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**Drop-out from Individual Development Accounts:
Prediction and Prevention**

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Abstract

Individual Development Accounts (IDAs) are a new policy instrument designed to help the poor save and accumulate assets. IDAs provide matches for savings used for home purchase, post-secondary education, or microenterprise. IDAs cannot help participants, however, if they drop out. What determines drop-out, and what can be done to help participants to stay in? Three findings emerge from an analysis of IDAs in the American Dream Demonstration. First, drop-out depends more on transaction costs and previous debt than on income. Second, program design—and match rates in particular—affect drop-out risk. Third, drop-out can be predicted with some accuracy, so IDA programs could use statistical targeting to identify candidates for special preventive attention before they drop out.

Drop-out from Individual Development Accounts: Prediction and Prevention

1. Introduction

To escape from poverty requires saving and asset accumulation. Many U.S. programs subsidize savings, but low-income people rarely take full advantage of them because the incentive systems require participants to have wealth already, to be in high tax brackets, or to take on debt.

Individual Development Accounts (IDAs) are a new policy instrument designed to help the poor to save and to accumulate assets (Sherraden, 1991). IDAs do not require existing wealth, do not work through tax breaks, and do not require borrowing. IDAs provide matches for savings used to build human capital (through post-secondary education), physical capital (through home purchase), or business capital (through microenterprise). IDAs also seek to build human capital (through financial education) and social capital (through support from peers and program staff). In sum, the match and the institutional structure of IDAs seek to address obstacles to savings by the poor so as to foster their long-term personal development.

IDAs, however, do ask participants to save, and saving requires reduced consumption and/or increased work. Because IDAs require short-term sacrifice, the poorest (or those who do not already have savings that they can readily shift to IDAs) may choose not to sign up. Even if the poorest do sign up, they may be more likely—because the sacrifice of saving is greatest for those who have the least—to drop out.

Drop-out is costly all around; programs lose their investment in participants, and participants lose potential match funds. Worse yet, drop-outs from IDAs may become discouraged with saving in general. How common is drop-out in IDA programs? Do the very poor drop out more than the less-poor? Is program design linked with drop-out? Can at-risk participants be identified for preventive attention before it is too late?

This paper addresses these questions with data from IDAs in the American Dream Demonstration (ADD). About 16 percent of participants in ADD dropped out. Three findings emerge from an analysis of the association between drop-out and the characteristics of participants and programs:

- Participants who had low debt or low transaction costs in making deposits were less likely to drop-out, but the level of income had no association with drop-out.
- Higher match rates were associated with less risk of drop-out. Furthermore, other unobserved program characteristics were strongly linked with drop-out.

- Statistical targeting based on characteristics observed at enrollment has some power to identify those participants with the highest risk of drop-out.

Thus, drop-out depends partly on factors that IDA programs can manage. In particular, drop-out is not purely a function of income, something IDA programs have little control over. Programs can reduce drop-out, for example by raising match rates, by counseling participants with large debts, or by working to decrease transaction costs, perhaps by arranging for direct deposit with employers or by training participants in checkbook management or in the use of automatic teller machines. Such prevention efforts are costly, but they can be targeted to the most at-risk participants.

Section 2 below describes drop-out from IDAs in ADD. Sections 3 and 4 relate drop-out to characteristics of participants and programs. Section 5 tests the predictive power of a statistical targeting model, and Section 6 summarizes policy implications.

2. Drop-out from IDAs in ADD

2.1 The American Dream Demonstration

ADD comprises 14 IDA programs across the United States. Between July 1997 and June 30, 2000, 2,378 participants opened an IDA in ADD (Schreiner et al., 2001).

Data on ADD come from administrative software used by the IDA programs (Johnson, Hinterlong, and Sherraden, 2001). The system records account structures, participant characteristics, and monthly IDA cash flows. The cash flows are accurate and complete; they come from bank records, satisfy accounting identities, and were extensively cross-checked. They may be the best high-frequency data on matched savings by the poor.

2.2 Drop-out

Participants who leave ADD without a matched withdrawal are drop-outs. As of June 30, 2000, about 16 percent of ADD participants had dropped out.[1]

Of course, observed drop-out is censored; some active participants as of June 30, 2000 might still drop out after that. Figure 1 is a Kaplan-Meier hazard function that controls for censoring. It shows the relationship between the risk of drop-out and months of participation. Risk increases from almost zero in the first month to a peak of about 1.6 percent in month 6. (That is, 1.6 percent of participants who reached month 6 then dropped out in month 6.) Drop-out risk averaged about 1 percent per month for months 7-17, but then it fell to about 0.25 percent per month for months 18-24.

