Learning the Impact of Financial Education When Take-Up is Low
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Low levels of financial literacy are pervasive in both developed and developing countries, leading to many governments, non-profits, and banks offering financial education programs. However, voluntary participation rates in these programs are often very low. This was the case with a recent experiment we implemented in Mexico.

We collaborated with the Mexican bank BBVA Bancomer in an experiment to measure the impact of Adelante con tu futuro (Go ahead with your future), a large-scale financial education workshop that BBVA Bancomer conducts in Mexico since 2008. As of 2016, about 1.2 million participants have received the training.

Over 100,000 credit card clients participated in the experiment. Of 73,654 clients who were assigned to the treatment group, only 583 attended it. That is, take-up was 0.8%. In a second experiment that we designed to test personalized financial coaching, again take-up was low (only 6.8% of clients in the treatment group received the coaching sessions).

With take-up rates this low, it is not surprising that we are unable to detect any effect of financial education using the pure experimental approach. As only a handful of clients received treatment, the trajectories of the treatment group follow closely those of the control group in the months after the intervention (see Figure 1). Thus, the experimental method ITT estimates (which measure the effect of being offered the program) are close to zero. The LATE estimates (which are the experimental treatment effects for those who actually receive treatment) are not statistically significant, with wide confidence intervals pointing at the lack of power to detect any effect.

Even if this program helps those who participate, low take-up rates dramatically reduce our ability to detect such an effect. This by no means is a unique situation. Despite their large number of users, the response to many financial product marketing campaigns such as those offering credit cards or selling insurance products are also incredibly low.

How Big Data Can Help
So, what can we do to credibly estimate the effect of financial education on the clients that did take-up the program?

Our solution is to use the richness of big data. As part of the study, we have access to a large administrative data set (of 660 MB), which follows the monthly financial indicators of each client for up to 18 months prior to the intervention and 6 months after it. Moreover, from the experimental approach we also had a large pool of clients randomly assigned to the control group.

This data enables us to obtain credible estimates by combining the experiment with two non-experimental approaches. We first use propensity score matching to find, among
the clients in the control group, a subset of clients that best mimics the pre-intervention financial trajectories of clients in the treatment group that received treatment.

To show that our results are robust to the choice of counterfactual, we conduct five different approaches to obtaining a non-experimental counterfactual, changing the variables used in the matching and using all matches in the common support vs just the nearest neighbor matches.

Importantly, we are able to overcome a common challenge of propensity score matching, referred to as selection on unobservables. That is, if individuals in the control and treatment groups are so similar, why don’t individuals in the control group participate in the intervention? In our case we know why: clients in the control group were randomly not invited.

With this matched control group, we then estimate the impact of attending the workshop or receiving coaching using difference-in-differences. As our control group matches by construction the trajectory of variables of the treated clients over 18 months before the intervention, we thus have a credible test of common trends, a usual concern with difference-in-differences.

Results

The effects of the workshops on the treated clients are summarized in Figure 2 (the coaching intervention had similar results). Under our preferred specification, we find that participating in the workshop increases by 11 percentage points the likelihood of paying more than the minimum payment, and reduces by 3.4 percentage points the likelihood of delaying payment. Monthly credit card spending increases by 63.7 percent, and the likelihood of owning a deposit account with our partner bank also increases by 2.7 percentage points.

![Figure 2: Trajectories of financial outcomes of those receiving workshops compared to nearest neighbor matched control group](image)

The two financial education interventions help clients reach the minimum payment and pay their bills on time more often, without reducing their credit card spending. Both interventions increase the likelihood that clients are profitable for the bank.

Policy Recommendations

Our results have the following policy implications:

1) While many clients do not want to participate in financial education, such programs can still offer some benefit to those who do decide to take these programs when offered – and doing so can be profitable for the bank.

2) Access and usage of big data (i.e., in the form of administrative information) can help experimental evaluations with very low take-up.


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