2020 eCAUG Virtual Conference

Evaluating the Impact of the Newspaper Search Scope: A Natural Experiment

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eCAUG

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Objective of this study

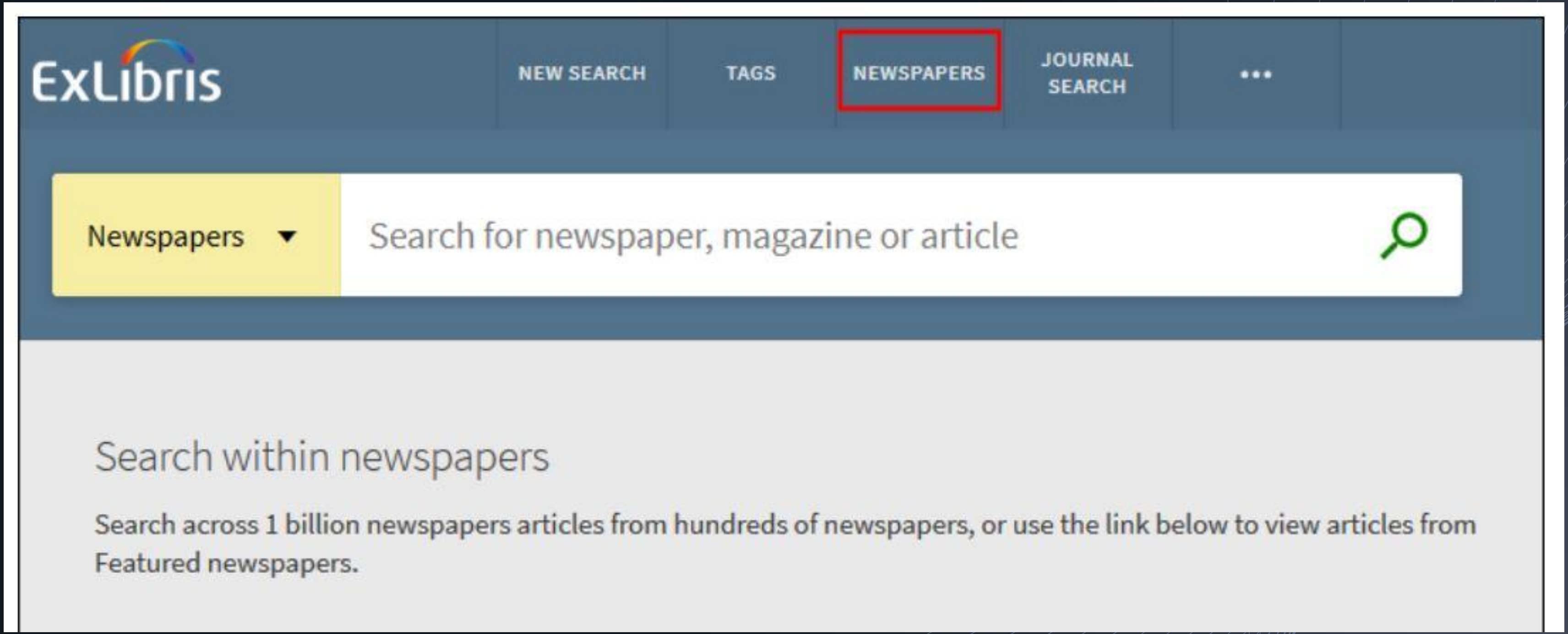
1. Develop understanding of how our users seek and use digital newspapers
2. Evaluate CSU Libraries electronic newspaper database subscription use
3. Provide a framework for evaluating effectiveness of Primo “enhancements”/new product release features

1.

Background

Ethnic NewsWatch & Global Newsstream

Newspaper Search interface



“The new feature increased the ability to discover content from newspapers, magazines, and other news resources” with the rational to increase “focus on scholarly content” within the Primo Central search index. - May 2019 Primo Release Notes

2.

Our Sample

California State University System

Participating CSU Libraries

Intervention	Control
CSU Bakersfield	CSU Stanislaus
CSU San Diego	CSU Long Beach
CSU San Luis Obispo	CSU San Bernardino
CSU San Marcos	CSU East Bay
CSU Sonoma	CSU Monterey Bay

Sonoma State U Library

Pseudo-Control	FTE student population	Intervention	FFTE student population	Date of intervention
CSU Monterey Bay	6,605	Sonoma State U	8,250	July 2019

Demographics: Sonoma State U enrolls more females 63% than males 37%. Business Administration is the largest major by enrollment.

CSU Bakersfield Library

Pseudo-Control	FTE student population	Intervention	FFTE student population	Date of intervention
CSU Stanislaus	9,217	CSU Bakersfield	9,920	April 2019

Demographics: CSU Bakersfield has a high hispanic and first generation to graduate population.
Turned on Newspaper Search at the recommendation of Ex Libris support to address an indexing mismatch.

CPSU San Marcos Library

Pseudo-Control	FTE student population	Intervention	FFTE student population	Date of intervention
CSU East Bay	12, 805	CSU San Marcos	12,389	June 2019

Demographics: CSU San Marcos gender split is 60% female to 40% male, and 47% of the student population is Latino/a. Business Administration is the biggest major by enrollment.

CPSU San Luis Obispo Library

Pseudo-Control	FTE student population	Intervention	FFTE student population	Date of intervention
CSU San Bernardino	18,319	CPSU San Luis Obispo	20,698	Sept. 2019

Demographics: CPSU San Luis Obispo enrolls slightly more men than women, 52% / 48%, with Engineering being their largest college by enrollment.

