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Match Rates, Individual Development Accounts, and Saving by the Poor

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Match Rates, Individual Development Accounts, and Saving by the Poor

Abstract

Individual Development Accounts (IDAs) provide low-income people with matches for savings used for home purchase, post-secondary education, or microenterprise. Match rates for the 2,350 IDA participants in the American Dream Demonstration (ADD) were typically 1:1 or 2:1 but ranged as high as 7:1. This paper looks at how these match rates were related with the likelihood of saving something and with the level of savings. The model controls for a number of confounding factors often ignored in similar studies of match rates in 401(k) plans. For IDAs in ADD, higher match rates were generally associated with a greater likelihood of saving something and—for participants who saved something—a lower level of IDA savings.

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1. Introduction

Individual Development Accounts provide low-income people with matches for savings used for home purchase, post-secondary education, or small business. IDAs have three goals: to include the poor in asset-building policies, to increase their savings, and to increase their asset accumulation (savings plus match).

The worldwide policy shift away from income support and toward asset-building may leave the poor behind (Sherraden, 1997). For example, the U.S. government spends billions each year on tax breaks for asset-building in Individual Retirement Accounts, 401(k) plans, and deductions for home-mortgage interest (Howard, 1997). Tax breaks, however, are worth little to people in low tax brackets, so direct matching via IDAs is one of the few ways to include low-income people in asset-building policies.

IDAs also aim to increase savings by low-income people. As income and consumption decrease, the opportunity cost of saving increases. Matching in IDAs boosts the return to saving to help compensate for the short-term sacrifice.

Finally, IDAs aim to increase asset accumulation. Matching turns a given level of savings into a larger amount of asset accumulation, sometimes enough to acquire a life-changing asset such as a house or a college education.

How do match rates affect savings by low-income people in IDAs? Matching is central to IDAs, yet very little is known about how people—poor or not—respond to match rates. The assessment of match-rate effects—whether for the poor in IDAs or the non-poor in 401(k) plans—is complex for several reasons.

First, matching sharpens a kink in the budget constraint, so how match rates affect whether something is saved may differ—even in sign—from how match rates affect the level of savings (Moffitt, 1990). Economic theory unambiguously predicts that higher match rates will increase the likelihood of saving something, and this accords with most participant-level evidence in the 401(k) literature (Clark, *et al.*, 2000; Clark and Schieber, 1998; General Accounting Office, 1997). But for the level of savings, theory is ambiguous. Higher returns to saving—that is, higher match rates—increase the cost of current consumption relative to future consumption. The resulting "substitution effect" tends to increase saving. But higher match rates also allow a household to save less and still reach a given goal. This "fixed-target" effect tends to depress saving.

Second, the level of matchable IDA savings is capped. Thus, desired savings are observed only if they are below the cap. Furthermore, higher match rates in IDAs—as in 401(k) plans (VanDerhei and Copeland, 2001)—are associated with lower caps. This means that even if higher match rates increase desired IDA savings, observed savings may be lower with higher match rates (and lower caps) than with lower match rates (and higher caps). Failure to adjust for censoring at the match cap biases estimates of match-rate effects downwards. Most participant-level studies of match rates in 401(k) plans do not adjust for censoring, and they usually find (perhaps spuriously) that higher match rates are linked with lower levels of savings as a percentage of income (Munnell, Sundén, and Taylor, 2002; VanDerhei and Copeland, 2001; Clark *et al.*, 2000; Andrews, 1992). In contrast, most specifications in the only papers to adjust for censoring (Engelhardt and Kumar, 2003; Cunningham and Engelhardt, 2002) find that higher match rates are associated with higher savings.

Third, unobserved participant characteristics may affect the response to match rates. In particular, people with high "propensities to save" may respond more strongly to higher match rates. This biases estimates of match-rate effects upwards. In the match-rate literature for 401(k) plans, only Engelhardt and Kumar (2003) and Cunningham and Engelhardt (2002) control for participant heterogeneity.

Fourth, IDA programs who expect participants to find it particularly difficult to save may try to compensate by setting higher match rates. In effect, they adjust the match rate based on participant characteristics that they observe but that the researcher does not. Failure to account for this program heterogeneity biases estimates of match-rate effects downwards. No known papers control for this. There may also be other sources of program heterogeneity. For example, all IDA programs examined here required that participants attend financial education, but class quality was both varied and unobserved. The strictness of rule enforcement was also varied and unobserved.

The econometric technique here is unique in the match-rate literature in that it accounts for these four sources of bias. It allows distinct match-rate effects for the choice to save something and for the level of IDA savings. It uses a Tobit to control for censoring, and it uses fixed effects to control for program heterogeneity. Finally, it controls for participant heterogeneity via a Heckman-type selection term and—more importantly—by including a large range of participant characteristics as regressors.

The model is applied to the 2,350 IDA participants in the 14 programs of the American Dream Demonstration. Match rates were typically 1:1 or 2:1 but ranged as high as 7:1, and they varied not only between programs but also within programs.

In accord with theory, higher match rates were associated with a greater likelihood of saving something. For participants who did save something, the "fixed-goal" effect apparently dominated the "substitution effect", as higher match rates were generally associated with a lower level of IDA savings.

What do these results mean for the three policy goals of IDAs? First, higher match rates help include low-income people in asset-building policies. Second, match rates above 1:1 may decrease savings. Third, the higher match and the greater likelihood of saving something more than compensates for the decrease in savings, so higher match rates increase asset accumulation.

Part 2 below describes IDAs and participants in ADD and presents simple cross-tabs between match rates and savings outcomes. Part 3 describes the model and its results. Part 4 concludes with some implications for policy.