[1] Some drop-outs may have been kicked out for disobeying programs rules, for example for missing required financial-education classes. The data do not distinguish between drop-outs and kick-outs, although most kick-outs probably would have dropped-out later anyway. Schreiner et al. (2001) discuss this and other data issues.

Figure 2 shows cumulative drop-out risk. Controlling for censoring, 11 percent dropped out in their first 12 months, 14 percent in their first 18 months, and 16 percent in their first 24 months. Both the highest drop-out rates and the most drop-outs occurred between months 2 and 14.

2.3 Discussion

Given the patterns in Figures 1 and 2, perhaps one-fifth to one-fourth of ADD participants will drop out. These drop-outs are costly all around. For programs, they are costly because they usually take place only after enrollment, counseling, and financial education, the most costly stages of IDA programs (Schreiner, 2001a; Sherraden, 2000). For participants, drop-outs are costly because they lose potential match funds, because they decrease consumption and/or increase work in vain, and because, after failing to save under the facilitating institutional structure of IDAs, they may despair at ever saving again. What can be done to prevent these costs?

3. Participant Characteristics

If programs knew how participant characteristics related to drop-out risk, then they might be able to do something about it. The regression results described below suggest that low-income per se does not drive drop-out; rather, what matters are previous savings, previous debt, and the transaction costs of making deposits.

3.1 Probit on drop-out

Participants are assumed to drop-out if the benefits of doing so exceed the costs. The structural random-utility model used here boils down to a Probit regression of drop-out on a wide range of participant and program characteristics (Schreiner et al., 2001; Greene, 1993). To account for censoring, a spline in months of participation is included. Thus, the Probit resembles a hazard model with a semi-parametric baseline (Kennedy, 1998). The dependent variable is unity (1.00) for drop-outs and zero otherwise, so positive coefficients indicate a positive association with drop-out risk.[2]

The Probit includes an unusually large number of independent variables: 9 program characteristics, and 27 participant characteristics. Because some characteristics are polychotomous, because some continuous characteristics are specified as piece-wise linear splines[3], and because many characteristics have many missing values[4], 99 parameters were estimated.

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[2] Compared with Schreiner et al. (2001), this convention reverses the signs on the coefficients, but it affects nothing of substance.
[3] Suits, Mason, and Chan (1978).
[4] Following Orme and Reis (1991), each variable with many missing values has a corresponding dummy variable. When the "original" variable is not missing, then its dummy is set to zero. When the "original" is missing, then it is set to zero and its dummy is set to unity. Assuming that the presence of missing values is uncorrelated with drop-out, this cleanses the estimates of the

The model includes 2,338 participants (40 were omitted due to missing values). The log-likelihood is −457, and the Probit differs statistically from an intercept-only model with 99-percent confidence. Comparing pairs of cases in which one was a drop-out and the other was not, the predicted risk of drop-out was higher for the drop-out 95 percent of the time. Overall, the model had a good fit.

3.2 Regression results

Tables 1 through 8 display means for the independent variables, estimated marginal effects in units of percentage points, and p-values.[5] Although presented in 8 tables, all the results come from a single regression. Space limits dictate discussing only the most interesting results.[6]

3.2.1 Race/ethnicity

Drop-out risk is about the same for African Americans, Caucasians, Hispanics, and Asian Americans (Table 1). Native Americans are more at-risk, and "other" is less at-risk. Age and location of residence are linked with drop-out, but programs have little control over these characteristics.

3.2.2 Income and public assistance

Did the poorest IDA participants—those with very low income or those who received public assistance—drop-out more? The specification of income (Table 3) distinguishes between recurrent income (wages, retirement benefits, and public assistance) and intermittent income (self-employment, child support, gifts, investments, and "other") because a large body of theory and evidence (e.g., Thaler and Shefrin, 1981) suggests that the propensity to save varies with the source of the income. To allow for different effects at very low income versus at higher incomes, recurrent income is represented by a two-piece spline. None of the estimates is statistically significant; it appears that income does not matter for saving in IDAs.[7]

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effects of missing values and—more importantly—avoids the common practice of throwing out cases with any missing values and thus decimating the data set. (Dummy results are available on request.)