San Diego State U Library

Pseudo-Control	FTE student population	Intervention	FFTE student population	Date of intervention
CSU Long Beach	32,673	San Diego State U	32,169	June 2019

Demographics: 30% of SDSU enrollment is Hispanic, and 10% of enrollment is military affiliated. Business is the largest college by enrollment.

3.

Relevant literature

User behavior in a digital landscape

"Libraries today have many different options to enable their users to discover and gain access to their collections of information resources." Marshall Breeding (2019)

4.
Method

Data collection

Data generation timeline

January 2018 - February 2020	March - April 2020	May 2020	June 2020 - beyond
(Unbeknownst) Data Generation	**Data Collection**	**Data Analysis**	**Data Presentation**
Campuses randomly activate Newspaper search feature at their own discretion.	Directions sent out to participating campuses on how to pull and supply data.	Comparison of pre- and post- data among treatment and control groups, tests of statistical significance.	eCAUG 2020 virtual conference presentation.

“Natural experiments are neither **natural** nor **experiments**.”

- Thad Dunning

Neyman–Rubin Potential Outcomes Framework

Subject	$Y^T(u)$	$Y^C(u)$
Unit A	?	6
Unit B	7	?
Unit C	?	4
Unit D	3	?

Let Y=outcome, u=unit, T=treatment, C=control

We only ever observe either $Y^T(u)$ or $Y^C(u)$. Causal inference is a missing data problem

Random assignment allows us to use the control observations to fill in the missing outcomes for the treated observations (on average)

The Neyman–Rubin causal model

Necessary Assumptions:

- Randomization of treatment assignment
- Potential outcomes for a unit should be unaffected by the treatment assignment status or response to treatment of other units in the study group

Simple analysis:

- Comparison of treatment & control means
- Check for statistical significance

Why should we believe "as-if" random?

Quantitative evidence:

- Compared treatment and control groups along 68 variables contained in the Carnegie Classifications of Institutions of Higher Education dataset.

- Two-tailed Student's *t*-test was performed
  - *t*-statistic values were uniformly low
  - *No* statistically significant differences between the intervention and pseudo-control campuses

Qualitative Evidence for "as if" Randomness

Information	Do units have information that will be/are being exposed to a treatment?	Did students/faculty know that only some campuses were using NPS?
Incentives	Do units have incentives to self-select into treatment or control groups?	Would using the catalog/NPS at a different campus benefit students/faculty?
Capacities	Do units have the capacity to self-select into treatment or control groups?	Could students/faculty have used the catalog at a different campus to get superior NPS?

COUNTER R4 usage metrics

- **Result clicks** count all of the clicks originating from the result list of the database, including links to external resources.
- **Record views** count only views of detailed metadata within the database.

Note: Often criticized for inflation or misrepresenting how users interact with digital resources.

5.