2. IDAs and the American Dream Demonstration

2.1 Assets, development, and the poor

Development—that is, improvement in well-being—requires saving for the accumulation of human, physical, financial, and social capital. Many U.S. policies subsidize saving, usually via tax breaks. But tax breaks usually do not benefit for the poor very much.

IDAs aim to include low-income people in asset-building policy and to help them save and accumulate assets (Sherraden, 1991). Instead of tax breaks, IDAs provide matches for savings used to build human capital (via post-secondary education), physical capital (via home purchase), or business capital (via microenterprise). IDA programs also seek to build human capital (via financial education) and social capital (via support from peers and program staff).

Although the field of development economics has long seen saving as central to long-term improvement in well-being, public policy in the United States somehow overlooked the importance of saving for the poor. Public assistance provided cash to meet subsistence requirements, but it stopped short of transfers in the amounts and forms that might help people improve their well-being (develop) in the long term.

In 1988, a movement started to include the poor in asset-building policies. Friedman's *The Safety Net as Ladder* suggested that public assistance could aid development beyond mere subsistence. Haveman's *Starting Even* argued that "transfer payments are necessary but not sufficient" (p. 149). Sherraden's "Rethinking Social Policy: Towards Assets" proposed IDAs as one step toward a development-oriented policy paradigm.

The movement has since gained intellectual momentum (Sherraden and Morris, forthcoming; Shapiro and Wolff, 2001; Ackerman and Alstott, 1999; Conley, 1999; Oliver and Shapiro, 1995). It has also attracted broad political support. Bill Clinton—who as governor of Arkansas wrote the foreword to *The Safety Net as Ladder*—supported IDAs in his 1992 campaign and later proposed a large matched-savings program (Wayne, 1999). In 2000, both George W. Bush and Al Gore had IDA proposals in their platforms (Bush, 2000; Kessler, 2000). About 34 states have IDA legislation (Edwards and Mason, 2003), and the Assets for Independence Act authorized $250 million for IDAs in 1999–2009. Furthermore, the Savings for Working Families Act—if passed—would provide $450 million for 300,000 IDAs over 10 years. Outside the United States, Taiwan has an IDA-like demonstration, and Canada has sponsored a randomized IDA experiment. In the United Kingdom, the Savings Gateway resembles IDAs (Kempson, McKay, and Collard, 2003), and the new Child Trust Fund will give each newborn an account and a deposit, with larger deposits for children in poor families (H.M. Treasury, 2003).

2.2 The American Dream Demonstration

The first large-scale IDA project was the American Dream Demonstration. From 1997 to 2003, ADD had 2,350 participants at 14 IDA programs across the United States. All programs provided matches for home purchase, post-secondary education, and small business, and some also provided matches for job training, home repair, and retirement saving. Unmatched withdrawals were allowed for other purposes. Most programs were housed in non-profit community-development organizations. Schreiner *et al.* (2001) and Schreiner, Clancy and Sherraden (2002) give more detail on each program.

ADD participants held their IDAs as passbook accounts in banks or credit unions. Deposits received no special tax treatment, but the IRS counted matches as gifts. Match monies were not commingled with participant savings, and matches were disbursed directly to vendors (for example, a home seller or a college) or to participants upon presentation of receipts (for example, small-business investment). Participants had to attend financial-education classes.

Program staff in ADD collected data with a software package designed to help them manage IDAs (Johnson, Hinterlong, and Sherraden, 2001). The system recorded account-structure parameters at start-up, participant demographic and economic data at enrollment, and IDA cash flows in each month. The cash-flow data are accurate and complete; they come from bank records and satisfy accounting identities. Participant data ware extensively cross-checked, and program parameters were double-checked. While the ADD data are not perfect, they are unusually clean, and these may be the only high-frequency data on matched savings by low-income people.

2.2.1 Participants in ADD

People with household income under 200 percent of poverty were eligible to participate in ADD. For participants, average monthly household income was about $1,400, and median income/poverty (controlling for household size) was 107 percent. The sum of passbook and checking balances averaged about $500.

At enrollment, 16 percent of participants owned a home, 60 percent owned a car, and 18 percent reported small-business assets or self-employment income. Almost half (48 percent) intended to make a matched withdrawal for home purchase, 19 percent for small business, 16 percent for post-secondary education, and 17 percent for home repair, retirement saving, or job training.

Compared to low-income people in general, participants in ADD were more disadvantaged in that they were disproportionately female (80 percent), African-American (47 percent), and/or not married (about 75 percent) (Sherraden *et al.*, 2000).

About 44 percent were single mothers, and 50 percent had received public assistance at some point before enrollment. Participants were disproportionately advantaged in that they were more likely at enrollment to be employed or to be students (90 percent), to have a college degree (24 percent), and/or to own a bank account (77 percent).

The ADD data cover *participants*, that is, low-income people who could choose to open an IDA and who did so. The data do not cover *eligibles*, those people who could have opened an IDA but who chose not to. Participants likely differ from eligibles. In particular, if both eligibles and actual participants had opened IDAs, the actual participants probably would have had better savings outcomes, as they were drawn more heavily from those who expected—based on their knowledge of their own characteristics—large rewards from IDA participation. While it is useful to know how participants behaved, for many policy purposes it is more useful to know how eligibles would have behaved.

Participants in ADD were not only self-selected but also program-selected. IDA programs usually targeted specific groups such as the working poor, women, and/or people of color. Furthermore, the host organizations often promoted IDAs most among people who were already clients of their other services. Program selection could have increased or decreased savings for participants (relative to eligibles).

