No Control Group? No Problem!

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Abstract: There are a variety of business scenarios where it is desirable to simulate the results of a controlled test, but no robust control cell exists. We identify and describe one approach to addressing this need, called the "synthetic control" method. We show how this approach has been applied in two specific industry contexts. We compare actual in-market controlled test results to the results of the synthetic control method. We describe a number of business scenarios in which this method could provide accurate, actionable results.

Introduction and Methods

There are a variety of business scenarios where it is desirable to simulate the results of a controlled test, but no robust control cell exists. For example, marketing campaigns and other communications are often sent to customers based on their profile, without "holding out" a subset of customers to study later (or where the control cell is too small to study in detail); web and interactive marketing is often done based on customer profile and behavior without creating a control cell; and changes in product and customer service are often done to entire populations simultaneously.

While several approaches have been proposed in the past to address such issues[1-8], their application is limited in many common situations. They generally require large and/or broadly distributed test populations, accompanied by a large number of well-populated segmentation variables[9]. These methods also break down when strict statistical benchmarks are not met and are thus predicated on building an accurate propensity model which can be used to identify the appropriate control members. Building this propensity model requires a large pool of potential control members from which to pull from and must also include those same segmentation variables. Finally, missing data, a common problem in many real world business applications, can cause problems when trying to build and validate the propensity model[10].

To combat these issues, the use of "synthetic" control groups has recently been adopted in several contexts, with generally positive results. By approximating the baseline response without the need for a robust in-market control group, the synthetic control method may enable managers to measure the impact of differential treatments in situations where other methods may fail.

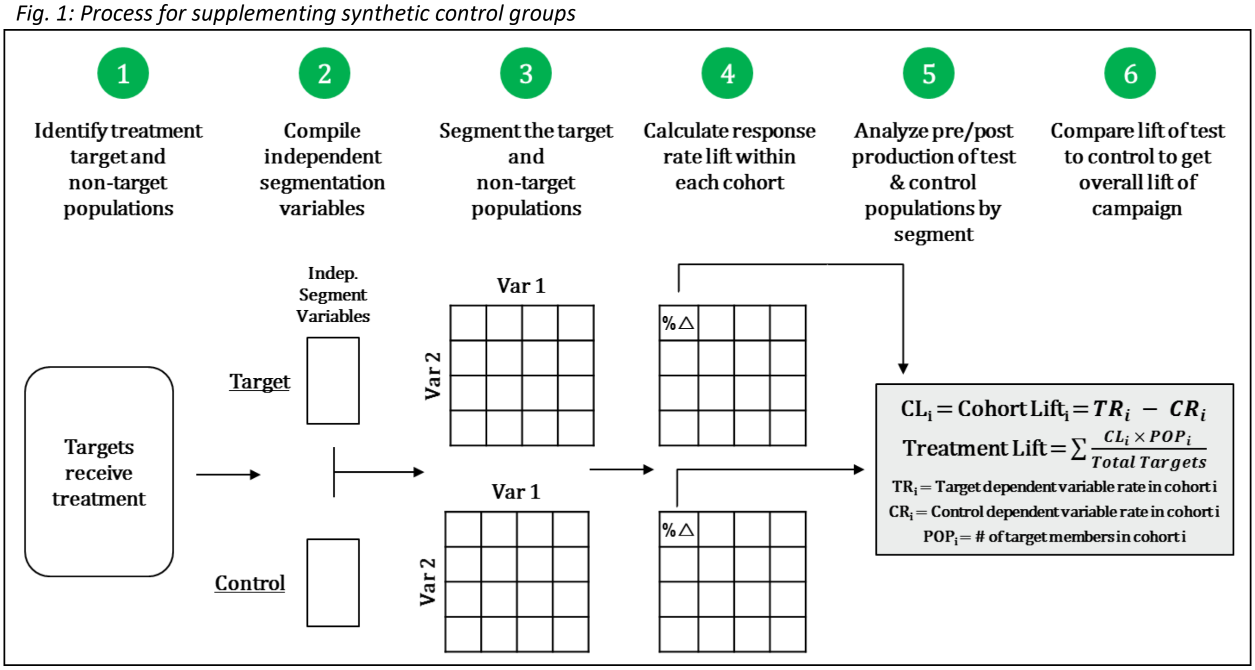
Approach

A synthetic control group is created by identifying the unique characteristics of the test population and matching each member of that population to a statistically similar member of a non-target population.