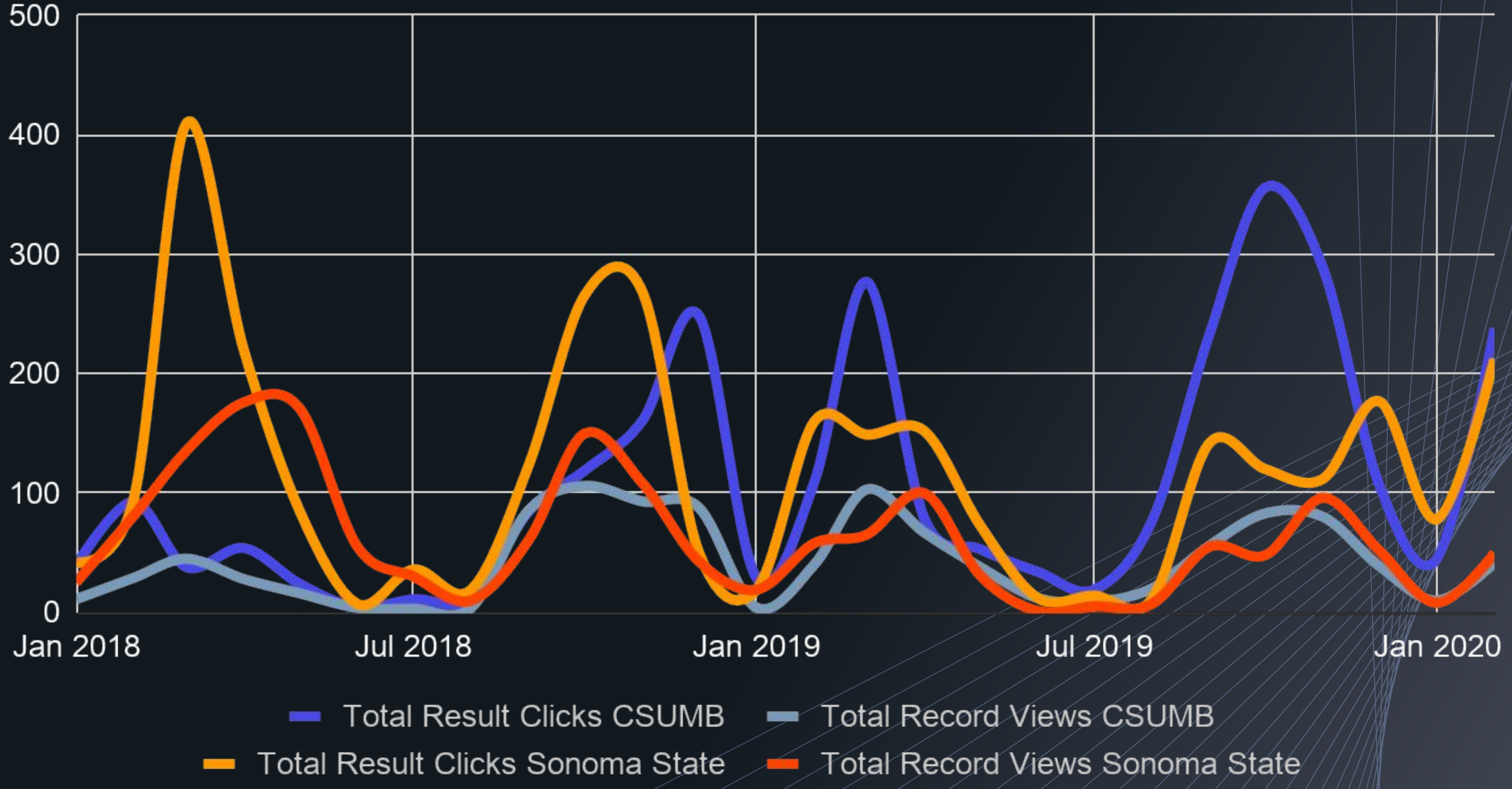
Graphical Comparisons

Intervention vs. pseudo-control

Pair 1: Sonoma & Monterey Bay

Intervention vs. Control COUNTER R4 usage data

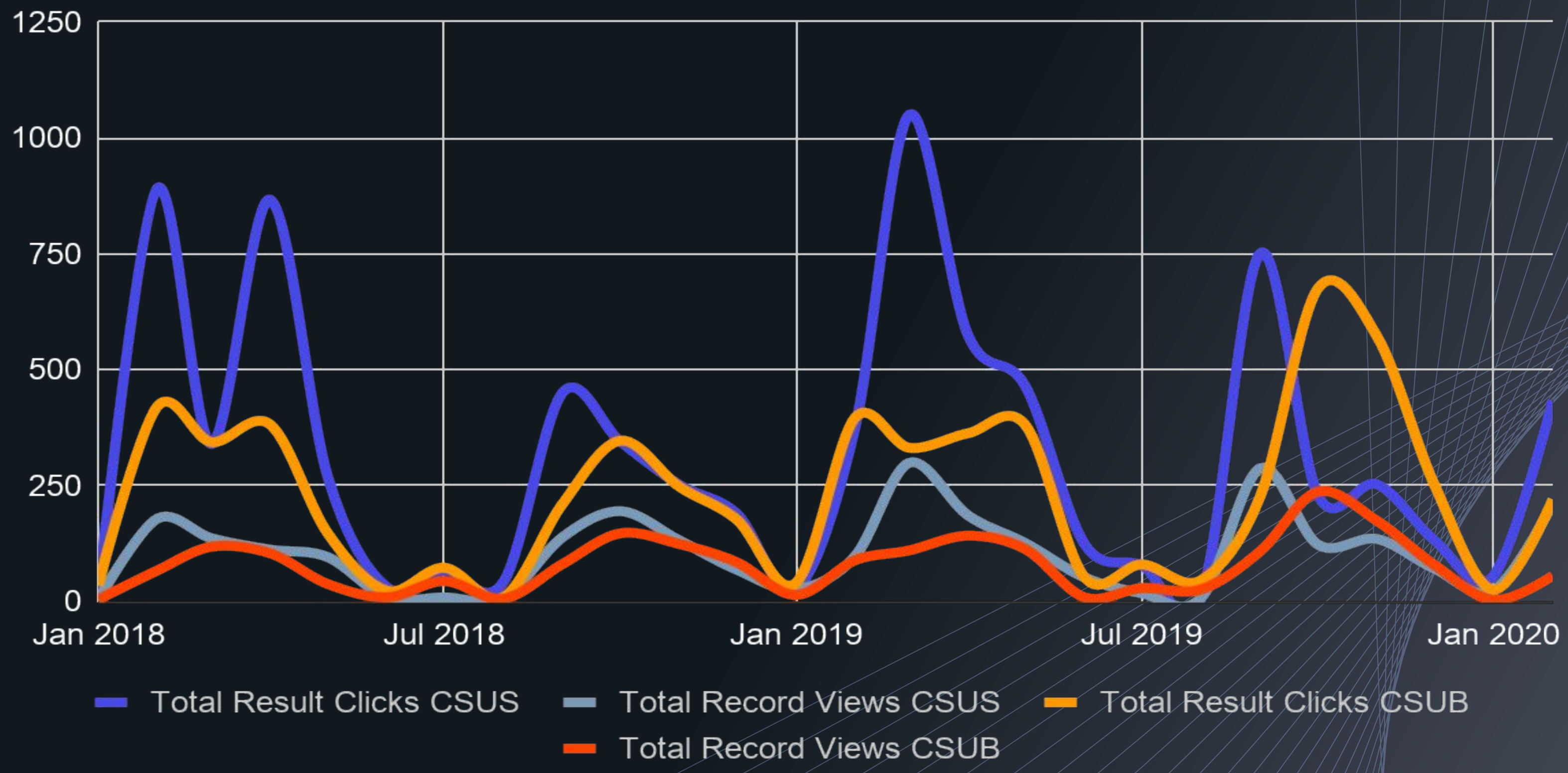
Intervention date: June 2019