2.2.1 Match rates and savings outcomes in ADD

Figure 1 relates match rates with savings outcomes. For IDAs in ADD, match rates had no clear link with the likelihood of being a "saver", defined as having at least $100 of matchable savings (including matched withdrawals) as of the last day when deposits could be matched. About 53 percent of participants were "savers". Note that "savers" refers to participants with at least $100 of matchable savings, not to eligibles who opened IDAs. Most "non-savers" saved something for a time but then made unmatched withdrawals.

In the cross-tabs for "savers", higher match rates were associated with lower IDA savings. Across match rates of 1:1, 2:1, and above 2:1, matchable savings were $1,357, $887, and $739. The percentage of income saved in IDAs was 3.4, 2.4, and 2.3. Likewise, "matchable savings per month" was $36.91, $26.67, and $22.07.

The apparent negative link between higher match rates and lower IDA savings in Figure 1 may, however, be an artifact of censoring. Programs in ADD tended to couple higher match rates with lower match caps: looking at the 1,233 "savers" across match rates, the average match cap was $2,060, $1,325, and $917. Furthermore, IDA savings for participants with higher match rates (and hence lower match caps) were more likely to be censored: while 27 percent of participants with match rates of 1:1 had IDA savings at the match cap, the figure was 44 percent for match rates of 2:1, and 57 percent for match rates above 2:1. (To allow for what the literature on kinked budget constraints calls “optimization error”, participants were counted as “censored” if they were within 95 percent of the match cap.) Thus, censoring at the lower match caps that were associated with higher match rates may explain the apparently negative match-rate effect on IDA savings. The model below controls for this.

3. Results

3.1 Econometric model

The modelling problem has four aspects. First, match rate may have a different effect on the likelihood of being a "saver" than on the level of IDA savings. Second, desired IDA savings may be censored at the match cap. Third and fourth, match rates may interact with unobserved characteristics of programs and participants.

A two-step model accounts for these issues. For all 2,350 participants, the first step is a Probit on the likelihood of being a "saver". For the 1,243 "savers", the second step is a Tobit on "matchable savings per month". Each step has a distinct match-rate effect. The second-step Tobit controls for censoring, and both steps use fixed effects to control for program heterogeneity. To control for participant heterogeneity, the Tobit includes a Heckman-type selection term. More importantly, both steps include an unusually large number of variables, many of them correlated with unobserved factors such as "propensity to save". The idea is to control for unobserved factors by including many observed factors that are likely to be correlated with them.

The model can be seen as a variant of Greene's (2002) Tobit with selection, Amemiya's (1984) "Type II Tobit", or Cragg's (1971) two-step Tobit. In the first step, a participant is a "saver" ($z = 1$) if the (unobserved) desired "saver" status z^* is positive:

$$\begin{aligned} z &= 1 \text{ if } z^* = \alpha' W + u > 0, \\ z &= 0 \text{ if } z^* = \alpha' W + u \leq 0. \end{aligned} \tag{1}$$

For "savers" in the second step, the level of observed IDA savings y equals desired IDA savings y^* if y^* is less than the match cap m. Otherwise, observed IDA savings y equals the match cap m. The second step includes the selection term λ:

$$\begin{aligned} y &= y^* \text{ if } y^* = \beta' X + \theta\lambda + \varepsilon < m, \\ y &= m \text{ if } y^* = \beta' X + \theta\lambda + \varepsilon \geq m. \end{aligned} \tag{2}$$

The errors u and ε are joint-normal with parameters $(0, 0, 1, \sigma^2, \rho)$.

Full-information maximum likelihood estimation of (1) and (2) proved difficult. The full model has more than 200 regressors, but LIMDEP 8.0 allows only 140. SAS 9.0 has no such limits, but its QLIM procedure has a documented bug. In the end, a stripped-down full-information model was estimated in LIMDEP, and a limited-information version of the full model was estimated in SAS. Match-rate effects were virtually identical in both cases, so estimates for the full model are reported here.

The final specification omits the selection term λ, as it was always insignificant ($p>0.95$). Although participants who were more likely to be "savers" probably also had higher expected IDA savings, the wealth of variables included in both steps apparently absorbed this heterogeneity. As one check, the second step was estimated with least-squares, and adjusted R^2 was about 0.46. For a cross-section, individual-level savings regression, this is a high level of explanatory power, suggesting that many important factors—whether observed directly or not—were controlled for.

3.2 Exogenous variation in match rates

Before getting to the model's results, this section addresses two more questions: Was there sufficient variation in match rates, and was this variation exogenous?

Match rates in ADD did vary, both between and within programs (Figure 2). Looking between programs with 30 or more participants (or "savers") with a given match rate, there were 5 (5) programs with 1:1, 10 (8) programs with 2:1, and 5 (5) programs above 2:1. Looking within programs, there were 4 (3) programs with 30 or more participants with 1:1 match rates and 30 or more participants to 2:1 match rates. There were 2 (1) programs with 30 or more participants with 2:1 match rates and 30 or more participants above 2:1. In principle, this is sufficient to identify match-rate effects, even after controlling for program fixed effects.

Were match rates exogenous? In most cases, programs set match rates independently of their beliefs about how participants would save, and the model controls for other cases.

First, match rates were (sub-)program-wide, not participant-specific. Still, if programs expected their participants as a group to save less, then they may in some cases have set higher match rates at the outset of ADD (Sherraden *et al.*, 2000). Program fixed effects, however, should help control for this.

Second, as ADD progressed, some programs assigned different match rates to later cohorts. Staff state, however, that these new match rates were driven by the availability of match funds rather than beliefs about how later cohorts would save. In any case, the model controls indirectly for cohort via the number of months in which a participant could have made matchable deposits. The model also directly controls for membership in ADD's last cohort, because—regardless of match rates—this group was hastily recruited to meet enrollment goals and ended up with lower savings.