A synthetic control group can be implemented via the following step-wise process, as in Fig. 1:

1. Identify the population of targets who received the treatment being measured and a population of non-targets who have not received this treatment. These non-targets will form the basis of the synthetic control group.
2. Compile a list of independent segmentation and descriptive variables which describe unique cohorts of the target population.
3. Divide the target and non-target population into these cohorts. For a given cohort, the members of the non-target population will serve as the synthetic control group for the target population in that cohort.
4. Calculate the dependent variable (e.g. response rate) for members of the target and synthetic control groups within each cohort. The difference between the dependent variable of a cohort's target and synthetic control populations is the dependent variable lift for the treatment within that cohort.
5. Weight the dependent variable lift of each cohort by the proportion of the target population within that cohort.
6. The sum of the weighted dependent variable lifts equals the overall dependent variable lift for the treatment.

Fig. 1: Process for supplementing synthetic control groups



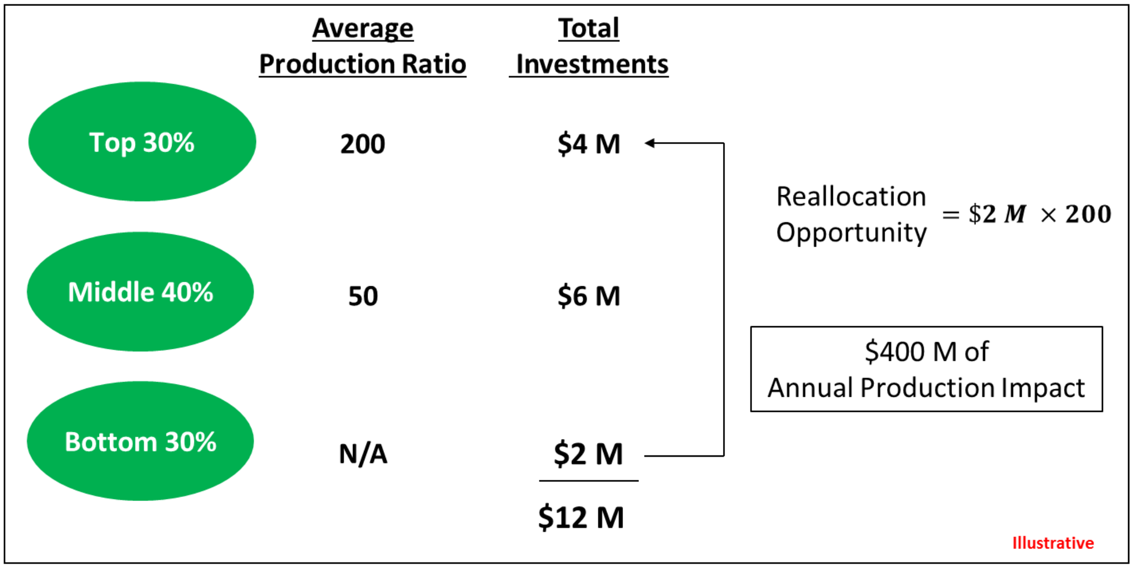
Case Studies:

Several firms have recently adopted the synthetic control approach to extract actionable insights from historical actions without a robust control sample. Two examples include:

1. Fortune 100 Financial Services Firm: At a Fortune Global 100 financial services firm, the marketing group have used a multichannel communication strategy to market to their customers and prospects. The group wanted to understand the relative impact of these various marketing efforts on their collective success metrics and KPIs.

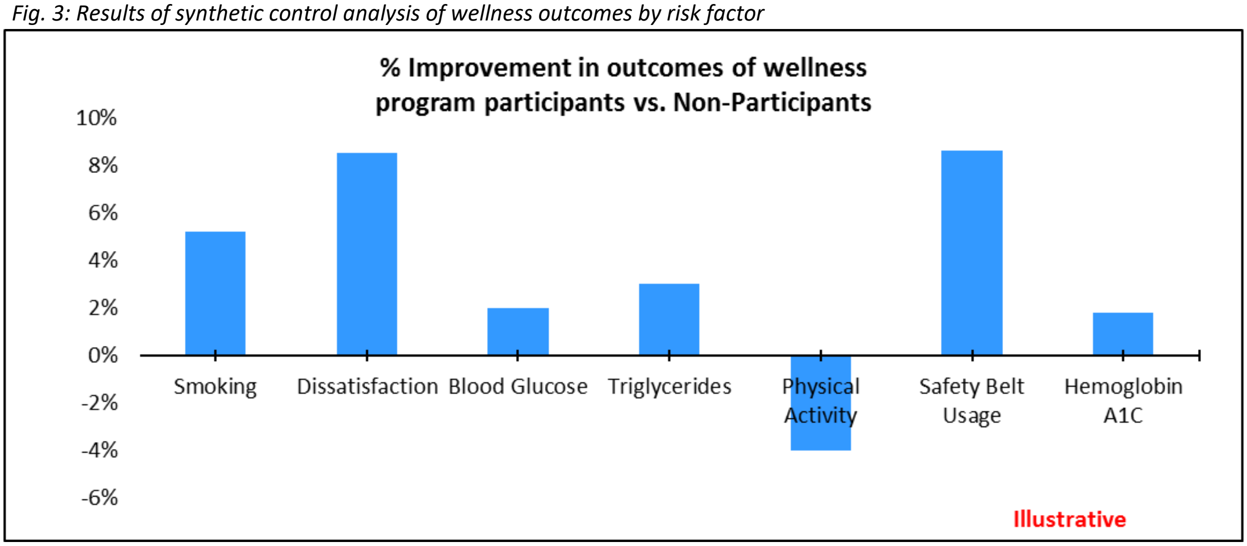
Through the use of synthetic control groups, they were able to quantify the financial impact of each marketing campaign by segment, and measure the change in scorecard metrics such as capture rate, retention, and reactivation. This allowed marketing leaders to reinvest a substantial share of their marketing investment into high impact activities, adding millions to the company's top and bottom lines, as shown in Fig. 2.

