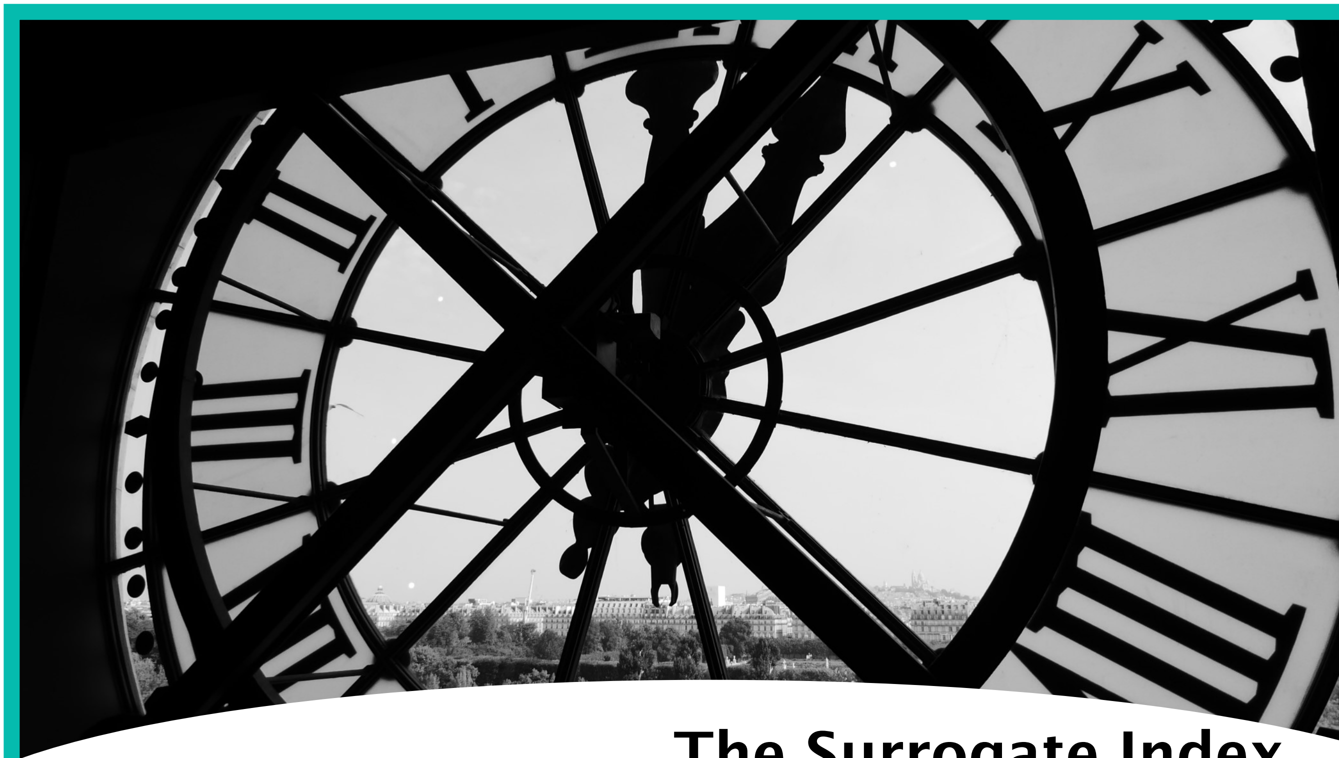

The Surrogate Index

A Tool to Facilitate Early Detection of Policies' Long-Term Impacts

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The impacts of many policies are observed with long delays. For example, it can take decades to see the effects of early childhood interventions on lifetime earnings or long-term health outcomes. This problem has greatly limited researchers' and policymakers' ability to test and improve policies.

We develop a new method of estimating the long-term impacts of policies more rapidly and precisely using short-term proxies. We predict the impacts of a policy change on long-term outcomes (e.g., lifetime earnings) by looking at the impact of the policy change on short-term proxies (e.g., earnings in early adulthood or test scores). We call these proxies "surrogates", following the statistical literature.

The use of surrogates is familiar from drug trials in medicine. For example, drug trials often use indicators such as cholesterol or blood pressure as surrogates for long-term outcomes such as mortality rates.

In social science, the long-term effects of a policy change often cannot be fully captured by a single short-term measure. This has made it difficult for social scientists to make use of statistical surrogates.

We develop a new method to combine multiple short-term indicators into a single "surrogate index" and show that this index can predict long-term outcomes, even when any single short-term indicator fails to do so. We demonstrate that the causal effect of a policy change on the surrogate index can help us learn about the policy's long-term impacts more quickly and precisely under certain assumptions described in the full paper.