Third, the largest program in ADD offered a 2:1 match rate for home purchase and a 1:1 match rate for all other uses. But the model controls for intended use, and the match rate is based on the participant's "intended use" at enrollment.

Fourth, except in Chicago (which had two ADD programs), it was impossible for participants to self-select into programs based on unobserved characteristics that made them extra-sensitive to match rates.

3.3 Estimated match-rate effects

Figure 3 presents the estimated match-rate effects from the two-step model with the ADD data (other model results are in the Appendix). In accord with theory, higher match rates in the first-step Probit were associated with a greater likelihood of being a "saver". Compared with a 1:1 match rate, a 2:1 match rate was associated with an increase in the likelihood of being a "saver" of 7.3 percentage points (p-value 0.14). Match rates above 2:1 were associated with an increase of 14.7 percentage points (p-value 0.06). Just more than half of participants were "savers", so these are large effects. Despite the one not-quite-significant p-value, the pattern is that higher match rates were associated with a greater likelihood of saving something.

For "savers", the theoretical effect of higher match rates on the level of IDA savings is ambiguous; either the "substitution effect" or the "fixed-goal effect" could win out. In the second-step Tobit with the ADD data, the move from a match rate of 1:1 to 2:1 was associated with an increase in "matchable savings per month" of $5.76 (p-value 0.03). Average "matchable savings per month" for "savers" was $28.57, this is again a large effect. IDA savings with match rates of more than 2:1 were not significantly different than with match rates of 1:1, but this may be due to the minimal within-program variation involving "savers" with match rates above 2:1 in ADD.

Broadly, the "fixed-goal effect" seems to have dominated the "substitution effect". For low-income people saving for a "lumpy" purchase, this is plausible. If the minimum down payment on a home is $2,000, the cost of lost matches due to not saving an additional $100 is the same at $1,900 as at $2,100, but participants may stop saving once they can buy the house, either because they need cash for closing costs or because the marginal utility of consumption now exceeds the opportunity cost of lost matches.

IDAs are not 401(k) plans; IDA participants are poorer, and IDA match rates are higher (the typical match rate in 401(k)s is 0.5:1). Thus, the IDA results here have few—if any—implications for 401(k)s. In particular, the association of higher match rates with lower IDA savings does not contradict the best work on 401(k)s and its association of higher match rates with higher savings (Engelhardt and Kumar, 2003; Cunningham and Engelhardt, 2002). The IDA results may indicate, however, possible conflicts between the three goals of inclusion, saving, and asset accumulation.

4. Conclusion

In IDAs in ADD, higher match rates were associated with a greater likelihood of saving something but—for “savers”—a lower level of IDA savings. Unlike work on match rates in 401(k) plans, this paper estimates two distinct match-rate effects and controls for censoring and for unobserved heterogeneity in programs and participants.

In terms of the three basic goals of IDAs, higher match rates encourage inclusion because they make participants more likely to save something. Higher match rates also, however, depress IDA savings. On net, asset accumulation could rise or fall. On one hand, increasing the likelihood of being a “saver” increases asset accumulation. On the other hand, decreasing IDA savings by “savers” decreases asset accumulation. Finally, for a given level of IDA savings, a higher match rate increases asset accumulation.

For ADD, simulations based on the regression predict that, with a match rate of 1:1, 47.3 percent of participants would be “savers” with an average (censored) “matchable balance per month” of $32.69 (Figure 4). With a match rate of 2:1, 52.7 percent would be “savers” (an increase of 5.4 percentage points) with average “matchable savings per month” of $29.16 (a decrease of $3.53). Looking at all participants, average “matchable savings per month” would decrease by about 10 cents; the increase in the likelihood of being a “saver” almost exactly cancels the decrease in the level of IDA savings. Thus, compared with a 1:1 match rate, a 2:1 match rate increases asset accumulation per participant per month by almost 50 percent, from $30.92 to $46.10.

What does this mean for IDAs as a possible universal, lifelong, progressive asset-building policy? If participants in ADD do not resemble participants in a long-term, large-scale policy, then these results may mean little. If ADD is somewhat representative, however, then the results highlight trade-offs among the basic goals of IDAs. Higher match rates are associated with greater inclusion and increased asset accumulation but with decreased IDA savings per “saver” and with essentially unchanged IDA savings per participant.

Inclusion and asset accumulation probably matter more than increased savings. Even though ADD participants were poor, at least some of their IDA savings were “reshuffled” rather than “new” (Schreiner *et al.*, 2001). Even if all IDA savings were “new”, $15 per participant per month (about 1 percent of income in these low-income households) probably would not be a large boost to the household saving rate.

In qualitative work, ADD participants say that inclusion in IDAs sparked hope and helped them focus on future goals (Sherraden *et al.*, 2003). Also, preliminary results from the one program in ADD that randomized access to IDAs across qualified applicants suggest that IDAs accelerated asset accumulation, not only for the three fundamental matched uses of home ownership, post-secondary education, and small-business ownership, but also for household durables (cars, refrigerators, clothes dryers, and dishwashers) even though these purchases were not matched.

All this argues for higher match rates. The goals of increased inclusion and asset accumulation—if not also increased savings—would be better served with a match rate of 2:1.

Of course, the match rate is just one policy lever in IDA design. In particular, the match cap also matters. Qualitative work in ADD suggests that participants see the match cap not as a limit but as a goal. This fits with work in behavioral economics that finds that people often believe—without bothering to see if it holds for their own case—that subsidized savings opportunities should be "maxed out" (Milligan, 2003; Thaler and Sunstein, 2003). In this sense, the effects of a lower match rate might be at least partly compensated by being coupled with a higher match cap.