Pair 2: Bakersfield & Stanislaus

Intervention vs. Control COUNTER R4 usage data

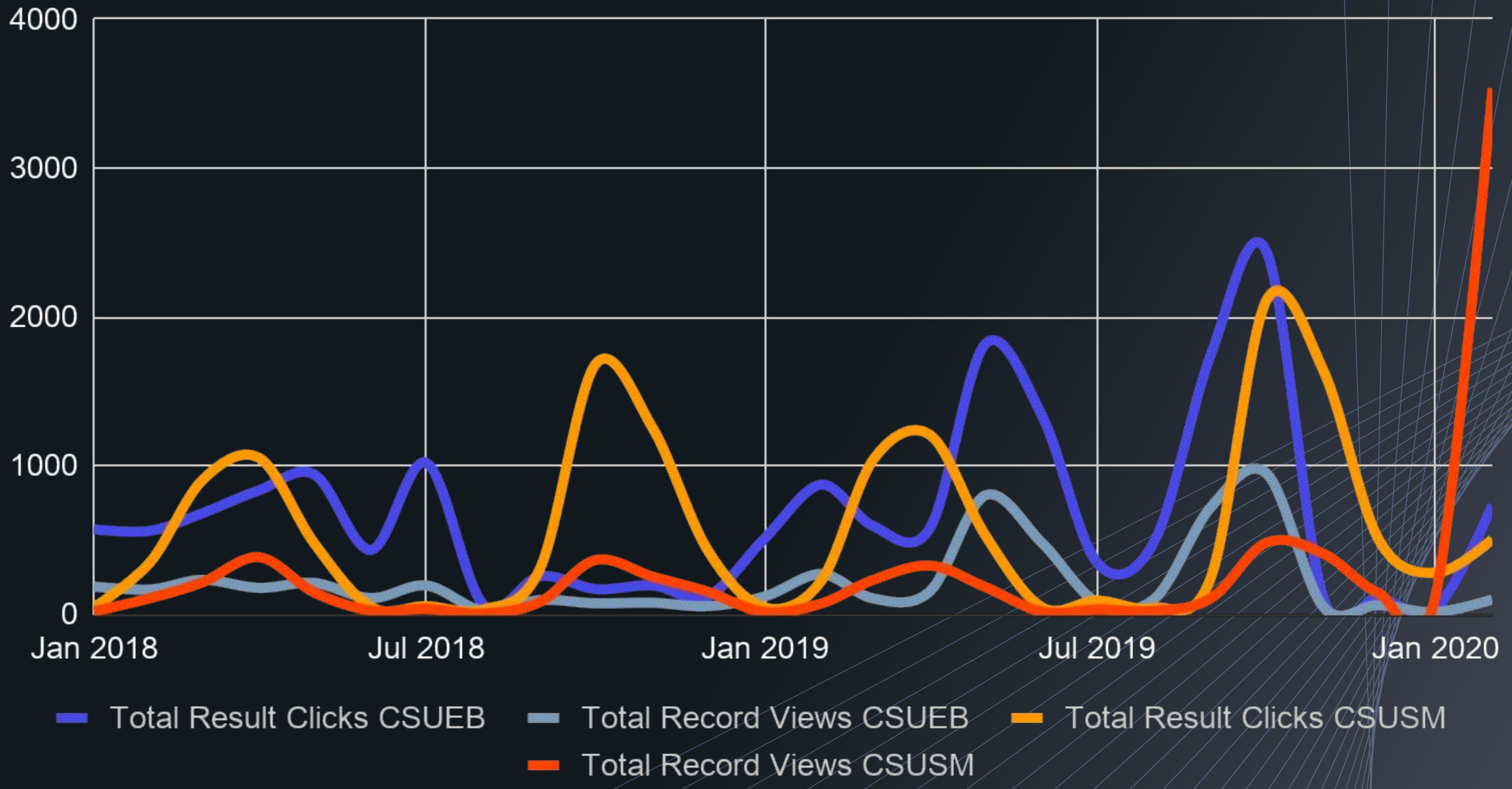
Intervention date: April 2019



Pair 3: San Marcos & Easy Bay

Intervention vs. Control COUNTER R4 usage data

