

Data Mining

Inference 1

Santiago Alonso-Díaz

Tecnológico de Monterrey
EGADE, Business School

Startups and experimentation (Koning et al., 2022)

Discuss:

Why do startups succeed?

What is the role, if any, of experimentation (A/B testing)?

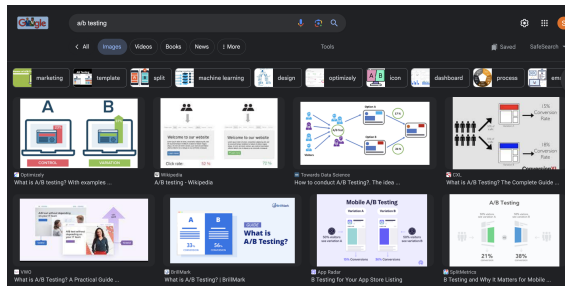


Figure: A/B testing

Startups and experimentation

Reflections around experimentation (Koning et al., 2022)

- Doing experiments in digital businesses is easier (e.g. Mercadolibre testing layouts)
- Experiments should improve organization learning, but not enough evidence
- It is not always clear for organizations what ideas to test
- Incremental or disruptive changes due to experimentation?

Startups and experimentation

To bring more clarity on the effects of A/B testing, Koning et al., 2022 evaluate 35,000 global startups over a 4-year period. Main results:

- A/B testing improves startup performance (e.g. introduce new products at higher rates).
- Venture capital (VC) startups do more A/B testing than non-financed startups.
- Silicon Valley startups do more A/B testing
- Regardless of the previous two results, A/B testing is beneficial to all.

Takeaway

"... experimentation helps drive both valuable incremental changes and the development of significant product improvements." (Koning et al., 2022, pp. 6436)

Data sources

Range of data: 2008-2013

Crunchbase Pro: tracks technology startups across the globe.

Builtwith sales intelligence and market share analysis platform for web technologies. This one has info. on A/B software use.

SimilarWeb is a market intelligence platform that estimates website and app growth metrics.

Internet Archive's Wayback Machine nonprofit archive of websites on the internet.

Exogenous shock (IV)

March 2017: Google launches Optimize and Optimize 360. Tools for A/B testing tools.

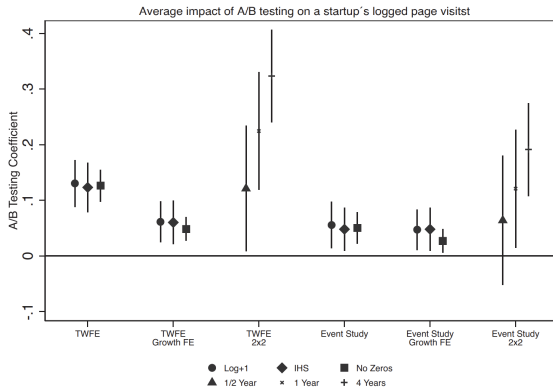
Results

Panel B: Start-up level		
	Number of start-ups	Percentage A/B testing
Not angel/VC funded	22,250	12.9
Angel/VC funded	13,012	25.2
Founded 2012–13	14,569	15.3
Founded 2010–11	11,966	16.5
Founded 2008–09	8,727	15.2
Outside United States	14,645	16.1
In United States, outside Bay Area	12,493	18.9
Bay Area	4,187	25.4
1–10 employees	15,393	13.0
11+ employees	19,840	20.7
Fewer than 1,500 weekly visits	17,189	8.1
More than 1,500 weekly visits	18,073	26.3
Commerce and shopping	4,517	24.1
Advertising	2,445	14.8
Internet services	2,079	17.2
Software	2,047	16.1
Data and analytics	1,940	21.6
Apps	1,746	17.1
Content and publishing	1,579	14.8
Financial services	1,547	23.6
Education	1,386	19.3
Information technology	1,233	20.0
Healthcare	1,042	19.2
Hardware	1,030	16.5
Other	12,671	14.2

Notes. Panel A provides summary statistics at the startup-week level. Panel B shows the number of startups of each type and the percent that use an A/B testing tool for at least one week during our panel.

Figure: Heterogeneity in A/B testing (Koning et al., 2022)

Results



Notes. "TWFE" indicates standard two-way fixed effects models, "Growth FE" indicates the model includes firm growth fixed effects, and "2x2" indicates that the estimate is from a simplified difference-in-differences model that includes only data from the first week in our panel and a single observation either a half-year, year, or four years later. "Event study" indicates that only A/B switchers are included in the data. "IHS" indicates that we use the inverse hyperbolic sine instead of logged-plus-one visits. "No Zeros" indicates that all weeks in which page views are zero have been excluded from the data. All models include start-up fixed effects, week fixed effects, and a control for the size of the start-up's technology stack. Bars are 95% confidence intervals.