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Appendix: Variables and regression results

This appendix presents the control variables (other than match rates) in the two-step model and briefly discusses collateral results omitted from the main text.

A.1 Elements of IDA design

The average match cap in ADD was about \$41 per month (\$500 per year, Figure 5). A \$1 increase in the cap was linked with \$0.50 increase in IDA savings.

Match caps limited matchable deposits either in each year or over the lifetime of ADD. About half of participants had annual caps. Lifetime caps were linked with huge (\$18 per month) increases in IDA savings. Again, this is puzzling.

About 6 percent of ADD participants used automatic transfer to their IDA. All else constant, they were 17 percentage points more likely to be "savers".

"Months to make matchable deposits" was represented with a set of dummies. Participants with more than three years to save were much more likely to be "savers".

All programs in ADD required financial education. The Probit omits hours attended because of endogeneity; drop-outs had fewer hours, not because missing class caused them to drop-out but because dropping out caused them to miss class. In the Tobit, each additional hour of class attendance from 0 to 10 was associated with an increase in IDA savings of about \$1.60, a very large effect.

A.2 Intended use of matched withdrawals

At enrollment, 48 percent of participants planned to make a matched withdrawal for home purchase, 16 percent for post-secondary education, 19 percent for small-business ownership, and 17 percent for home repair, job training, or retirement saving (Figure 6). Those who planned for home ownership were the least likely to be "savers", while those who planned for home repair were the most likely. All else constant, those who planned for small-business ownership had lower IDA savings.

A.3 Participant demographics

Four of five participants in ADD were female, and they were 7 percentage points more likely than men to be "savers" (Figure 7).

In race/ethnicity, participants were African-American (47 percent), Caucasian (37 percent), Hispanic (9 percent), Native American (3 percent), "Other" (3 percent), and Asian-American (2 percent). Compared with Caucasians, Asian Americans and "Others" were more likely to be "savers". Asian Americans also saved about $7 more per month than Caucasians, while African Americans and Native Americans saved $8 less.

The average age in ADD was 36. Using linear splines (Smith, 1979), savings outcomes worsened sharply from ages 14 to 20, but they improved after that.

Married participants (28 percent) were more likely to be "savers" than the 49 percent who were never-married. About 28 percent were divorced or separated, and 3 percent were widowed.

The average household in ADD had 1.5 adults and 1.7 children. Neither variable was associated with savings outcomes.

Being in a household with other IDA participants (6 percent of cases) was not associated with savings outcomes.

Being in a rural area (13 percent of cases) was not linked with savings outcomes.

A.4 Education and employment

In ADD, 16 percent of participants did not finish high school, 23 percent finished high school, 39 percent attended college, and 22 percent had a college degree (Figure 8). Outcomes were generally worst for high-school drop-outs and best for college graduates.

About 91 percent of participants in ADD were employed or were students. Except for working students, employment status was not linked with savings outcomes.

A handful (2 percent) of ADD participants were also employees of the host organizations that housed the IDA programs. These participants had higher savings.

A.5 Income and receipt of public assistance

About half of participants received some sort of income-tested public assistance at or before enrollment. People with food stamps had lower IDA savings (Figure 9).

Income was divided into "recurrent" and "intermittent" because its regularity affects saving (Deaton, 1992). For each type, splines allowed for non-linearities. More income—up to the kink in the spline—was generally related with greater likelihood of being a "saver" and higher IDA savings, although the effects were small.

A.6 Bank accounts

At enrollment, 38 percent of ADD participants had both passbook and checking accounts, 26 percent had only checking accounts, 12 percent had only passbooks, and 23 percent were "unbanked" (Figure 10). Generally, those with checking accounts had better savings outcomes than the "unbanked" or those with only passbooks.

Balances in passbook and checking accounts were specified as splines. Higher balances—up to the kink—were usually associated with better savings outcomes.

A.7 Assets

About 16 percent of participants owned a home (one-fourth of those debt-free), 64 percent owned a car (63 percent of those debt-free), 2 percent owned land or property, 13 percent had financial investments, and 11 percent had small-business assets (Figure 11). In general, owners were more likely to be "savers", especially if they were debt-free. For the level of IDA savings, mortgage-free home owners and small-business owners saved more than others.

A.8 Debts

About 17 percent of participants had student loans, 18 percent informal debts, 28 percent late household bills, 18 percent late medical bills, and 33 percent credit-card debt (Figure 12). Credit-card debt was linked with a lower probability of being a "saver", overdue bills with lower IDA savings, and informal debts with higher savings.

A.9 Insurance coverage

In ADD, 61 percent of participants had health insurance, and 39 percent had life insurance (Figure 13). Those with life insurance were less likely to be “savers”.

A.10 Enrollment and referrals

About 41 percent of participants had been clients of the host organization that housed the IDA program (Figure 14). This was not linked with savings outcomes. The 30 percent who were referred to the IDA program by a partner organization were less likely to be “savers”. Finally, the 40 percent of participants who opened IDAs in the last six months of enrollment saved about $3 less per month.

A.10 Program fixed effects

Figure 15 reports program fixed effects. There were wide differences in savings outcomes that were associated with specific programs but not with other regressors.

A.10 Intercepts, zero-order dummies, and fit

Figure 16 reports regression intercepts, zero-order dummies, and measures of fit. For variables with missing values, a parallel zero-order dummy was set to unity (1) when the original variable was missing, and zero otherwise. Then the missing value was changed to zero, and both variables were included in the regression. In terms of the other estimated coefficients, this is equivalent to replacing missing values with the variable’s mean (Greene, 1993).