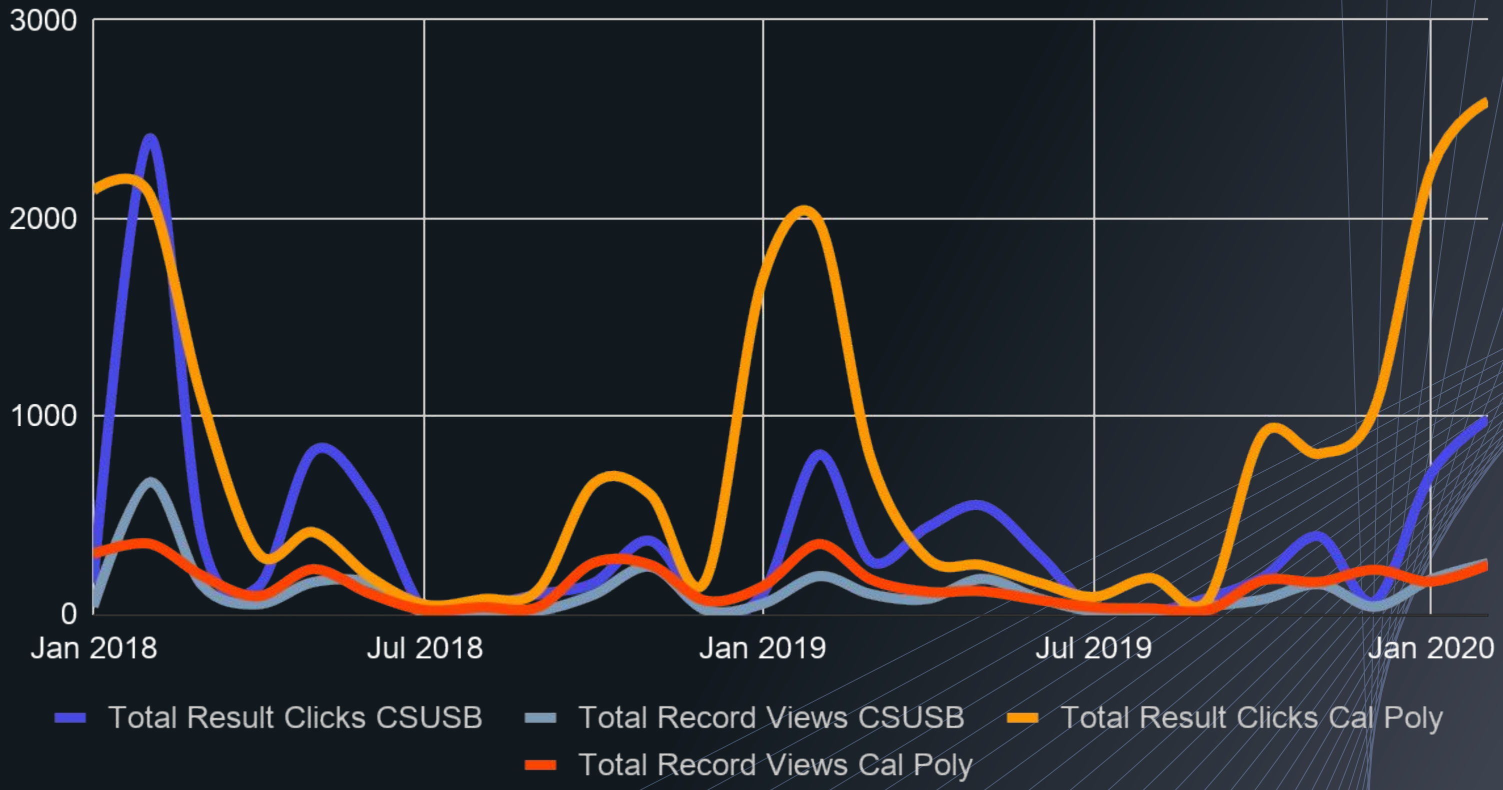
Intervention date: June 2019



Pair 4: San Luis Obispo & San Bernardino

Intervention date: July 2019

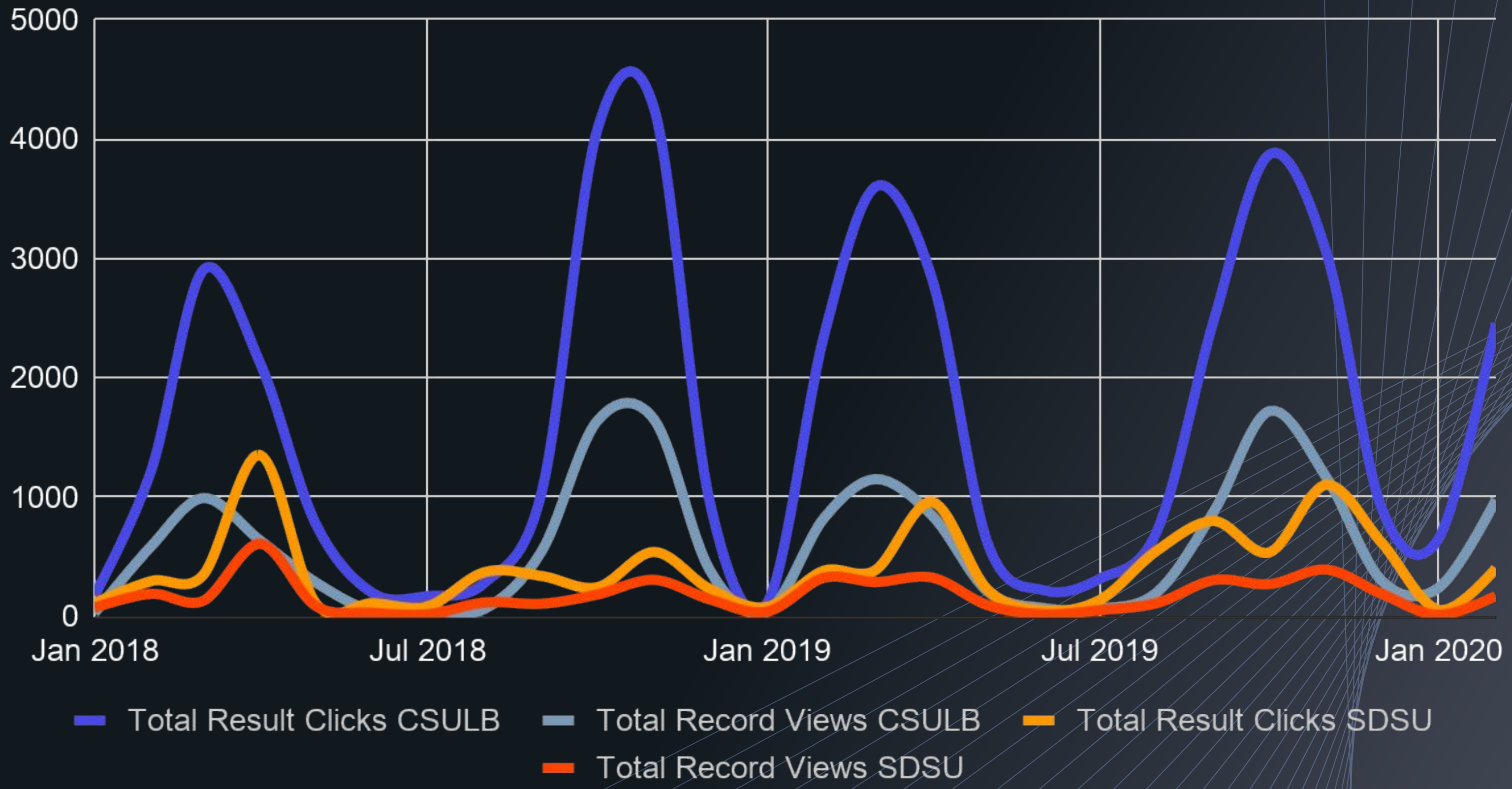
Intervention vs. Control COUNTER R4 usage data



