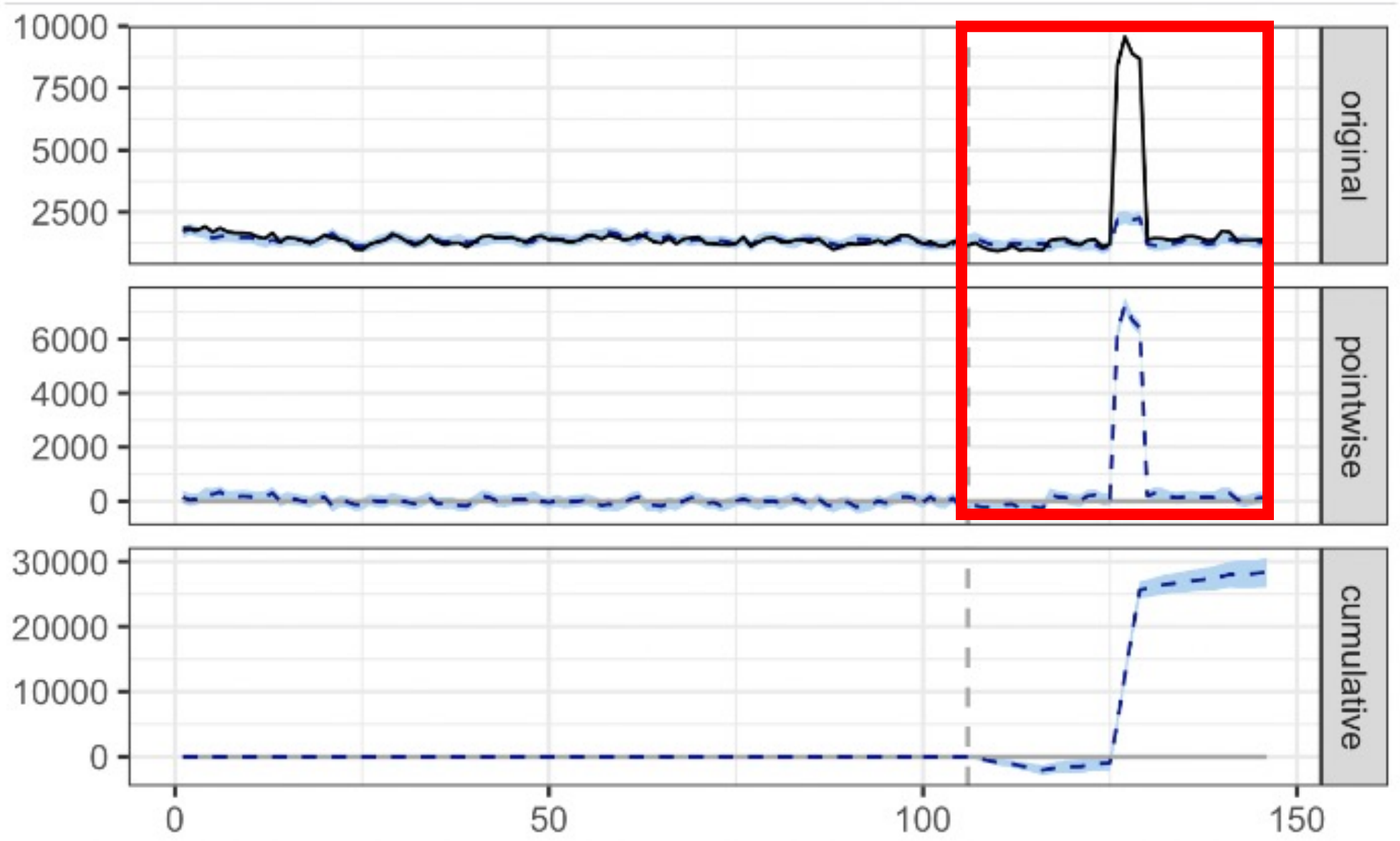
Create a document to map internal changes & external events