[5] Marginal effects (computed at the sample means) are shown because the Probit coefficients have no direct interpretation. Standard errors come from the delta method.

[6] Schreiner et al. (2001) discuss regression results in greater detail.

[7] The analysis experimented with many specifications of income (for example, without distinguishing between recurrent and intermittent, and without splines), but nothing ever came close to statistical significance. Sherraden and Schreiner (this issue) discuss in detail the relationship between income and savings in IDAs.

Nor was receipt of public assistance strongly linked with drop-out (Table 3). Although this does not necessarily mean that IDAs are a good way to help people on public assistance, it does mean that unobserved characteristics associated with the receipt of public assistance (such as a supposed "culture of welfare") were not also associated with drop-out risk.

3.2.3 Liquid assets

The presence of a checking account was linked with a large decrease in drop-out. Also, each additional $100 of checking balances was associated with slightly lower risk. Although these links are not particularly large or strong, they do suggest that people with checking accounts were less likely to drop-out of IDAs in ADD. The presence of a checking account may be a mere correlate of low drop-out risk (for example, if financial sophistication makes people both more likely to own a checking account and more likely to save successfully in IDAs) or a cause of low risk (for example, if checking-account owners avoid the transaction costs of making deposits by mailing checks in.)

The presence of a passbook savings account had no link with drop-out risk. Passbook savings balances were linked with a very small increase in the risk of drop-out (Table 4), about 0.04 percentage points for each additional $100. This fits evidence in Hogarth and Lee (2000) that suggests that owners of passbook savings accounts resemble the unbanked more closely than they resemble checkbook owners.

3.2.4 Illiquid assets

Although home owners were just as likely to drop out as renters (Table 4), participants who owned a car were much less likely to drop out than participants who did not own a car. Again, a car likely decreases the transaction costs of making deposits; without a car, the value of time spent walking or in public transportation could easily swamp the value of the deposit itself (Adams, 1995). Car ownership also decreases the marginal cost of attending required financial-education classes.

3.2.5 Liabilities

Participants with debt were more likely to drop out (Table 4), perhaps because they had greater pressure on cash flows and/or had less savings to shift into IDAs.

3.2.6 Direct deposit

ADD participants who used direct deposit to their IDA account were 2.7 percentage points less likely to drop out. Given an average drop-out risk of 16 percent, this is a huge effect. Like ownership of a checking account, the use of direct deposit may be a mere correlate with low drop-out risk, but, again like ownership of a checking account, for some participants it is almost certainly a cause.

3.3 Policy implications

Did the very poor drop out more? No; results here suggest that transaction costs (proxied by car ownership, checking-account ownership, and the use of direct deposit) mattered more than level of income. Also, debt was linked with increased drop out.

The policy implications are clear: IDA programs can reduce drop-out by reducing the transaction costs of making deposits and by helping participants manage their debt. To do this, programs might require participants to set up direct deposit or to open checking accounts. In the required financial-education classes, the programs might teach participants how to manage checkbooks and how to manage debt. IDA programs might also coordinate car pools, both to make deposits and to attend classes. Finally, IDA programs might counsel participants with large debts even before enrollment, perhaps encouraging some of them to enroll only after getting their debt under control.

4. Program design

For controlling drop-out, program design matters more than participant characteristics because policy directly affects program design. The Probit model shows that several elements of program design strongly influence drop-out.

4.1 Match rates

The central feature of IDAs is the match. In ADD, 51 percent of participants had a 2:1 match rate, 24 percent had a 1:1 match, 14 percent had 3:1, and 6 percent had match rates from 4:1 to 7:1 (Table 7). Higher match rates, because they increase the cost of lost potential matches, should reduce drop-out (Schreiner, 2001b).

This turns out to be the case. Compared with a match rate of 1:1, match rates of 2:1 had 1 percentage point less drop-out risk, match rates of 3:1 had 3.1 percentage points less risk, and match rates from 4:1 to 7:1 had 4.7 percentage points less risk. Higher match rates reduce drop-out.

