### Citation
Lambrecht, Anja, and Catherine E. Tucker. “On Storks and Babies: Correlation, Causality and Field Experiments.” GfK Marketing Intelligence Review 8, 2 (November 2016): 24–29

### As Published
http://dx.doi.org/10.1515/GFKMIR-2016-0012

### Publisher
de Gruyter

### Version
Final published version

### Citable link
https://hdl.handle.net/1721.1/123341

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On Storks and Babies: Correlation, Causality and Field Experiments

Anja Lambrecht and Catherine E. Tucker

Correlation is not causality /// The explosion of available data has created much excitement among marketing practitioners about their ability to better understand the impact of marketing investments. Big data allows for detecting patterns and often it seems plausible to interpret them as being causal. While it is quite obvious that storks do not bring babies, marketing relationships are usually less clear. If marketers want to be sure they are not walking into a causality trap, they need to conduct field experiments to detect true causal relationships. In the present digital environment, experiments are easier than ever to undertake, but they need to be prepared and interpreted with great care in order to deliver meaningful and genuinely causal results that help improve marketing decisions.

Apparent causalities often fail to hold up under examination /// The online marketing world is full of examples of organizations or journalists being tempted to make causal inferences from purely correlational data. For example, Twitter on its website reports the information displayed below in Figure 1. In the original headline it stated that engagement with promoted tweets translates to higher brand favorability and purchase intent and suggests that ‘this study result highlights the value of an engagement on Twitter.’

In reality, it is difficult to interpret this data as causal. It more likely illustrates that a consumer who views a brand more favorably is also more likely to engage with a promoted tweet by this brand. Similarly, a consumer who intends to purchase a certain brand is more likely to engage with a message promoting this brand. Indeed, the causality could also be reversed. Note that this does not mean the ad is ineffective, but since the data presented is purely correlational it is impossible to judge whether the ad was effective or not.

Keywords
Correlation, Causality, Field Experiments, Field Tests, Causal Inference

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Figure 1:
Correlation interpreted causally:
Does engagement with promoted tweets really translate to higher brand favorability and purchase intent?

- Non-engager: +30%
- Engager: +53%

Figure taken from the Twitter website:
https://blog.twitter.com/2013/nielesn-brand-effect-for-twitter-how-promoted-tweets-impact-brand-metrics

Figure 2:
How field experiments permit causal inferences

Marketing Treatment

- Random Sample
- Consumers
- Households
- Towns
- Stores

No Treatment

- Different Treatment
- No Spillover!
- Random Sample

Difference = Treatment Effect
In general, though, it is difficult to give practical advice on sample size beyond aiming for as large a sample and data collection effort as possible. Box 2 highlights the critical decisions necessary to plan and interpret field experiments.

Further applications of field tests to improve marketing decisions

When the 5 steps described in Box 2 are executed carefully, applications are numerous and we describe some more below.

> Comparing the effectiveness of generic and personalized ad content

In this study we compared personalized and generic ads for a travel site. Both groups were shown an ad but in one instance users were exposed to a generic brand ad for the site whereas in the other instance the ad...
IMPLEMENTING FIELD EXPERIMENTS SUCCESSFULLY

**Step 1: Decide on the unit of randomization**
Randomization could happen, for example, at the level of the individual, household, town, website, store, or company. While finely-grained units of observation, like single individuals, tend to provide higher statistical power, their setup is often more expensive and difficult to implement. Also, the risk of potential for spillovers and crossovers is higher.

**Step 2: Minimize spillovers and crossovers between experimental treatments**
Suppose a company randomly selects an individual to receive a free mobile phone. Potentially his or her adoption of a mobile phone could affect the adoption outcomes of relatives and friends even if the relatives and friends were supposedly not treated. If such spillovers are a large concern, one way of addressing them would be to randomize at the level of plausibly isolated social networks such as a community, rather than randomizing at the level of the individual.