Figure 1: Savings outcomes in ADD, match rates, match caps, and censoring

Measure	All	Match rate 1:1	Match rate 2:1	Match rate >2:1
Participants:				
All (number)	2,350	654	1,137	559
All (%)	100	28	48	24
"Savers" (Matchable balances =>$100):				
"Savers" (number)	1,243	367	572	304
"Savers" (% participants, given a match rate)	53	56	50	54
For "Savers" only:				
Matchable savings ($)	990	1,357	887	739
Share of income saved in IDAs (%)	2.7	3.4	2.4	2.3
Matchable savings per month ($)	28.57	36.91	26.67	22.07
Match cap	1,442	2,060	1,325	917
Months eligible for matchable deposits	34.4	36.6	33.4	33.5
Share censored at =>95% of match cap (%)	42	27	44	57

Note: T-tests for differences in means between all pairs have p<0.10, except 2:1 versus >2:1 for share of "Savers", months eligible, and saving rate.

Figure 2: Match-rate variation between and within programs in ADD

	All participants					"Savers"			
Program	**All**	**1:1**	**2:1**	**>2:1**		**All**	**1:1**	**2:1**	**>2:1**
ADVOCAP	82	0	82	0		58	0	58	0
Alternatives FCU	91	0	0	91		73	0	0	73
Bay Area	239	0	239	0		151	0	151	0
CAAB	142	1	37	104		72	1	15	56
CAPTC Large-scale	456	216	240	0		211	144	67	0
CAPTC Small-scale	163	105	58	0		95	81	14	0
CVCAC	154	61	69	24		105	38	49	18
Foundation Communities	125	1	119	5		53	0	53	0
Heart of America	91	0	90	1		68	0	68	0
MACED	65	16	15	34		42	0	11	31
Mercy Corps	118	118	0	0		54	54	0	0
Near Eastside	190	6	3	181		87	0	1	86
Shorebank	203	129	74	0		88	49	39	0
WSEP	231	1	111	119		86	0	46	40
All ADD:	2350	654	1137	559		1243	367	572	304

Figure 3: Estimated match-rate effects in IDAs in ADD

Independent variable	Prob.(Net deposits=>$100) Mean	Δ% pts.	p-value	Net deposits/month Mean	Δ$	p-value
Match rate						
1:1	0.28			0.21		
2:1	0.48	+7.3	0.14	0.46	–5.76	0.03
>2:1	0.24	+14.7	0.06	0.24	–0.48	0.92

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero (p = 0.95), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 4: Simulated changes in inclusion, IDA savings, and asset accumulation in ADD as match rates move from 1:1 to 2:1

	Match rate		Change
Measure	1:1	2:1	1:1 to 2:1
"Savers" (%)	47.3	52.7	5.4
"Matchable savings per month" for "savers" ($)	32.69	29.16	-3.53
"Matchable savings per month" per participant ($)	15.46	15.37	-0.10
Asset accumulation per month per participant ($)	30.92	46.10	15.18

Source: Simulations with ADD data and estimates from two-step model.

Figure 5: Elements of IDA design

Independent variable	Prob.(Net deposits=>$100) Mean	Δ% pts.	p-value	Net deposits/month Mean	Δ$	p-value
Match cap						
Limit on matchable deposits ($/month)	41	+0.1	0.19	42	+0.50	0.01
Match-cap structure						
Annual	0.52					
Lifetime	0.48	–6.9	0.44	0.50	+18.18	0.01
Use of automatic transfer to IDA						
No	0.94			0.93		
Yes	0.06	+17.3	0.01	0.07	+1.26	0.58
Months to make matchable deposits						
24 or less	0.25			0.22		
25 to 35	0.19	+7.4	0.36	0.20	–2.51	0.55
36	0.28	+2.4	0.81	0.25	–5.10	0.32
37 or more	0.28	+16.4	0.06	0.33	–5.58	0.22
Hours of general financial education						
Zero				0.09		
More than zero				0.91	–0.04	0.99
1 to 10 (spline)				9.0	+1.59	0.01
10 to 20 (spline)				2.3	–0.35	0.24
20 to 30 (spline)				0.4	+0.59	0.21

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero (p = 0.95), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 6: Intended use of match withdrawal as recorded at enrollment

	Prob.(Net deposits=>$100)			Net deposits/month		
Independent variable	**Mean**	**Δ% pts.**	**p-value**	**Mean**	**Δ$**	**p-value**
Intended use of matched withdrawal						
Home purchase	0.48			0.43		
Home repair	0.09	+35.5	0.01	0.13	+3.47	0.20
Post-secondary education	0.16	+17.3	0.01	0.18	–2.06	0.30
Job training	0.02	+4.3	0.62	0.02	–5.60	0.24
Retirement	0.06	+18.1	0.01	0.07	–0.28	0.92
Small-business ownership	0.19	+15.6	0.01	0.22	–3.96	0.04

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero ($p = 0.95$), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 7: Participant demographics

Independent variable	Prob.(Net deposits=>$100) Mean	Δ% pts.	p-value	Net deposits/month Mean	Δ$	p-value
Gender						
Male	0.20			0.21		
Female	0.80	+6.9	0.04	0.79	+0.14	0.93
Race/Ethnicity						
Caucasian	0.37			0.44		
African American	0.47	−2.7	0.44	0.39	−7.93	0.01
Asian American	0.02	+19.4	0.05	0.03	+6.86	0.10
Hispanic	0.09	+8.1	0.12	0.10	−0.41	0.87
Native American	0.03	−5.3	0.47	0.02	−7.91	0.04
Other race/ethnicity	0.03	+14.2	0.06	0.03	+0.59	0.87
Age						
14 to 20 (spline)	5.9	−7.2	0.01	5.9	−2.32	0.03
20 to 70 (spline)	16	+0.5	0.01	17	+0.20	0.01
Marital status						
Never-married	0.49			0.39		
Married	0.23	+8.1	0.04	0.27	−0.22	0.91
Divorced or separated	0.28	+1.0	0.76	0.30	−1.07	0.50
Widowed	0.03	+3.1	0.73	0.04	−8.42	0.03
Household composition						
Adults (18 or older)	1.5	+2.4	0.25	1.5	−0.27	0.80
Children (17 or younger)	1.7	−0.8	0.37	1.7	−0.13	0.79
Multiple IDA participants in household						
No	0.94			0.93		
Yes	0.06	−3.9	0.46	0.07	+1.02	0.70
Location of residence						
Urban (pop. 2,500 or more)	0.87			0.84		
Rural (pop. 2,500 or less)	0.13	+1.7	0.76	0.16	−0.68	0.80