Pair 5: San Diego & Long Beach

Intervention vs. Control COUNTER R4 usage data

Intervention date: June 2019



6.

Data Analysis

Putting the pieces together.

Post-treatment comparisons

"If treatment assignment is truly random or as good as random, a simple comparison of average outcomes in treatment and control groups can often suffice for valid causal inference." - Dunning (2012)

1. Subtract control group average from treatment group average for post-treatment time period
2. Calculate statistical significance of differences between groups post-treatment
3. Calculate margin of error (average effect is an *estimate*)

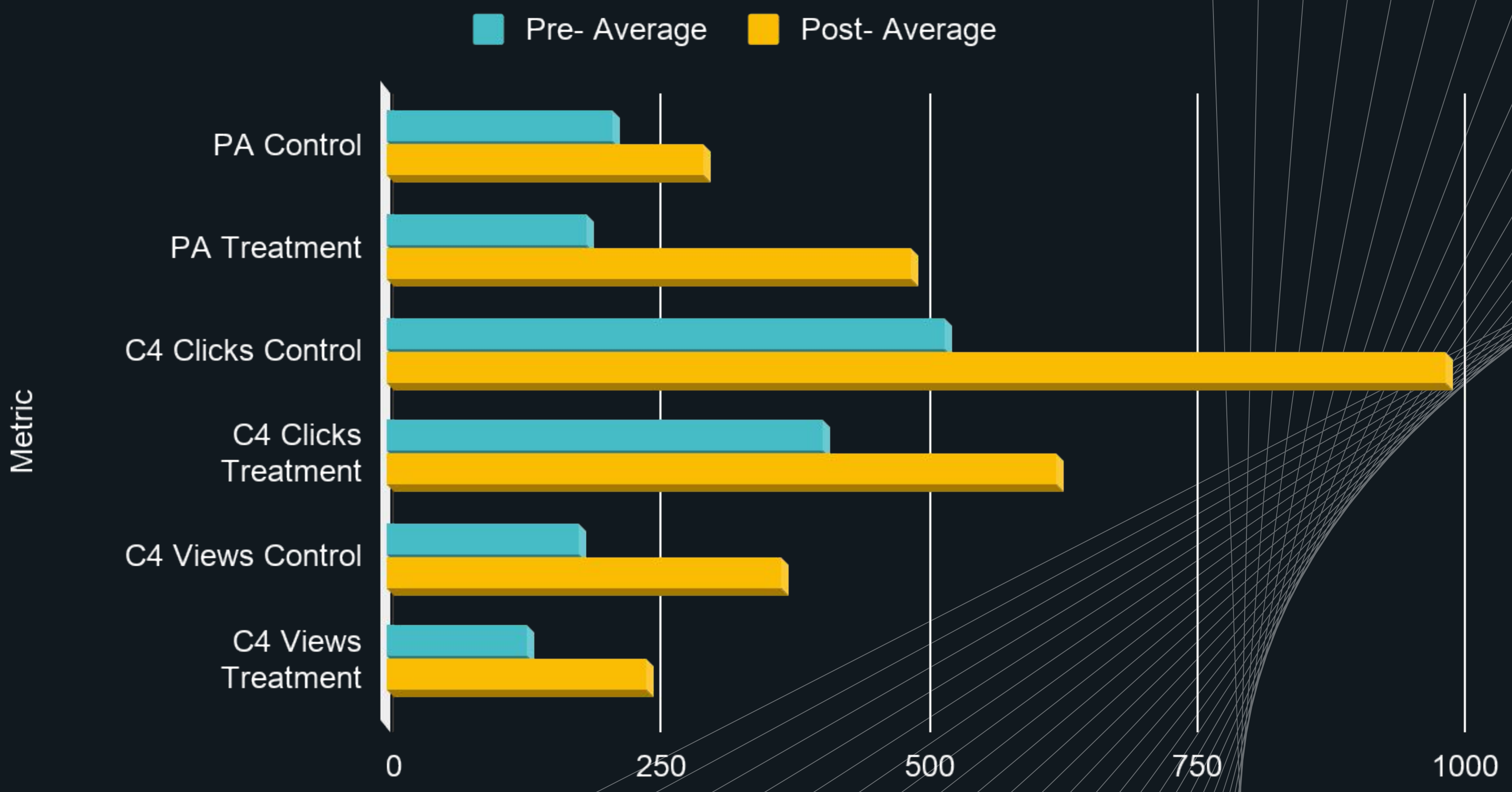
66%
-42%

7.