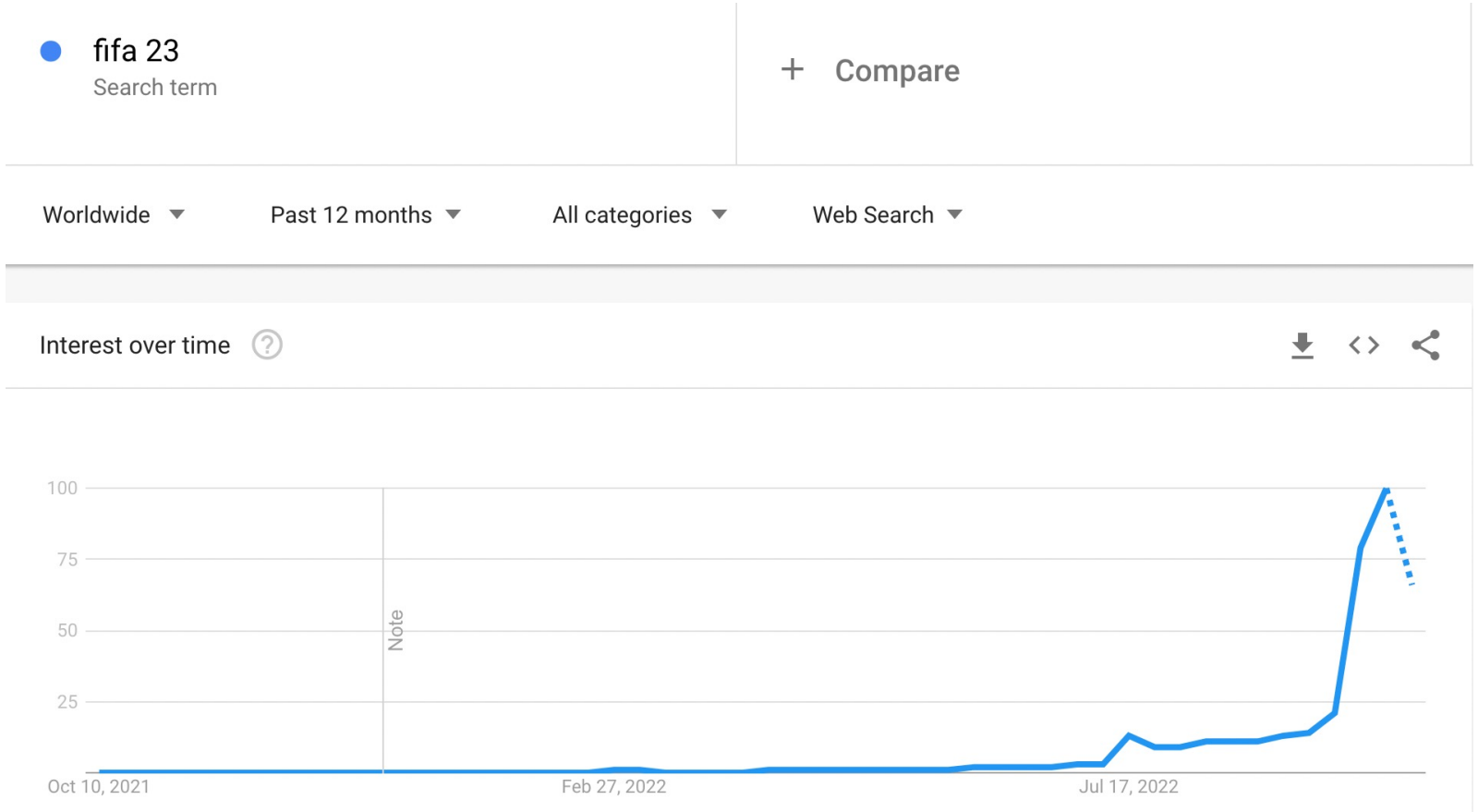
This will allow you to take into account any other known factors and isolate the treatment in the analysis

2. Mind the Outliers!


10000
7500
5000
2500
original
6000
4000
2000
0
pointwise
30000
20000
10000
0
cumulative
0
50
100
150

Outliers can originate from…

New product launches
(within the test group)