4.2 Monthly savings target

Match-eligible deposits in IDAs are capped, either year-by-year or for the lifetime of ADD. The match cap divided by the number of months the capped period is the monthly savings target. This is a target in two ways. First, it is the amount which, if saved each month, would produce savings equal to the match cap. Second, many programs in ADD explicitly exhort participants to save this amount each month.

A $10 increase in the monthly savings target was associated with a decrease in drop-out risk of 0.5 percentage points (Table 7). Given that savings targets are bunched in the range of $40-$60, a $10 increase is fairly large, but so is a 0.5 percentage-point decrease in drop-out risk.

Three factors contribute to this result (Schreiner, 2001b and Schreiner et al., 2001). The first is opportunity costs; participants allowed to save more have more to lose by dropping out. Second, the institutional theory of saving (Beverly and Sherraden, 1999) suggests that people save more if they are expected to save more and are assisted in doing so. Third, IDA programs in ADD may have assigned higher targets to groups whom they expected to save more, creating an endogenous link between savings targets and savings ability that would contribute to the positive association found here.

4.3 Match-cap structure and program inputs

Drop-out risk is not associated with the match-cap structure, be it annual or lifetime (Table 7). There are some odd associations between drop-out and program inputs, probably artifacts of noise in this part of the data set (Schreiner et al., 2001).[8]

4.4 Unobserved program characteristics

Observed characteristics in the model constant, the risk of drop-out varied greatly across the 14 programs in ADD (Table 8). These "fixed effects" are due partly to unobserved variation in local contexts, partly to variation in unobserved participant characteristics among programs, and partly to variation in unobserved elements of program design such as informal social support, strictness of rule enforcement, wait periods before matched withdrawals, and quality of financial education.

Again, the lesson is that program design matters. Knowledge of exactly what elements of design matter, however, must await future work.

4.5 Policy implications

Upping the ante by raising match rates and match caps increases the cost of drop-out and so effectively decreases drop-out. On the positive side, this would also allow poor people to accumulate more assets through IDAs. On the negative side, it would also increase costs.

5. Statistical targeting of drop-out prevention

One way to control costs is to target drop-out prevention—such as higher match rates or higher match caps—only to the most at-risk participants. But who are they?

Statistical targeting attempts to identify at-risk participants based on their characteristics at enrollment. It is triage, focusing extra attention where it is likely to have the greatest impact.

[8] Staff hours are significantly and positively associated with drop-out. Causality, however, likely goes from drop-out to staffing; IDA programs respond to high drop-out by adding staff and providing more intensive services. More staffing no more causes high drop-out than more prenatal medical care increases infant mortality, even though (ex post) high levels of medical care are positively associated with higher mortality.

Statistical targeting is not new in the social services, being used to identify hard-to-employ people in welfare-to-work programs (Eberts, 2001) and people likely to exhaust their unemployment insurance (Decker and Dickinson, 1996).

5.1 Statistical technique

Statistical targeting uses a Probit model like the one discussed above. The goal, however, is not just to derive the relationships between characteristics and drop-out but rather also to use the knowledge of those relationships to predict risk. What matters are not marginal effects but rather predictive power.

Statistical targeting constructs a regression from historical data on enrollees and drop-out. Combining the Probit estimates with the characteristics of a new enrollee gives an estimate of drop-out risk. Implementation is simple and can be automated; as soon as an enrollee's characteristics are key-punched, the administrative software can compute drop-out risk. If risk is "high" (for example, in the top decile or quintile), then the IDA program might target preventive incentives and services to the participant.

5.2 Tests of predictive power

Fair tests of predictive power are "out-of-sample"; cases used to test the model are not also used to construct the model.[9] For the test here, 1,900 of the 2,378 ADD cases were drawn at random and used to construct a new model with the same independent variables as above. Predicted risk was then computed from the Probit formula with the estimated coefficients and the characteristics of the 478 hold-out cases.

Measures of predictive power compare predicted drop-out risk with realized drop-out. The two standard measures are the "power curve" (also known as the "Receiver Operating Characteristic") and the Kolmogorov-Smirnov distance. Both measures suggest that the statistical targeting model was powerfully predictive.

5.2.1 Power curve

The power curve in Figure 3 relates the percentage of all cases targeted (horizontal axis) to the percentage of all drop-outs targeted (vertical axis). The diagonal is random targeting; for example, targeting 10 percent of all cases at random would mean targeting 10 percent of all drop-outs. The curved line is the result of the targeting model for drop-out from IDAs in ADD. Targeting is better as the curve is farther from the diagonal; a perfect model would form a right-angled "r" (Hand, 1994).