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero (p = 0.95), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 8: Education and employment status

Independent variable	Prob.(Net deposits=>$100) Mean	Δ% pts.	p-value	Net deposits/month Mean	Δ$	p-value
Education						
Did not complete high school	0.16			0.45		
Completed high school or GED	0.23	+5.0	0.22	0.21	–0.04	0.99
Attended college but did not graduate	0.39	+6.5	0.10	0.38	+1.14	0.61
Graduated 2-year college	0.04	+4.6	0.54	0.03	–5.87	0.13
Graduated college, 2-year/4-year unknowr	0.11	+18.5	0.01	0.14	+5.52	0.04
Graduated 4-year college	0.07	+21.1	0.01	0.10	+4.94	0.09
Employment						
Unemployed	0.05			0.13		
Homemaker, retired, or disabled	0.04	+1.8	0.82	0.05	–4.91	0.21
Student, not working	0.06	–6.7	0.38	0.04	+2.47	0.58
Student, also working	0.03	+15.0	0.09	0.03	+4.16	0.35
Employed part-time	0.23	+6.3	0.29	0.23	+1.80	0.57
Employed full-time	0.59	+6.7	0.25	0.60	–2.10	0.50
Employee of host organization						
No	0.98			0.97		
Yes	0.02	+3.4	0.68	0.03	+6.92	0.10

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero (p = 0.95), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 9: Income and receipt of public assistance

	Prob.(Net deposits=>$100)				Net deposits/month		
Independent variable	**Mean**	**Δ% pts.**	**p-value**		**Mean**	**Δ$**	**p-value**
AFDC or TANF before enrollment							
No	0.62				0.64		
Yes	0.38	+1.5	0.63		0.36	–0.36	0.80
AFDC or TANF at enrollment							
No	0.90				0.93		
Yes	0.10	–4.2	0.40		0.07	+3.06	0.27
SSI/SSDI at enrollment							
No	0.89				0.89		
Yes	0.11	+2.5	0.62		0.11	+2.94	0.27
Food stamps at enrollment							
No	0.83				0.84		
Yes	0.17	+5.0	0.24	0	0.16	–5.01	0.03
Recurrent income (monthly $)							
0 to $1,500 (spline)	1,000	–0.00003	0.35		990	+0.0033	0.07
$1,500 to $3,000 (spline)	155	+0.00003	0.47		165	–0.0002	0.92
Intermittent income (monthly $)							
0 to $2,000 (spline)	210	+0.00007	0.09		250	+0.0043	0.02
$2,000 to $3,000 (spline)	6	+0.00015	0.48		8	–0.0108	0.21

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero (p = 0.95), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 10: Bank accounts

Independent variable	Prob.(Net deposits=>$100) Mean	Δ% pts.	p-value	Net deposits/month Mean	Δ$	p-value
Passbook and checking accounts						
Both passbook and checkbook	0.38			0.45		
Checking only	0.26	+5.1	0.18	0.30	+2.81	0.12
Passbook only	0.12	–12.8	0.01	0.10	–3.24	0.14
Unbanked (no passbook, no checking)	0.23	–7.9	0.06	0.15	+0.92	0.68
Passbook savings balance ($)						
0 to $400 (spline)	94	+0.00049	0.01	113	+0.0197	0.01
$400 to $3,000 (spline)	134	–0.00007	0.03	175	+0.0024	0.10
Checking balance ($)						
0 to $1,500 (spline)	198	+0.00012	0.01	260	–0.0012	0.58
$1,500 to $3,000 (spline)	21	–0.00009	0.33	29	+0.0043	0.29

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero (p = 0.95), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 11: Assets

Independent variable	Prob.(Net deposits=>$100) Mean	Δ% pts.	p-value	Net deposits/month Mean	Δ$	p-value
Home ownership						
Renter	0.84			0.78		
Owned with mortgage	0.12	+9.3	0.05	0.17	+2.19	0.26
Owned free and clear	0.04	+3.5	0.61	0.05	+11.68	0.01
Car ownership						
None	0.36			0.26		
Owned with loan	0.24	+4.1	0.24	0.26	–0.85	0.65
Owned free and clear	0.40	+11.0	0.01	0.48	+1.49	0.35
Land or property ownership						
None	0.98			0.97		
Owned with mortgage	0.01	+54.7	0.07	0.01	–4.74	0.65
Owned free and clear	0.01	+68.0	0.02	0.02	–11.17	0.37
Financial investments						
No	0.87			0.84		
Yes	0.13	+13.1	0.01	0.16	–0.77	0.66
Small-business ownership						
No	0.89			0.86		
Yes	0.11	–0.6	0.91	0.14	+4.16	0.06

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero (p = 0.95), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 12: Debts