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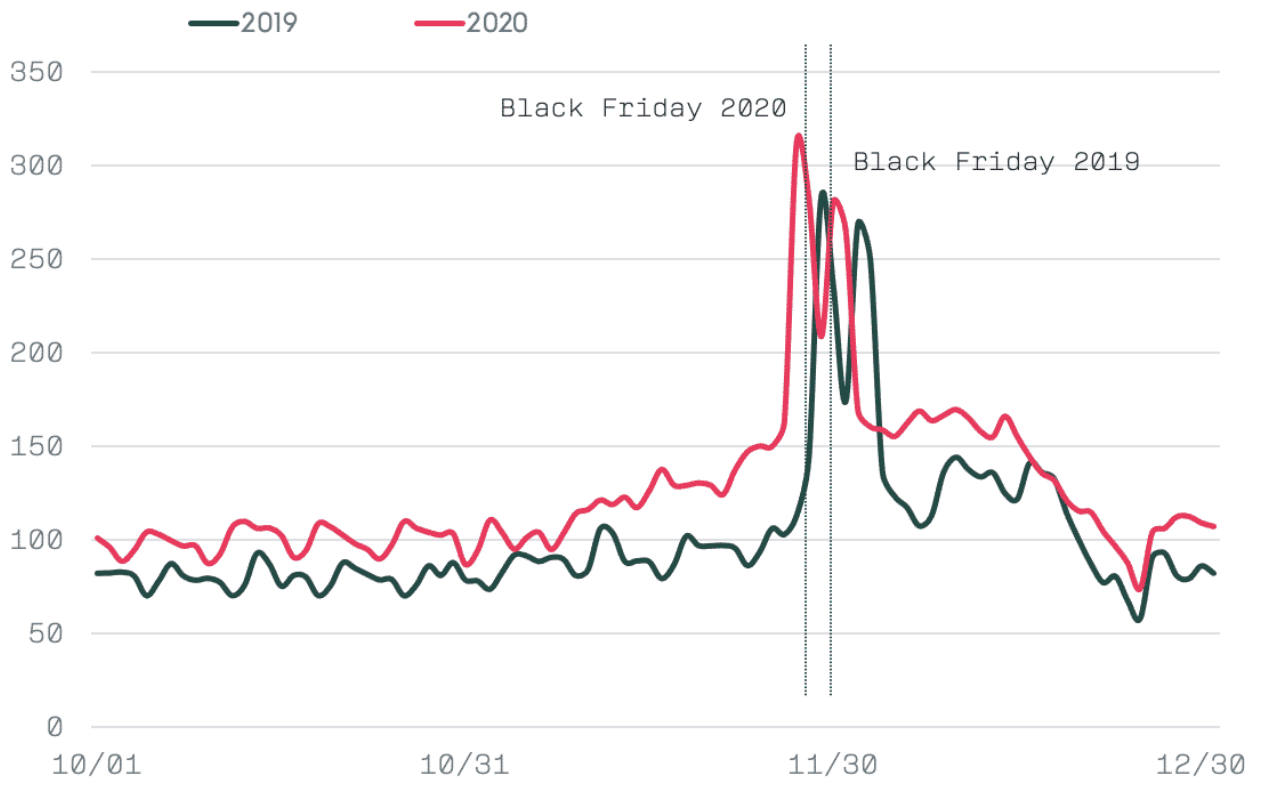
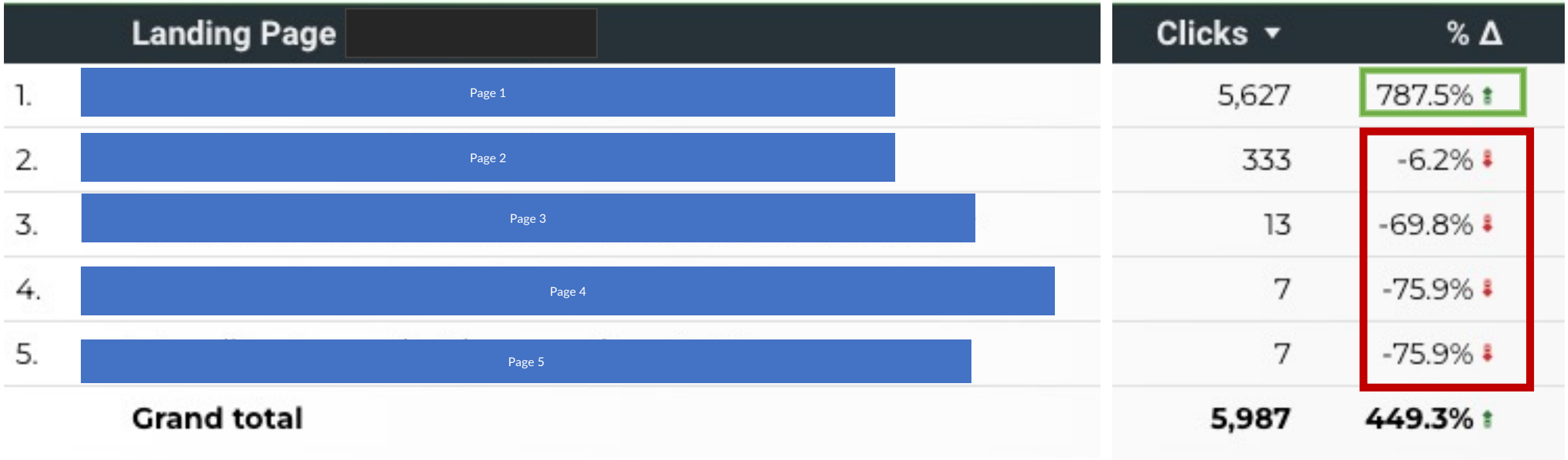
Holidays and seasonal events



Source: Criteo Data, All Retail, US. Indexed Daily Sales, compared to average in October 1-28 2020. Same set of retailers with stable sales tracking during the period in 2019 and 2020.