The curve in Figure 3 is quite far from the diagonal. For example, targeting the half of participants with the highest predicted risk would reach more than 90 percent of all drop-outs.

[9] Using the same cases for both model and test would overstate predictive power.

Perhaps more realistically, targeting the riskiest 10 percent would reach more than half of drop-outs.[10]

5.2.2 Kolmogorov-Smirnov distance

The KS distance measures predictive power as the maximum distance between the cumulative distribution functions of predicted risk for drop-outs versus non-drop-outs. KS ranges from 0 (no predictive power at all) to 100 (perfect predictive power). According to Mays (2000), models are "good" if KS exceeds 40, "very good" if KS exceeds 50, and "awesome" if KS exceeds 60. For this targeting model, KS is 68.

In sum, both the KS distance and the power curve suggest that IDA programs could use statistical models to target extra attention to participants at-risk of drop-out.

6. Discussion

Individual Development Accounts (IDAs) aim to help the poor to save and accumulate assets by matching deposits used for home purchase, post-secondary education, or microenterprise. Some IDA participants, however, drop out without ever having taken a matched withdrawal. What determines drop-out, and what can be done to reduce it?

Three main findings emerge from this analysis:

- Transaction costs and previous debt affect drop-out more than does income.
- Program design—especially match rates—affects drop-out risk.
- Statistical models can target extra attention just to the most at-risk participants.

6.1 Policy implications

Given the importance of transaction costs, IDA programs might require participants to open checking accounts and perhaps even to sign up for direct deposit, both from the employer to the checking account and from the checking account to the IDA. At the very least, the financial-education classes required of all IDA participants can focus on the benefits of both checking and direct deposit and on the basics of checkbook management. IDA programs might also facilitate car pools to help participants make deposits and attend classes. Given the weight of debt, IDA programs might screen new enrollees to make sure that they have a reasonable plan both to pay down debt and to build up IDA balances. Finally, given the importance of match rates (and to a lesser extent, match caps), IDA programs might increase matches (and perhaps also the amount eligible for matching). Statistical models can help programs target these costly preventative measures only to participants at high risk of drop-out.

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[10] Some IDA programs in ADD recorded almost no drop-out, so about 40 percent of participants had zero predicted (and realized) drop-out risk. Even with this group omitted, however, the model is still powerful; for example, an IDA program could reach more than half of would-be drop-outs by targeting 16 percent of all remaining cases.

IDA programs could also reduce drop-out by reducing kick-out. Programs sometimes force participants out who save too little or too infrequently. If the goal of IDAs is long-term improvement in well-being, however, then it makes little sense to cut off access precisely to those participants for whom saving is most difficult.

6.2 Abolishing drop-out from IDAs

Making IDAs universal and permanent would completely abolish drop-out. Subsidized-savings programs for the non-poor such as Individual Retirement Accounts (IRAs) are universal and permanent—why not IDAs?

From the perspective of long-term improvement in the well-being of the poor, the best IDA policy would involve permanent access (Schreiner et al., 2001). Then the poor could save in IDAs at their own pace; savings access would not depend on savings performance. Permanent access would also increase the sums that people could accumulate, and this could only boost developmental impact.

In fact, the original proposal for IDAs calls for accounts for all, opened at birth, with greater subsidies for the poor (Sherraden, 1991). Everyone would always be a participant; people would not be "on" or "off" IDAs—even if they had zero balances or no recent deposits—any more than they are now "on" or "off" IRAs. Of course, not everyone would use their IDA at all times, but permanent incentives to build assets would likely foster development better than would time-limited incentives.

IDAs in ADD are not permanent because ADD, as a demonstration, has limited budget with time limits. ADD programs reserve funds for each enrollee equal to the match rate multiplied by lifetime match eligibility. Given that programs must want to show a good performance record to attract funding, this creates an incentive to kick out participants who cannot keep up with program saving targets. Kicking out poor performers not only frees up match funds for new enrollees and reduces operating costs but also inflates savings outcomes per non-exited participant reported to potential funders. Thus, the demonstration nature of ADD—and of IDAs in general up to this point—creates a dysfunction. The dysfunction is a goal displacement from long-term asset building to short-term saving performance. Until IDAs are federally funded (and thus potentially permanent and universal), the need to attract new funds will likely maintain this dysfunction.