Figure: Robust effect on visits (Koning et al., 2022)

Results

Figure 2. Event Study Plot Showing the Effect of A/B Testing over Time

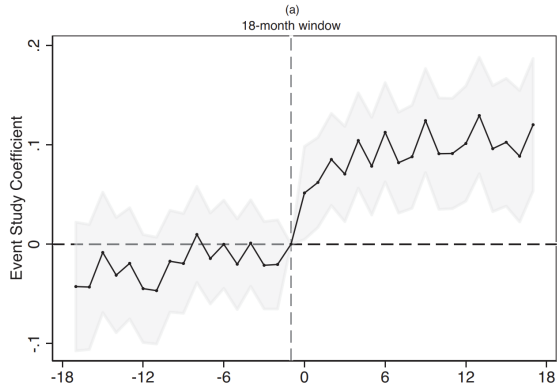
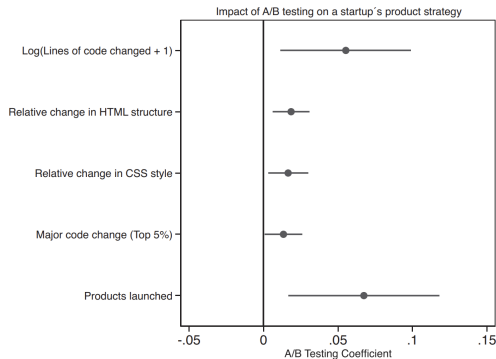


Figure: Persists over time (Koning et al., 2022)

Results

Figure 4. We Find That A/B Testing Does Not Lead to Incrementalism in Product and Website Development for the Nearly 10,000 Start-ups for Which We Have Website and Product Launch Data



Notes. Instead, these firms make larger changes to their website code, the structure of their homepage's HTML, and website style and are more likely to deploy major code changes. A/B testing firms are also more likely to launch a new product in a given week than those that do not.

Figure: A/B on other variables (Koning et al., 2022)

Conclusion

- Experimentation as a strategy (a single experiment may not work)
- Design the future with experiments
- Solving tension between routines and experimentation is critical
- Experimentation should aid innovation

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1 Statistical testing

- Means
- Proportions

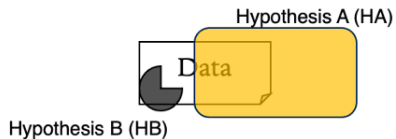
2 Case Study

- RRR
- TTTT

3 References

Statistical testing

Two approaches



Approach 1:

$\max. p(\text{Data}|\text{H})$

Given HB, the data covers most of HB. Pick HB

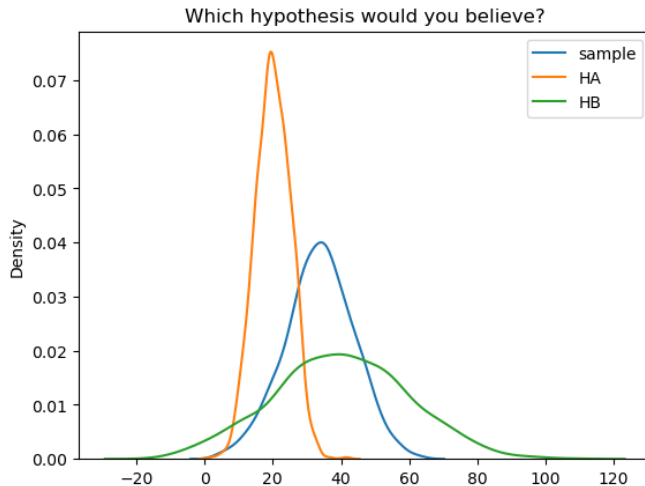
Approach 2:

$\max. p(\text{H}|\text{Data})$

Given the data, HA covers more data. Pick HA

Figure: Maximize data or hypotheses (or both).

Some hypotheses can be parameterized with distributions



What is null-hypothesis testing?

Test if the data is true given the null i.e. $p(\text{data} | H = \text{null})$.

But what is a null?

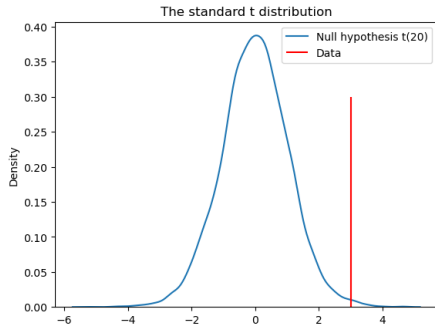
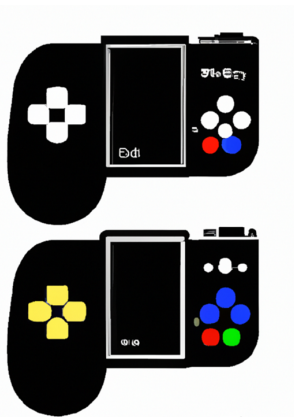


Figure: Used as a null because is centered at zero. We can evaluate the probability of data under the null

A/B test

Students: What A/B tests can you think of? In your jobs, business, life?

Option A



Option B

Figure: A/B testing

A/B test is a generic term for a simple experiment. We can apply different techniques to analyze the data.

Let's go to Python.

Example 2: test of proportions

Case Study

References



Koning, R., Hasan, S., & Chatterji, A. (2022).Experimentation and start-up performance: Evidence from a/b testing. *Management Science*, 68(9), 6434–6453.