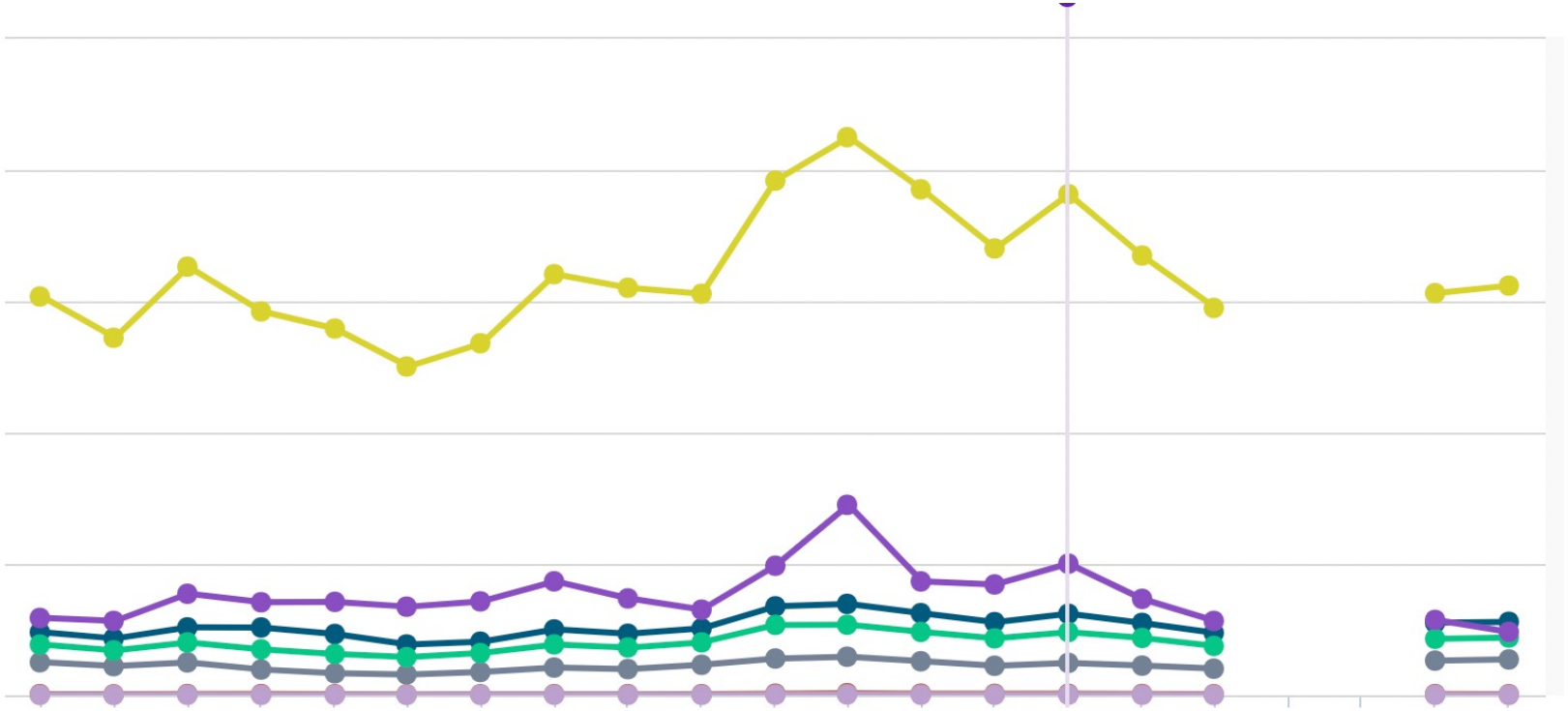
CRITEO

Results only from one page



Landing Page	Clicks	% Δ
1. Page 1	5,627	787.5%
2. Page 2	333	-6.2%
3. Page 3	13	-69.8%
4. Page 4	7	-75.9%
5. Page 5	7	-75.9%
Grand total	**5,987**	**449.3%**

Tracking bugs



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You can spot outliers and rule them out by…