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Figure 1: Risk of drop-out in a given month of participation
(Kaplan-Meier hazard)

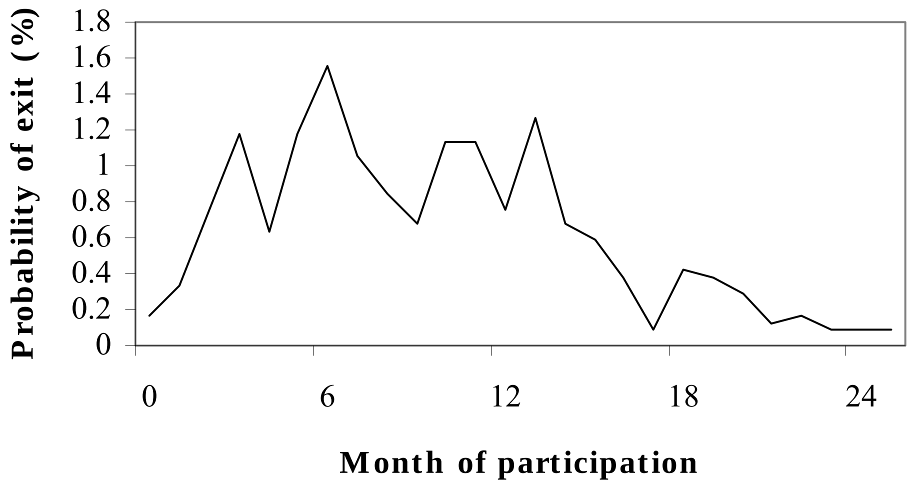

Figure 2: Cumulative risk of drop-out by length of participation

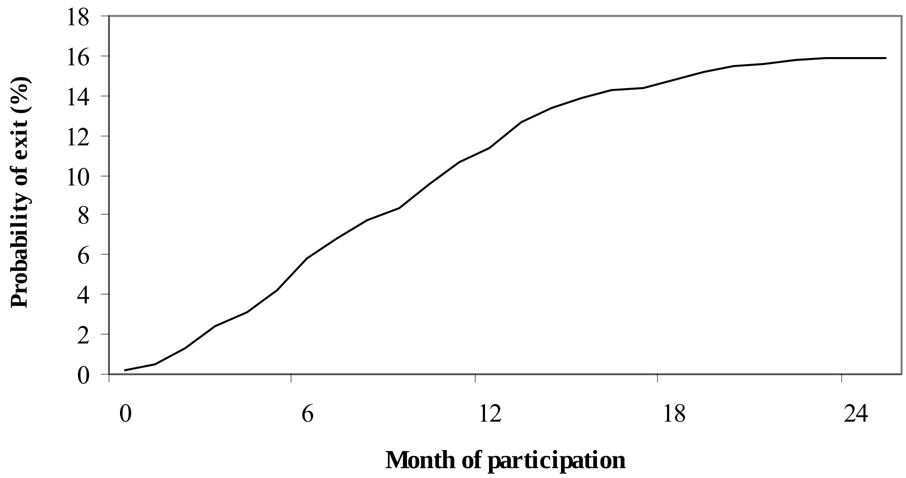

Figure 3: Power curve for statistical targeting

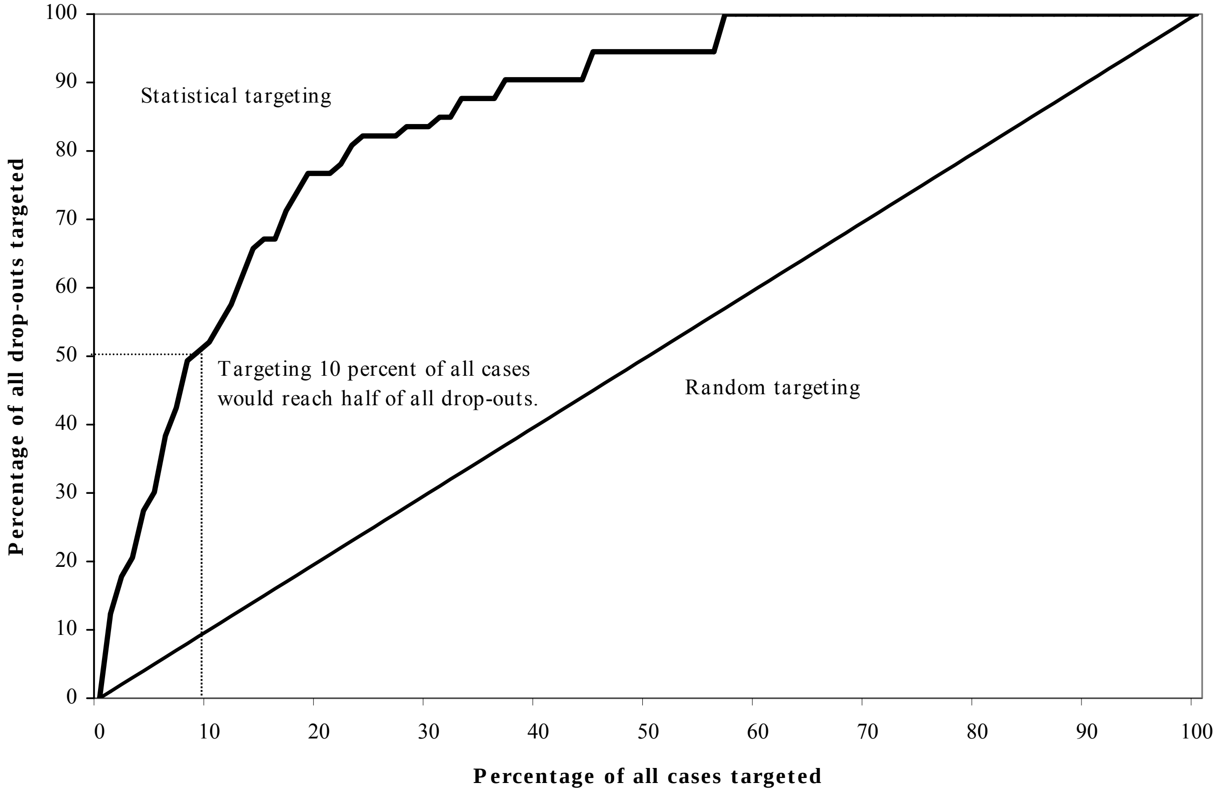

Table 1: Participant demographics

Independent variable	Mean	Change in % points	p-value
Gender			
Male	0.20		
Female	0.80	−0.05	0.92
Age (2-piece spline)	36		
0 to 40 years	33	+0.06	0.05
40 years or more	2	−0.11	0.07
Location of residence			
Population 2,500 or more	0.87		
Population less than 2,500	0.13	−2.5	0.02
Marital status			
Widowed	0.02	+0.12	0.94
Divorced or separated	0.27	−0.9	0.11
Never-married	0.51		
Married	0.20	−0.83	0.19
Household composition	3.2		
Adults (18 or older)	1.5	+0.19	0.51
Children (17 or younger)	1.7	−0.15	0.28
Participants in a household			
One	0.94		
More than one	0.06	+0.17	0.81
Race/ethnicity			
