Drop-Out from Individual Development Accounts: Prediction and Prevention

Mark Schreiner and Michael Sherraden

March 2, 2005

Center for Social Development, Washington University in Saint Louis
Campus Box 1196, One Brookings Drive
Saint Louis, MO 63130-4899, U.S.A.
schreiner@gwbmail.wustl.edu, sherrad@wustl.edu

JEL Code:	C53	Econometric forecasting
Other codes:	I38	Provision of welfare programs
	G21	Banks
	O16	Development of financial markets

Abstract

Individual Development Accounts help the poor build assets by providing matches for savings used for home ownership, post-secondary education, and microenterprise. IDAs cannot help, however, if participants drop out. What factors predict drop-out? And what can be done to prevent it? For IDAs in the American Dream Demonstration, drop-out is less likely if participants already own some assets, be they human capital in education or experience, financial capital in bank accounts, social capital in marriage, or physical capital in homes or cars. Income and welfare receipt are not linked with drop-out. Drop-out is strongly associated with aspects of IDA design such as match rates, time caps, and the use of automatic transfer. Because drop-out can be predicted, IDA programs can keep costs down while targeting additional assistance to the most at-risk enrollees.

Acknowledgments

We are grateful for help from Timothy Bates, Sondra Beverly, Margaret Clancy, Jami Curley, Constance Dunham, Michal Grinstein-Weiss, Lissa Johnson, Margaret Sherraden, Min Zhan, the Corporation for Enterprise Development, and the host organizations in the American Dream Demonstration. The Division of Asset Building and Community Development of the Ford Foundation provided financial support.

Drop-Out from Individual Development Accounts: Prediction and Prevention

1. Introduction

Development—that is, sustained improvement in well-being—requires saving to build human, financial, social, and physical capital. Many U.S. policies use tax breaks to subsidize saving, but tax breaks are weak incentives for poor people (Woo, Schweke, and Buchholz, 2004; Seidman, 2001; Howard, 1997; Sherraden, 1991).

Individual Development Accounts are a new policy instrument designed to help the poor build assets (Sherraden, 1988). 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). IDAs also build human capital via financial education and social capital via support from program staff. Overall, IDAs seek to help the poor build assets by making saving more rewarding.

Saving requires consuming less and/or earning more. This is difficult for anyone, but it is especially difficult for the poor because they have less income available to save, fewer existing assets available to shift into IDAs, and more frequent shocks to income and expenses. Thus, some IDA participants end up saving little or nothing.

These *drop-outs* are costly all around; IDA programs lose their investment in participants, and participants lose potential matches. Worse yet, drop-outs may become discouraged with saving in general.

What characteristics of participants and of IDA design help to predict drop-out? Can participants at-risk of drop-out be targeted for preventive attention?

This paper addresses these questions with data from 2,350 IDA participants in the American Dream Demonstration. About 48 percent of IDA participants in ADD "dropped out", that is, had net IDA savings of less than $100.

Participant characteristics do predict drop-out. Drop-out is less likely if, before enrolling, participants already have assets, whether human (education or age), financial (checking accounts), physical (homes or cars), or social (marriage). In contrast, debt is linked with greater drop-out. Unlike assets and debt, income and receipt of welfare are not associated with drop-out. Overall, asset-poverty—but not income-poverty—is linked with greater risk of drop-out.

Aspects of IDA design also predict drop-out. This is useful for drop-out prevention; even if policy cannot change participant characteristics, policy can change IDA design. In particular, drop-out risk can be reduced by setting higher match rates, helping participants set up automatic transfers to their IDAs, and increasing the time cap on the months eligible to make matchable deposits.

This paper first describes IDAs in ADD. It then reports on a Probit regression that predicts drop-out with participant characteristics and aspects of IDA design. After checking the model's profiling accuracy, the final section presents a summary and discusses implications for saving and asset-building in general.

2. IDAs in ADD

The American Dream Demonstration ran from 1997 to 2003 at 14 IDA programs across the United States. Program staff used special-purpose administrative software to record account-design features at start-up, participant characteristics at enrollment, and IDA cash flows each month (Johnson, Hinterlong, and Sherraden, 2001). Cash flows are accurate and complete; they come from bank statements and satisfy accounting identities. Other data were also extensively cross-checked.

ADD was open to people with household income under 200 percent of the federal poverty guideline. Half of participants were below 100 percent of poverty, and one-fifth was below 50 percent. Compared to the general low-income population, IDA participants were more disadvantaged in that they were disproportionately female (80 percent), African-American (47 percent), and/or not married (75 percent) (Sherraden *et al.*, 2000). About 44 percent were single mothers, and 50 percent had received welfare. Participants were disproportionately advantaged in that they were more likely to be employed or in school (90 percent), to have a college degree (24 percent), or to own a bank account (66 percent).

IDAs in ADD were kept in passbook accounts in banks or credit unions. These intermediaries sometimes waived their usual fees on low-balance accounts. Deposits into IDAs received no special tax treatment, but the IRS counted matches as gifts.

Match rates varied, but the typical match rate was 2:1. All programs provided matches for the three cornerstone uses of home ownership, post-secondary education (including job training), and microenterprise. Some programs also provided matches for home improvement or retirement savings. Unmatched withdrawals could be made for other purposes.