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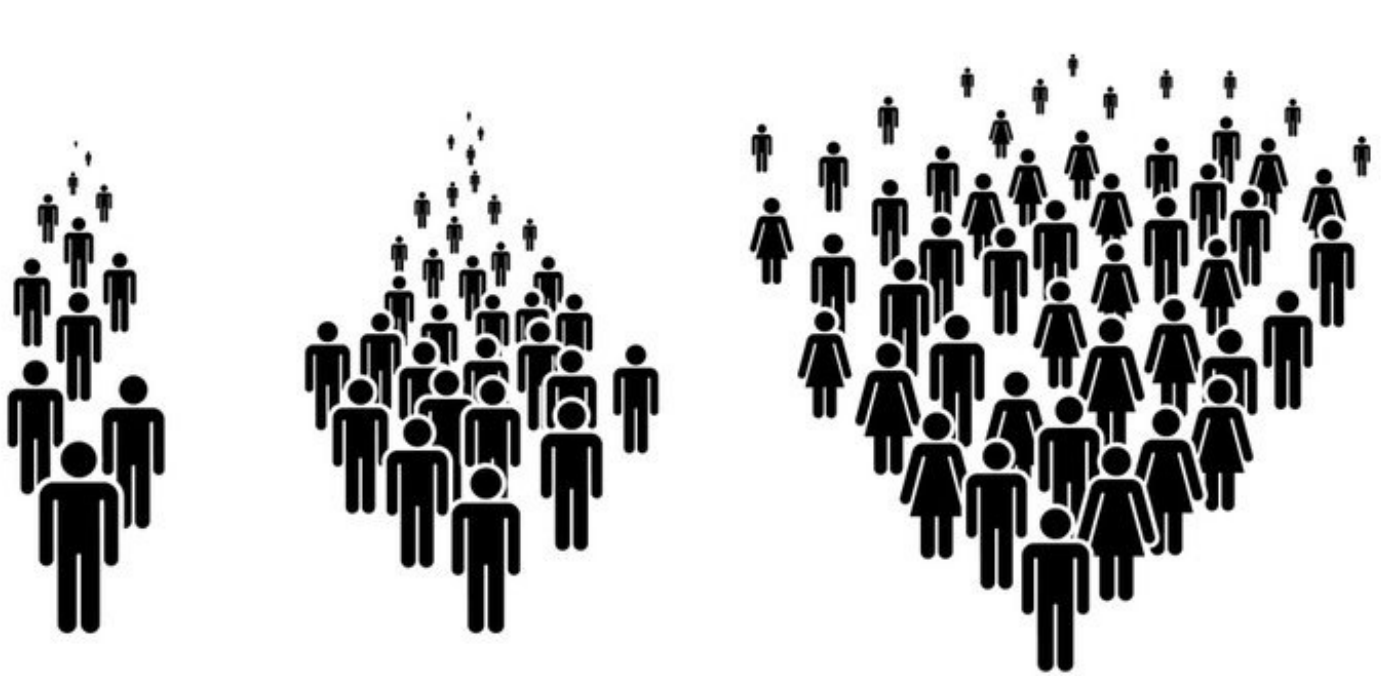
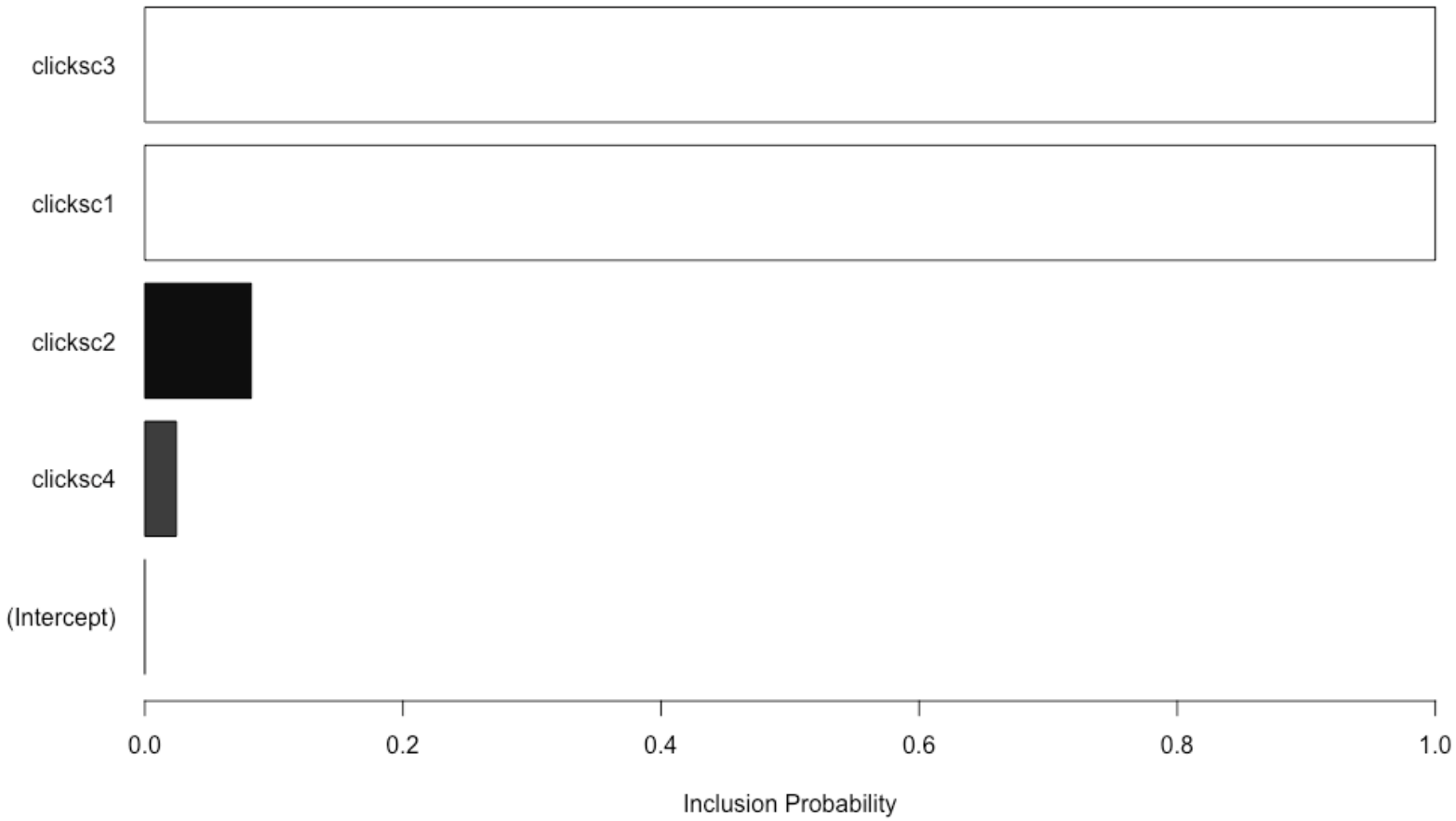
Increasing the size of the test group