Fig. 2: Impact of utilizing synthetic control groups to reallocation marketing investments



Fortune 50 Health Care Firm: Executives at a Fortune 50 health care firm wanted to measure which of their Care Management programs had maximal impact for specific member segments. A synthetic control approach enabled them to retroactively evaluate the impacts of various programs across member segments, as shown in Fig. 3 for the Wellness program. Such an exercise would have been prohibitively onerous and expensive had it required actual in-market controlled testing.

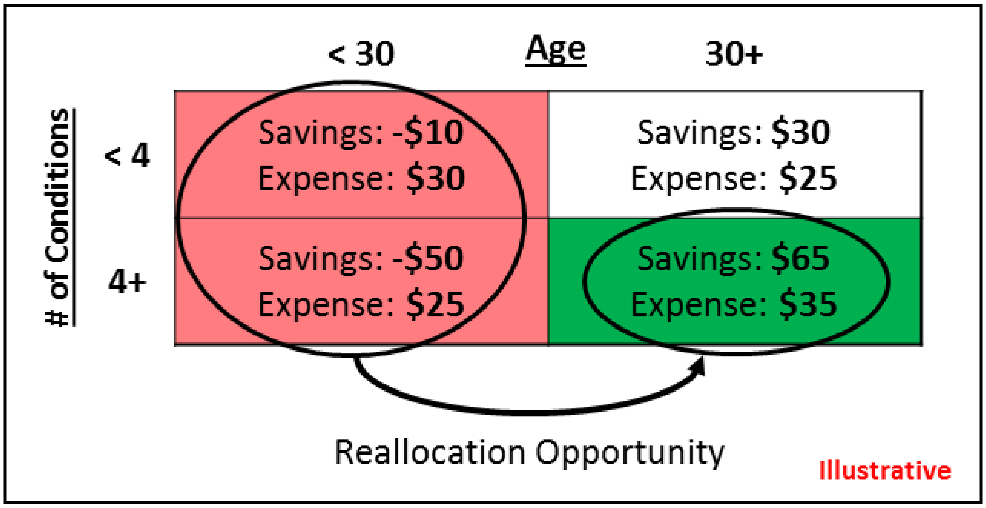
Fig. 3: Results of synthetic control analysis of wellness outcomes by risk factor



Once the impact of each program was quantified, a financial benefit was assigned to each segment, and investments were reallocated to the segments in which program impact was the highest, as shown in Fig. 4 for the Disease Management program.

The use of a synthetic control group also helped the management team validate the financial and medical value of each of their programs, which in turn drove increased sales and retention.

Fig. 4: Opportunities to reallocate core management investments to segments with highest impact.



Validation

In order to validate the statistical efficacy of this method, we have tested the results using actual in-market campaign test and control groups. This testing shows that measurements using a synthetic control group are generally in-line with actual control group measurements, with a correlation of 89% between actual control and synthetic control results. This was achieved with synthetic controls utilizing only 2 independent variables due to data availability, and it is likely that by using additional control variables the results can be further improved.

Conclusion

Synthetic control groups represent an actionable, flexible approach to approximating the results of a controlled test where no actual control group exists, or the control group is too small to draw desired conclusions (e.g. segmented results). It is applicable in a broad range of business scenarios, and when implemented with appropriate care can yield results approximating those of a true control group.

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