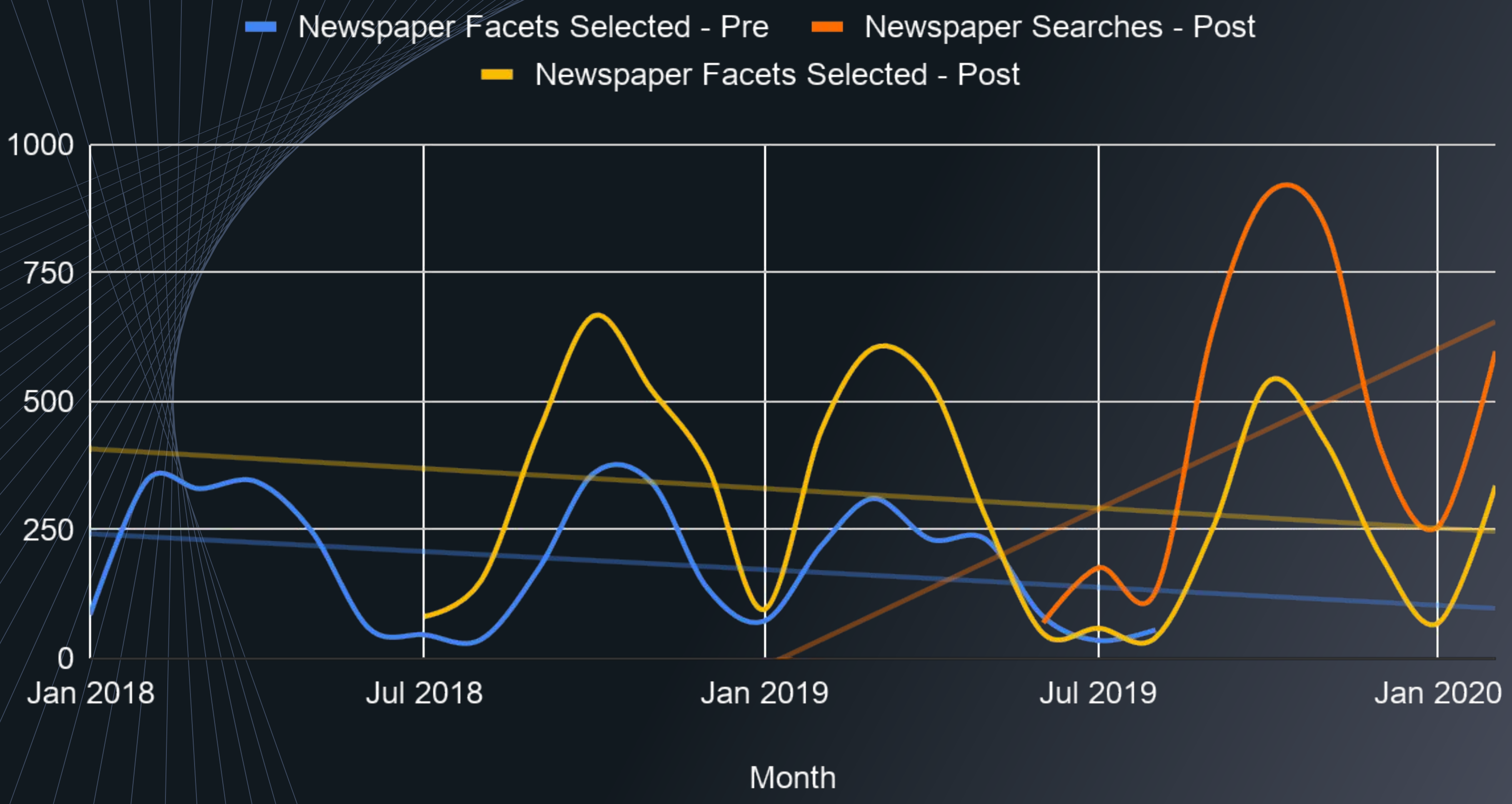
Results

Intervention vs. control

Monthly Average Pre and Post Treatment Comparisons



Monthly Average Newspaper Discovery in Primo



Average Causal Effects

Primo Analytics data

195.71 (searches/facet use)

p=0.01

±35.25 (99% CI)

COUNTER R4 usage data

-367.16 (Result Clicks)

p=0.02

±53.45 (99% CI)

No statistically significant difference in Record Views

Database List page traffic

No hypothesized causal relationship.

No statistically significant difference between groups after treatment

Effect is an *estimate*

The ‘real’ or ‘actual’ causal effect can never be observed since any library can either have the Newspaper Search turned on or off at any given time.