Predicting the Long-Term Impacts of the California GAIN Job Assistance Program

We illustrate our method by re-analyzing the impacts of a trial of California's Greater Avenues to Independence (GAIN) job assistance program. This multi-site trial, which was conducted by MDRC in the late 1980s, provided job training and search services to a randomly selected group of unemployed individuals in four urban counties in California: Alameda (Oakland), Los Angeles, Riverside, and San Diego. These sites implemented different types of programs, with

Figure 1. Employment Rates for Participants in California GAIN Trial, by Quarter

Riverside focusing on a "jobs first" approach while other sites prioritized the development of human capital.

We begin by analyzing the Riverside program, which previous work has shown led to the largest impacts on employment and earnings over nine years. Previous work has shown that the GAIN intervention led to large increases in employment rates in Riverside that gradually diminished over time, as shown in Figure 1, which plots employment rates in the treatment vs. the control group in the nine years after the experiment.

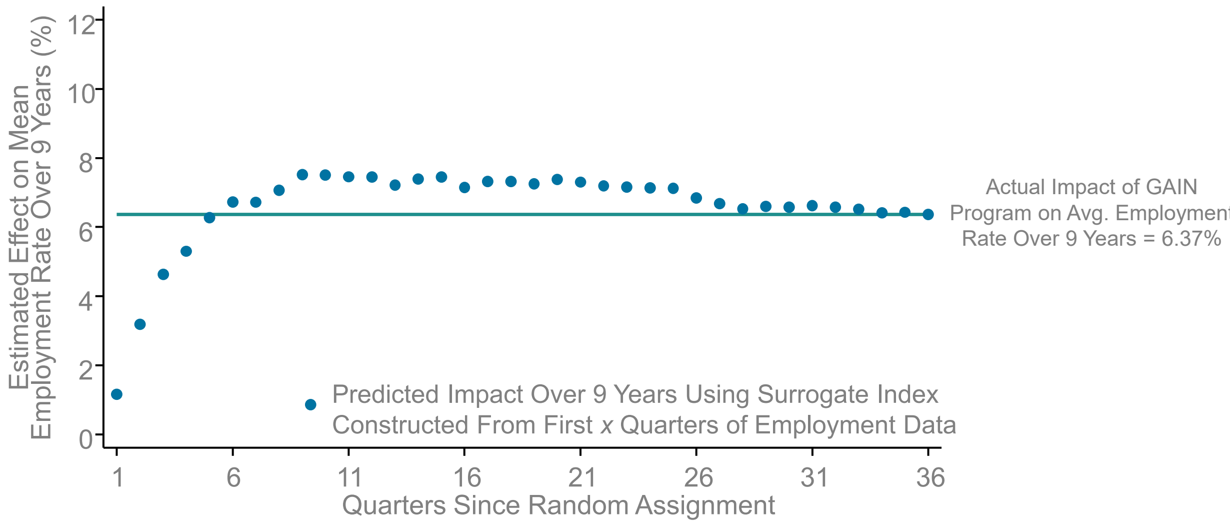
Over nine years, the GAIN program increased employment rates by 6.37 percentage points on average. We ask whether this nine-year impact could have been detected more rapidly using the employment impacts in the quarters immediately after the experiment. Intuitively, we use short-term employment outcomes as early indicators of the program's long-term effects on employment.

Figure 2 shows the long-run impact on employment rates that we estimate using data on employment only in the first quarter, the first two quarters, etc. For example, to construct the point plotted for the fifth quarter in the figure, we first predict each individual's average employment rate over nine years based on employment rates in the first five quarters (using a linear regression). We then calculate the difference in the average *predicted* employment rate (based on five quarters of data) between the treatment and control groups to estimate the long-term employment effect. The other estimates on the figure are constructed analogously, varying the number of quarters used to construct the surrogate index from 1 to 36.

The horizontal line in the figure shows the actual long-term impact of the Riverside GAIN program which we would observe if we waited nine years to measure long-term outcomes: a 6.37% increase in mean employment for enrolled individuals. We compare this long-term impact to the effect we would have predicted based on the surrogate index. The surrogate index predictions are very similar to the mean nine-year effect within six quarters. That is, one can **accurately estimate the program's impact over nine years using data for just 1.5 years** after the experiment. Moreover, the estimate from the surrogate index is much more precise: the confidence interval (margin of error) for the estimate

Figure 2. Effects of the Riverside GAIN Program on Employment Rates

Predictions Using Surrogate Indices Based on Short-Term Employment Rates



based on the six-quarter surrogate index is about one-third smaller than the estimate based on the full nine years of data.