A crossover occurs when an individual who was supposed to be assigned to one treatment is accidentally exposed to another. Suppose, for example, a canned soup company is testing different advertising messages in different cable markets, and individuals are exposed to a different advertising message from that of their home market because they are traveling. This could potentially lead to mismeasurement of the treatment, especially if there were systematic patterns in travel that led to such crossovers not simply being random noise.

**Step 3: Decide on complete or stratified randomization**
The experimenter then needs to decide whether to conduct stratified or complete randomization. In complete randomization, individuals (or the relevant unit of randomization) are simply allocated at random into a treatment. In stratified randomization, individuals are first divided into more homogenous subsamples. Then each individual in each of these subsets is randomized to a treatment. This stratified technique is useful if some variables are strongly correlated with an outcome. For example, household income may be strongly correlated with purchase behavior toward private label brands. Therefore, it may make sense, if the researcher has access to household-level data, to stratify the sample prior to randomization to ensure sufficient randomization occurs within, for example, the high-income category.

**Step 4: Ensure that appropriate data is collected**
Researchers also need to carefully consider what type of data they need for their later analysis and to ensure that the practical set-up allows them to collect this data. This is especially important in digital environments where different parties have access to different types of data and it is not always obvious how these can be collected and linked. For example, advertising networks have access to ad exposure data but may require additional steps to ensure that they likewise capture purchase data and can link those to ad exposures.

**Step 5: Interpret results from a field experiment carefully**
In theory, interpretation of field experimental data should be straightforward, but in practice there are numerous issues to consider when interpreting the statistical results. The key issue is to understand exactly the difference between the groups and to be careful about how to generalize this difference. Also, the duration of the field experiment is critical and will affect the interpretation of results. For example, the researcher needs to have access to a long enough period to understand whether any treatment they measure is stable, dissipates or increases in its effect over time. However, for many field experiments it is hard to measure long-term effects because experiments are limited in time. Therefore, in most settings researchers should carefully consider whether the causal effect they establish truly reflects the long-term treatment effect.
reflected the specific hotels the user had previously looked at on the company’s website. We compared the performance of the different ads and found that on average the generic brand ad was more likely to convert a user to purchase. Only when a consumer’s browsing history indicated that they had reached a stage where they were actively comparing attributes of different hotels, did the personalized ads become equally effective.

> **Testing website design**  
Companies may also wish to compare which of two different designs of their home page is more effective in getting a user to browse products in detail. In this case a company may randomly direct a user to either of the home page versions. The company could then compare the number of users who went on browsing specific products, and later purchased, across the two experimental conditions. Provided that users were randomly assigned to the experimental conditions, the difference in the likelihood to browse or to purchase can be attributed to the difference in the design of the home page.

> **Optimizing pricing policy**  
In this article we have mostly focused on marketing communications, but other types of marketing decisions can likewise benefit from insights that come from field experiments. Imagine a company that wishes to estimate how shipping fees affect purchases from their online store. Marketing could set up two different checkout pages where in the first instance the checkout page charges the usual shipping fee and in the second instance the shipping fee is discounted or entirely removed. They could then compare the number of consumers who do not complete their purchase upon reaching the checkout page across conditions and adjust their pricing accordingly.

For companies that want to make sure that they do not invest in storks to get more babies, field experiments represent a very useful avenue in which to obtain truly causal data. When planned and interpreted with care, the results can help to guide a wide range of marketing decisions.

> In the present digital environment, experiments are easier than ever to undertake.

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**FURTHER READING**

**Lambrecht, A.; Tucker C. (2015):** “When Does Retargeting Work? Information Specificity in Online Advertising,” Journal of Marketing Research, Vol. 50 (5), pp. 561 – 576.

“When Personalized Ads Really Work,” https://hbr.org/2013/06/marketers-serve-no-ad-before-i

“Field Experiments in Marketing,” working paper. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2630209

**Lewis, R. A.; Rao, J. M. (2015):** “The Unfavorable Economics of Measuring the Returns to Advertising,” Quarterly Journal of Economics, Vol. 130 (4), pp. 1941 – 1973.