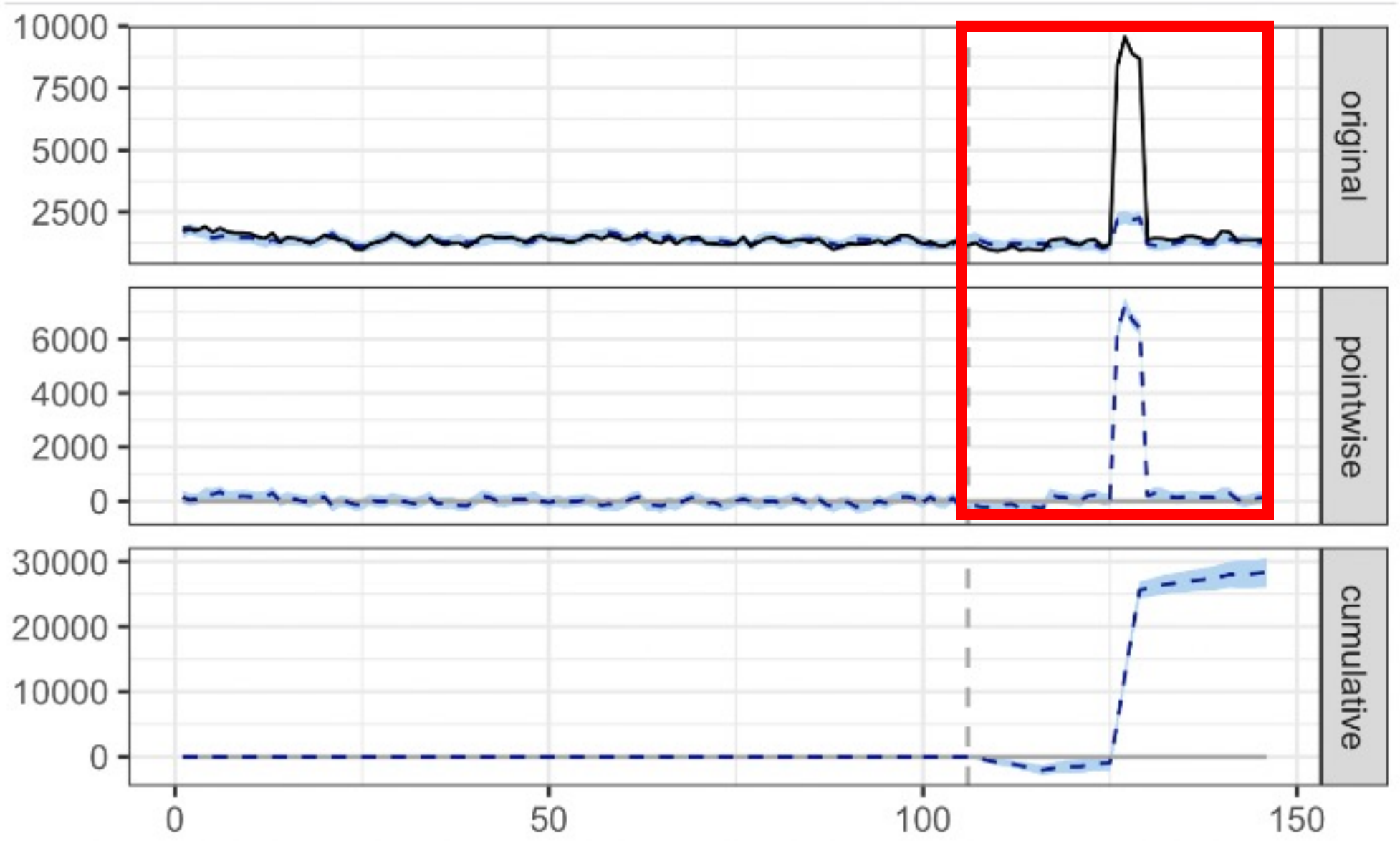
Adding control groups



Pre-processing your raw data

2022-05-28	1,362	68,274	1.99%
2022-05-29	1,415	97,155	1.46%
2022-05-30	1,429	91,694	1.56%
2022-05-31	1,269	83,984	1.51%
2022-06-01	1,174	82,342	1.43%
2022-06-02	1,365	85,380	1.6%
2022-06-03	1,400	84,253	1.66%
2022-06-04	1,108	68,384	1.62%
2022-06-05	1,217	70,160	1.73%
2022-06-06	8,407	82,419	10.2%
2022-06-07	9,567	87,732	10.9%
2022-06-08	8,885	83,187	10.68%
2022-06-09	8,675	97,327	8.91%
2022-06-10	1,399	84,884	1.65%
2022-06-11	1,454	85,745	1.7%
2022-06-12	1,439	84,720	1.7%
2022-06-13	1,377	95,840	1.44%
2022-06-14	1,382	87,826	1.57%
2022-06-15	1,517	97,692	1.55%
2022-06-16	1,535	96,529	1.59%
2022-06-17	1,467	87,061	1.69%