The surrogate index we estimated using data from Riverside predicts long-term treatment effects on employment and earnings in other sites quite accurately. The GAIN program implemented in Los Angeles had small effects on earnings; the programs in Alameda and San Diego had mid-sized effects; and the program in Riverside had the largest effect. Our six-quarter surrogate-index estimates closely mirror this pattern, as shown in Figure 3 below. This result shows that surrogate indices estimated in one setting can provide reliable predictions in other settings as well.

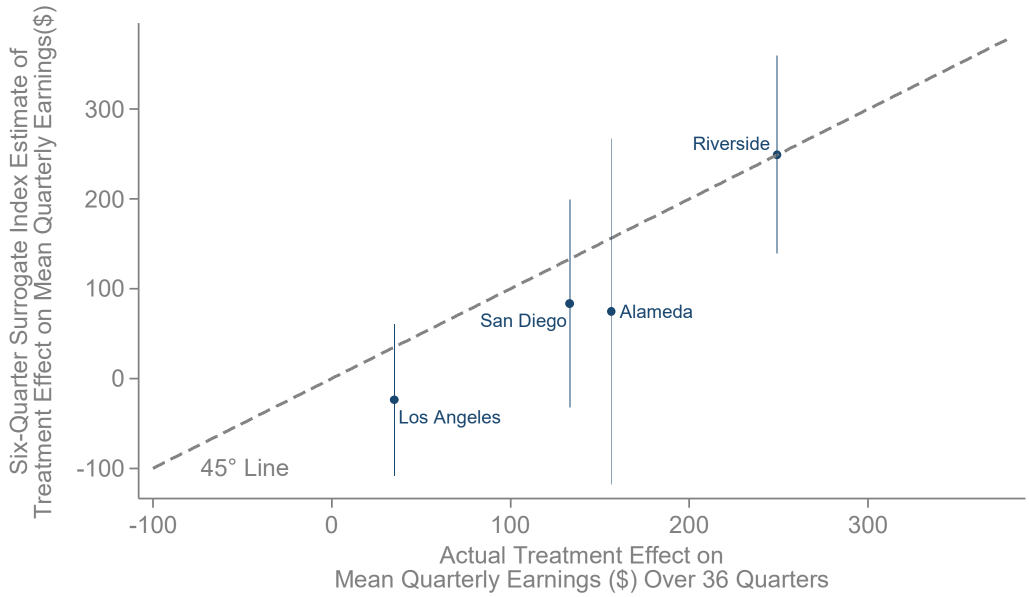
Intuitively, short-term employment rates are good predictors of the program's long-term impacts because individuals who have rapidly improved employment in the first few quarters tend to have long-lasting gains in employment (perhaps because they found a good job match or acquired valuable training). Conversely, those who have short-lived gains within the first few quarters tend to have smaller gains in the long run as well. Thus, one can forecast long-term impacts accurately by combining data on short-term employment indicators.

The key assumption underlying our approach is that the short-term proxies (surrogates) fully capture the causal link between the intervention and the long-term outcome. In the California GAIN application, that assumption appears to hold once we have six quarters of employment data. More broadly, we show how the assumption can be validated and how one can bound the bias that may arise if it fails.

Building a Library of Early Indicators for Social Science

The success of the surrogate index in the GAIN application across sites suggests that our method could be applied to predict the long-term impacts of ongoing job training programs. Going forward, it would be useful to establish surrogate outcomes that accurately predict the long-term impacts estimated in other experiments, in the same way that six quarters of employment data were adequate to predict the long-term impacts of the GAIN program.

Figure 3. Surrogate Index Estimates vs. Actual Experimental Estimates, by County



Note: Vertical lines represent 95% confidence intervals (margins of error) for the estimates

Building a library of surrogate indices for long-term outcomes would expedite the analysis of ongoing and future interventions, much as the identification of cholesterol as a surrogate for mortality due to heart disease has expedited the development of drugs to treat heart disease.

At Opportunity Insights, we plan to support the development of a public library of early indicators (surrogate indices) for social science by harnessing historical experiments along with the large-scale datasets we have built. If you would like to contribute to this effort by reporting a surrogate index that predicts long-term impacts estimated in an experiment you have analyzed, as in the GAIN program, please click here.

Want to learn more?

Read the full paper

See Presentation Slides

Use Our Illustrative Code to Implement the Method

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