Independent variable	Prob.(Net deposits=>$100) Mean	Δ% pts.	p-value	Net deposits/month Mean	Δ$	p-value
Student loans						
No	0.83			0.84		
Yes	0.17	+3.2	0.37	0.16	+2.67	0.15
Informal loans from family or friends						
No	0.82			0.82		
Yes	0.18	–4.0	0.23	0.18	+3.38	0.04
Debt as overdue household bills						
No	0.72			0.75		
Yes	0.28	–1.3	0.64	0.25	–3.67	0.01
Debt as overdue medical bills						
No	0.82			0.84		
Yes	0.18	–3.9	0.24	0.16	–2.98	0.09
Credit-card debt						
No	0.67			0.67		
Yes	0.33	–4.7	0.10	0.33	+0.42	0.76

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero (p = 0.95), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 13: Insurance coverage

Independent variable	Prob.(Net deposits=>$100) Mean	Δ% pts.	p-value	Net deposits/month Mean	Δ$	p-value
Health insurance						
No	0.39			0.33		
Yes	0.61	+6.4	0.16	0.67	+0.10	0.97
Life insurance						
No	0.61			0.59		
Yes	0.39	–8.1	0.07	0.41	–1.51	0.50

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero (p = 0.95), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 14: Enrollment and referral

Independent variable	Prob.(Net deposits=>$100) Mean	Δ% pts.	p-value	Net deposits/month Mean	Δ$	p-value
Previous relationship with IDA host organization						
No	0.70			0.73		
Yes	0.41	–3.5	0.23	0.41	–0.32	0.82
Referred by a partner organization						
No	0.70			0.73		
Yes	0.30	–5.9	0.10	0.27	–1.14	0.51
Enrolled in last six months possible						
No	0.58			0.61		
Yes	0.42	–1.6	0.63	0.39	–3.05	0.08

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero ($p = 0.95$), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 15: Program fixed effects

Independent variable	Prob.(Net deposits=>$100) Mean	Δ% pts.	p-value	Net deposits/month Mean	Δ$	p-value
Program and AFIA status						
Foundation Communities	0.05	–12.7	0.21	0.04	–2.68	0.63
WSEP	0.07	–6.0	0.75	0.04	–19.48	0.04
WSEP AFIA	0.03	–3.5	0.86	0.02	–29.44	0.01
MACED	0.03	–0.0	0.99	0.03	–3.78	0.72
CAPTC Large-Scale	0.19			0.30		
Mercy Corps	0.05	+0.7	0.94	0.04	–9.12	0.09
CAPTC Small-Scale	0.07	+7.1	0.43	0.08	–10.61	0.02
Near Eastside	0.08	+8.3	0.54	0.07	–7.93	0.29
CVCAC AFIA	0.02	+10.4	0.51	0.03	+10.66	0.13
Shorebank	0.09	+19.2	0.08	0.08	–4.07	0.47
ADVOCAP	0.03	+19.6	0.29	0.04	–9.19	0.33
Heart of America	0.04	+30.5	0.04	0.06	–22.10	0.01
CVCAC	0.07	+31.9	0.01	0.09	–17.51	0.01
Alternatives FCU	0.04	+33.1	0.04	0.06	–14.85	0.08
CAAB	0.04	+46.0	0.01	0.03	–22.59	0.07
Bay Area	0.10	+64.8	0.01	0.12	–16.90	0.09
CAAB AFIA	0.02	+73.8	0.01	0.03	–19.54	0.12

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero (p = 0.95), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.

Figure 16: Intercept, zero-order regression dummies, and fit

	Prob.(Net deposits=>$100)			Net deposits/month		
Independent variable	**Mean**	**Δ% pts.**	**p-value**	**Mean**	**Δ$**	**p-value**
Regression constant						
Intercept	1.0	–25.3	0.18	1.0	+14.44	0.16
Zero-order regression dummies						
Use of automatic transfer	0.06	–26.8	0.01	0.03	–3.27	0.50
Marital status	0.01	+18.3	0.26	0.01	+7.12	0.28
Number of children	0.00	+34.7	0.14	0.00	+3.61	0.65
Existing relationship with host org.	0.06	–0.1	0.99	0.03	–13.96	0.05
Referred by partner org.	0.21	–43.5	0.01	0.21	+8.36	0.24
AFDC or TANF before enrollment	0.01	–11.9	0.45	0.01	–6.58	0.44
Received SSI at enrollment	0.34	+22.3	0.02	0.37	+3.47	0.46
Received food stamps at enrollment	0.35	+5.8	0.54	0.38	+0.12	0.98
Recurrent income	0.02	–57.7	0.02	0.03	+11.77	0.31
Passbook balances	0.03	+12.7	0.12	0.03	+3.55	0.38
Checking balances	0.04	–14.8	0.03	0.04	–0.75	0.83
Financial investments	0.00	+28.3	0.28	0.00	–1.08	0.92
Car	0.00	–9.5	0.78	0.00	+11.70	0.50
Presence of some type of debt	0.01	+20.5	0.32	0.01	+7.29	0.40
Insurance coverage	0.62	–13.1	0.01	0.61	–0.22	0.92
Variables with rare missings	0.01	–3.8	0.79	0.01	–5.10	0.53
Intermittent income				0.00	+7.27	0.50
General financial education				0.06	+15.47	0.12
Regression fit						
–2 x Log-likelihood		2465.64			6702.92	
Share (%) of pairs correctly predicted (c)		81.2				

Note: All tables derived from a single "Heckit"-type selection specification with two steps.
The "lambda" selection term was statistically zero (p = 0.95), so the two steps were estimated separately.
The first step was a Probit (n=2,350, k=105) for the likelihood of being a "saver".
The second step was a Tobit (n=1,233, k=111) for "matchable savings per month" for "savers".
Means taken over non-missing observations.