Limitations of Natural Experiment framework

- Is “as if” random plausible? Is it good enough?
- Natural experiments (in the technical sense) often occur with small/trivial differences, very little Grand Theory

Many questions we might have simply aren’t answerable using this framework due to either:

1. “as if” randomness cannot be credibly established using quantitative and qualitative data, or
2. research questions are not able to be mapped to actually existing institutional operations

Limitations of Primo Analytics data

- Primo Analytics did not record *any* data about the Newspapers Search prior to June 2019.
    - This reduced our sample size but we still had enough data (9 months from 10 campuses) for believable calculations
- PA has multiple known issues
    - Head to head comparisons of Google Analytics and PA data typically find differences
    - Sandbox and Production data are lumped together (Erhardt & McMunn, 2019)
    - Documented bizarre spikes along sessions and browser/device metrics (Heller & Martin, 2019)
    - Literally dozens of open cases about inconsistent or missing PA data (Heller & Martin, 2019)

Limitations of COUNTER R4 data

Global Newsstream is a "top-level" database (metrics broken down by sub-database usage).

IMPACT:

- Regular searches for each database and subdatabase can be different i.e. user can search in all the Global Newsstream database OR in each subdatabase.
- Alternate nonstandard metrics for Database Activity - Summary report

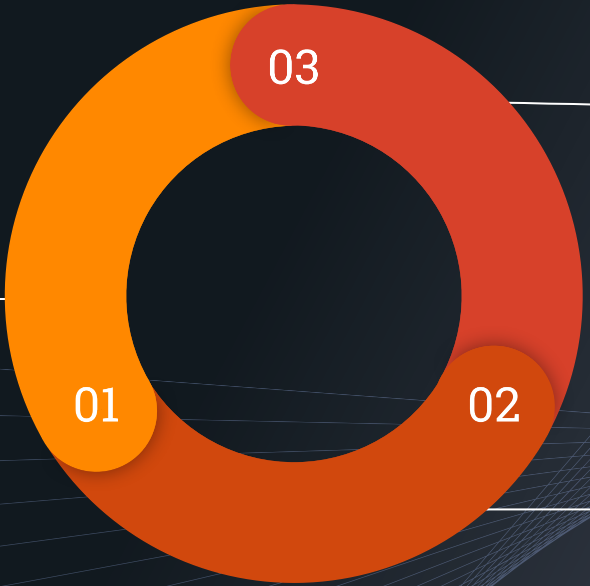
COUNTER R5 improvements to metric:

- **Result clicks:** To eliminate duplication, COUNTER R5 handles click and views as one metric: Total_Item_Investigations
- **Record views:** A supier metric might have been COUNTER R5 Total_Item_Requests which corresponds to total full text downloads.

“Conduct” your own experiment

Look

Form initial hypothesis and observe control and variation



Share

Published/public natural experiment results allow for real-world reliable measurements that other libraries can rely on

Analyze

Using validated research methods, Chi square or Z test

Discussion & further research

Possible Improvements

COUNTER R5 Total Item Requests over a longer time period

Add qualitative mixed methods such as a survey or usability test.

Data driven decisions

Can we use data alone to represent the user's experience?

How to continue to evaluate new enhancements and improvements for the impact on users.

Other considerations not addressed

Information literacy and students understanding of source format.

Impact of Google on searching.

Thanks!

Any questions?

Please use Q&A panel

Contact information / Questions?

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Credits 👍

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- Illustrations by Undraw.co

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Appendix:
Tabular Comparisons

Additional charts

Campus comparison table

All data from Fall 2019
Source: Enrollment Dashboard: Institutional Research & Analyses, The California State University
https://www2.calstate.edu/data-center/institutional-research-analyses/Pages/enrollment.aspx

* Denotes first month where Newspapers Search was turned on in production Primo, zero-ing out Newspaper facet usage

Pseudo-Control	Full-time equivalent student population	Intervention	Full-time equivalent student population	Date of intervention*
CSU Monterey Bay	6,605	Sonoma State University	8,250	July 2019
CSU Stanislaus	9,217	CSU Bakersfield	9,920	April 2019
CSU East Bay	12,805	CSU San Marcos	12,389	June 2019
CSU San Bernardino	18,319	CPSU San Luis Obispo	20,698	September 2019
CSU Long Beach	32,673	San Diego State University	32,169	June 2019

Primo Analytics

Campus	Pre Mean (Mo)	Post Mean (Mo)
Sonoma[t]	207.84	369
Monterey Bay[c]	121.63	127.57
Bakersfield[t]	169.81	182.56
Stanislaus[c]	206.88	194.1
San Marcos[t]	149.38	483.56
East Bay[c]	110	89.33
San Luis Obispo[t]	176.95	640.67
San Bernardino[c]	220.95	256.67
San Diego[t]	252.33	802.89
Long Beach[c]	600.17	602.15

COUNTER DB1 (R4) - Result Clicks

Campus	Pre Mean (Mo)	Post Mean (Mo)
Sonoma[t]	115.84	121.86
Monterey Bay[c]	78.37	192
Bakersfield[t]	221.81	253.2
Stanislaus[c]	361.56	253.5
San Marcos[t]	370.25	677.78
East Bay[c]	638	693.06
San Luis Obispo[t]	668.3	1277.33
San Bernardino[c]	386.2	404.33
San Diego[t]	389	405.7
Long Beach[c]	1235.17	1749

Database List Views

Campus	Pre Mean (Mo)	Post Mean (Mo)
Sonoma[t]	2546.32	2485.71
Monterey Bay[c]	4,694	2718.71
Bakersfield[t]	2174.50	1904.90
Stanislaus[c]	4541.94	3538.90
San Marcos[t]	16,989	22,494
East Bay[c]	8403.25	6838.22
San Luis Obispo[t]	11681.85	11127
San Bernardino[c]	20,287	25,942
San Diego[t]	10237.83	8582.4
Long Beach[c]	19497.83	19253.3