Native American	0.03	+2.5	0.06
African-American	0.47	+0.13	0.81
Caucasian	0.37		
Hispanic	0.09	−0.2	0.82
Asian-American	0.02	−1.5	0.40
Other	0.03	−4.0	0.02

Table 2: Education and employment status

Independent variable	Mean	Change in % points	p-value
Education	1.00		
Did not graduate from high school	0.15		
Completed high school or earned GED	0.26	+0.8	0.18
Attended college but did not graduate	0.37	+0.8	0.18
Graduated from 2-year college	0.03		
Graduated college (2-year/4-year unspecified)	0.11	+0.7	0.34
Graduated from 4-year college	0.07	−0.2	0.85
Employment	1.00		
Unemployed	0.05		
Employed, full-time (> 35 hours per week)	0.58	+0.16	0.84
Employed, part-time (< 35 hours per week)	0.24	−0.62	0.44
Not working (homemakers, retired, disabled)	0.04	−0.25	0.82
Student, not working	0.06	−0.6	0.51
Student, also working	0.03	−0.21	0.86
Employee of IDA host organization			
No	0.98		
Yes	0.02	+0.09	0.94
Self-employment in microenterprise			
None	0.80		
Active	0.07	−1.3	0.29
Inactive	0.14	+0.07	0.91