2022-06-03	1,400	84,253	1.66%
2022-06-04	1,108	68,384	1.62%
2022-06-05	1,217	70,160	1.73%
2022-06-06	8,407	82,419	10.2%
2022-06-07	9,567	87,732	10.9%
2022-06-08	8,885	83,187	10.68%
2022-06-09	8,675	97,327	8.91%
2022-06-10	1,399	84,884	1.65%
2022-06-11	1,454	85,745	1.7%
2022-06-12	1,439	84,720	1.7%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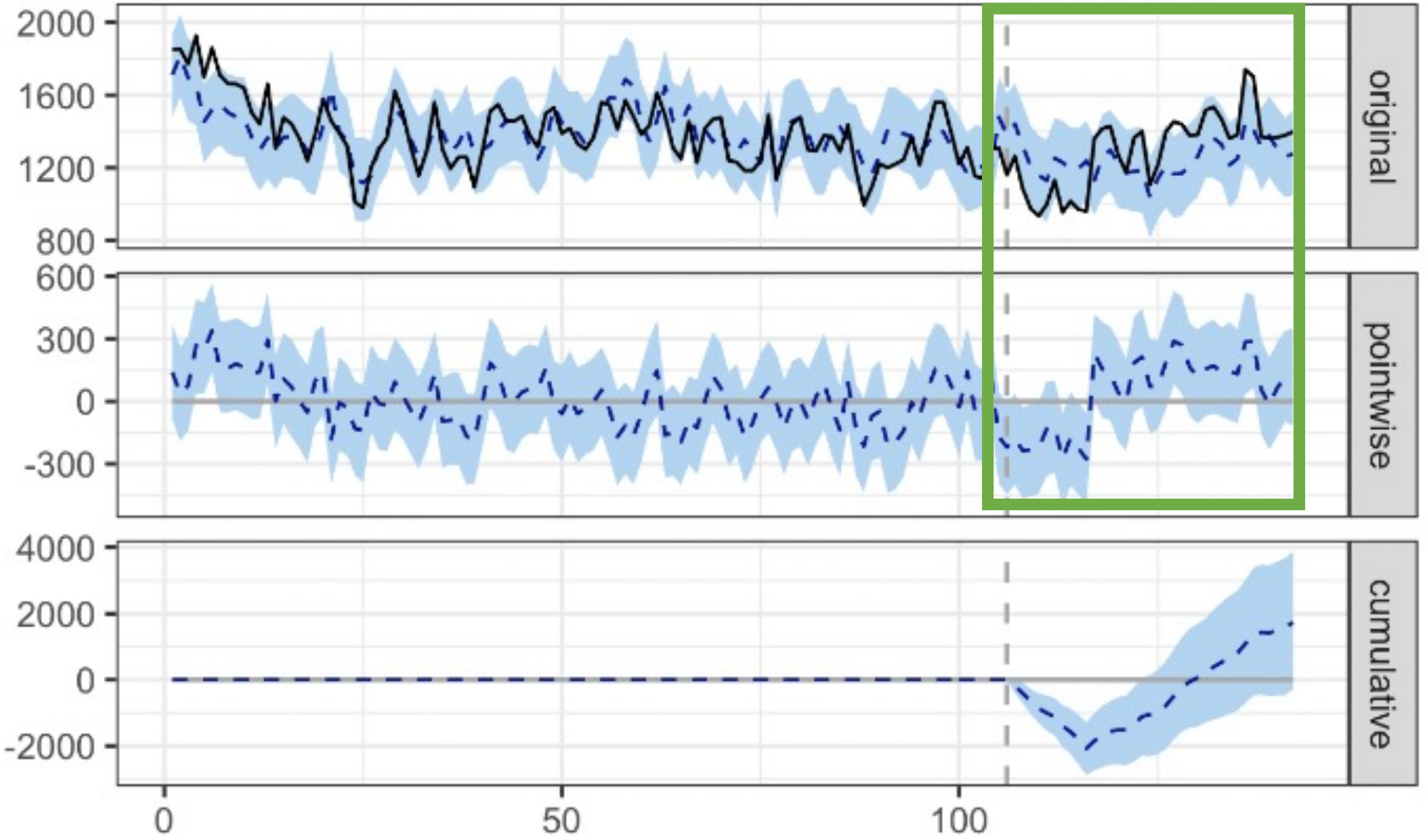
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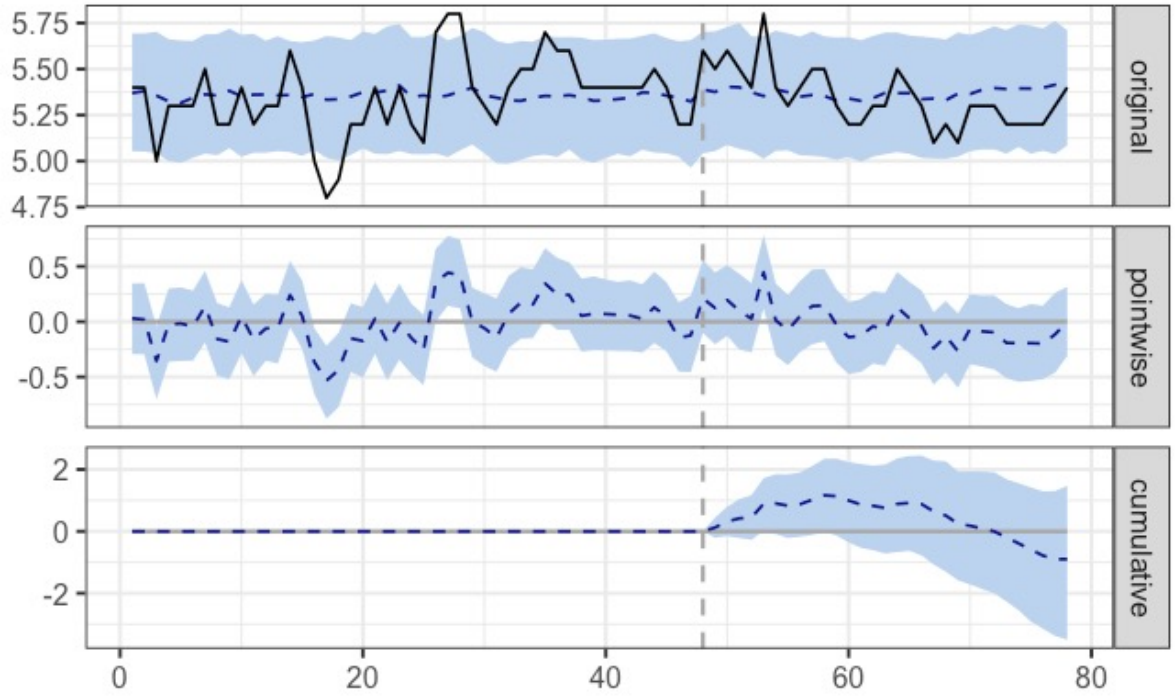
3. Beware of confirmation bias

Sometimes, your test will be inconclusive, or might be a loser even when you thought it'd be an easy winner



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In that case, you can run the test a little longer, or repeat the test with bigger groups

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If it’s still inconclusive or a loser, it’s probably best to revert the change and focus on other tests

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References and useful resources

- How we use causal impact analysis to validate campaign success - Part and Sum
- Measuring No-ID Campaigns with Causal Impact - Remerge & Alicia Horsch
- Causal Impact – Data Skeptic
- R Studio on GitHub
- The Comprehensive R Archive Network
- Causal Impact for App Store Analysis - William Martin

Thank You!

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