Table 3: Income and public assistance

Independent variable	Mean	Change in % points	p-value
Household income ($100/month)			
Recurrent income (2-piece spline)	−11.4		
0 to $799	−4.8	0.00	1.00
$800 or more	−6.6	+0.05	0.62
Intermittent income	−2.2	−0.02	0.74
Receipt of public assistance			
TANF or AFDC never	−0.62		
TANF or AFDC formerly	−0.38	−0.09	0.86
TANF currently	−0.10	+0.76	0.27
No SSI/SSDI	−0.89		
Receives SSI/SSDI	−0.11	+0.10	0.91
No food stamps	−0.79		
Receives food stamps	−0.21	−1.0	0.23

Table 4: Assets, liabilities, and insurance

Independent variable	Mean	Change in % points	p-value
Liquid assets			
No passbook savings account	0.48		
Owned passbook savings account	0.52	−0.23	0.59
Balance in passbook savings account ($100s)	2.36	+0.04	0.18
No checking account	0.34		
Owned checking account	0.66	−0.6	0.22
Balance in checking account ($100s)	2.11	−0.09	0.20
Illiquid assets			
Renter	0.85		
Home owner	0.15	−0.41	0.68
No car	0.37		
Car owner	0.63	−1.1	0.05
Value of illiquid assets ($100s)	112	0.000	0.99
Liabilities			
No debt	0.35		
Some debt	0.65	+0.8	0.09
Value of liabilities ($100s)	89	0.000	0.99
Insurance coverage			
No health insurance	0.34		
Had health insurance	0.66	+0.36	0.65
No life insurance	0.68		
Had life insurance	0.32	−1.5	0.14

Table 5: Enrollment characteristics

Independent variable	Mean	Change in % points	p-value
Previous relationship with host organization			
No	0.59		
Yes	0.41	+0.34	0.53
Referred by partner organization			
No	0.70		
Yes	0.30	+1.0	0.13
Date of enrollment			
Before June 30, 1999	0.58		
After June 30, 1999	0.42	−6.4	0.01
Months of participation (5-piece spline)	13.3		
1 to 6	5.7	−1.0	0.01
7 to 12	3.8	−0.45	0.02
13 to 18	2.2	−0.7	0.01
19 to 24	1.2	−0.54	0.02
24 or more	0.4	−0.24	0.47

Table 6: Number of accounts and direct deposit

Independent variable	Mean	Change in % points	p-value
Number of accounts			
One	0.99		
More than one	0.01	+4.6	0.02
Use of direct deposit to IDA account			
No	0.95		
Yes	0.05	−2.7	0.17

Table 7: Program-design characteristics

Independent variable	Mean	Change in % points	p-value
Match rate			
1:1	0.24	+4.7	0.01
2:1	0.51	+3.7	0.01
3:1	0.14	+1.6	0.14
4:1 to 7:1	0.06		
Match cap			
Monthly savings target	43	−0.05	0.01
Match-cap structure			
Annual	0.56		
Lifetime	0.44	−1.0	0.27
Program inputs per participant per month			
Salaried IDA staff (hours)	2.8	+1.2	0.07
Partner staff (hours)	0.5	−0.88	0.16
Volunteer staff (hours)	1.1	+0.06	0.90
Salary expense ($)	46	−0.02	0.62
Non-salary expense ($)	24	0.00	1.00

Table 8: Program fixed effects

Independent variable	Mean	Change in % points	p-value
CAPTC Large-scale	0.19		
CVCAC (ADD/AFIA)	0.02	+4	0.12
Human Solutions	0.05	+11	0.01
CAAB (ADD/AFIA)	0.03	+13	0.01
CVCAC	0.07	+13	0.01
EBALDC	0.10	+13	0.01
Heart of America	0.04	+14	0.01
Shorebank	0.09	+14	0.01
MACED	0.02	+14	0.01
CAPTC Small-scale	0.07	+15	0.01
ADVOCAP	0.03	+15	0.01
CTMHA	0.05	+15	0.01
Alternatives FCU	0.04	+16	0.01
CAAB	0.04	+17	0.01
Near Eastside	0.08	+19	0.01
WSEP (ADD/AFIA)	0.04	+22	0.01
WSEP	0.06	+23	0.01