IDA participants in ADD had to attend financial-education classes. They also received encouragement from program staff (for example, monthly phone calls to remind them to make a deposit). Staff also provided one-on-one financial counseling, especially for participants planning to make a matched withdrawal for home purchase.

The median annual match cap (limit on matchable deposits) was $500, and the median time cap for making matchable deposits was 36 months. Participants made deposits about every other month. Net IDA savings per month was $16.60, or 42 percent of the match cap. A typical participant with a match rate of 2:1 and a time cap of 36 months built about $1,800 IDAs ($16.60/month x 36 months x [1 saved + 2 match] = $1,793). Schreiner *et al.* (2001) give more detail on ADD programs.

About 48 percent of IDA participants in ADD were defined as *drop-outs* with net IDA savings of less than $100. Drop-outs were costly for programs, for the drop-outs themselves, and for non-participants. First, programs spent resources enrolling, training, and tracking participants who eventually dropped out. Second, drop-outs themselves—having not saved despite an unusually supportive and rewarding savings structure—may despair of ever saving. Third, non-participants may have been denied access to IDAs because drop-outs had already filled some of the programs' available slots.

3. Predicting drop-out

If IDA programs knew what factors were related with drop-out risk, then they might be able to do something about it. The Probit regression in this section shows that assets matter more for drop-out than income. Furthermore, several aspects of IDA design are strongly predictive of drop-out risk.

3.1 Probit on drop-out

Participants are assumed to drop out because their benefits exceed their costs. The structural random-utility model of this choice is estimated as a Probit regression (Greene, 1993). The dependent variable is unity (1) for drop-outs and zero for others, so positive coefficients signal greater drop-out risk. The independent variables include a wide range of participant characteristics and aspects of IDA design, essentially all the factors in the available data that might be expected to be linked with drop-out.

To allow for non-linearities, continuous variables such as age, income, and bank-account balances are specified as two-piece splines (Suits, Mason, and Chan, 1978). To avoid discarding cases with some missing values, modified zero-order dummies were used. As long as missing values occur at random, this provides unbiased estimates. All in all, 104 parameters were estimated. To conserve space, coefficients for zero-order dummies are not reported, nor are coefficients for a few minor variables and program fixed effects. Full results are available on request.

The model includes 2,350 participants. The log-likelihood is . 1,231, and the full model differs from an intercept-only model with 99-percent confidence. Overall, fit is good; in 81 percent of all drop-out/non-drop-out pairs, predicted risk is higher for the drop-out. The next section discusses other measures of predictive power.

Tables 1–6 display means for the independent variables, estimated marginal effects in percentage points, and p-values. The marginal effects were computed at sample means with standard errors from the delta method (Greene, 1993). Even though the results appear in six tables, they all come from a single regression.

3.2 Participant demographics

Greater human capital due to greater age (and thus experience) is associated with less drop-out, at least after age 20 (Table 1 and Figure 1). For example, being 50 instead of 30 is—all else constant—linked with 10 percentage points less risk. Given that overall drop-out risk is 48 percent, this is a very strong association.

Compared to never-married participants, married participants are 7.9 percentage points less likely to drop out. Again, this is a strong association. Marriage signals greater social capital and is associated with drop-out for two reasons. First, married people have been "selected" partly on characteristics (such as trustworthiness and economic prospects) observed by the potential spouse but omitted from the data. Hence, marriage *per se* does not cause low drop-out risk but rather signals the presence of other characteristics that do. Second, marriage can directly reduce drop-out, for example if the spouse assists in saving by earning income or providing encouragement.

Women are much less likely (6.8 percentage points) to drop out than men. The microfinance literature argues that women have a greater motivation to save because they care more about children and because they face disadvantages in the labor market and after marital break-up (Vonderlack and Schreiner, 2002; Rutherford, 2000). In short, women save more because they have more "rainy days".

Looking at the rest of Table 1, drop-out is not associated with household composition or location of residence. In terms of race/ethnicity, Asian Americans, "Others", and Hispanics are less likely to drop out than Caucasians, African Americans, and Native Americans. Of course, this reflects not genetics but rather "social capital" in terms of a constellation of characteristics omitted from the regression that social forces cause to be correlated with both race/ethnicity and saving.

Overall, greater assets upon entering ADD—whether human capital or social capital—means less drop-out risk. What does this mean for policy? IDA programs cannot accelerate aging, play match-maker for unmarried participants, or alter gender or race/ethnicity. Demographic characteristics, however, often signal the presence of omitted causes that policy might influence. For example, perhaps young people drop out more because they have not yet learned the importance of saving. If so, IDA programs might target financial education to them. If married participants drop-out less because their spouse helps them persevere, then IDA programs might assign unmarried participants a peer “saving buddy” to supply the missing peer pressure. Finally, if Native Americans and African Americans save less because history teaches that their assets will be stolen and their savings scammed (Oliver and Shapiro, 1995; Massey and Denton, 1994), then IDA programs must put in extra effort to show that IDAs are safe and that matches are for real (Page-Adams, 2000).

3.3 Education, employment, and planned use

Graduates of four-year colleges have more human capital, and in ADD, they are far less likely (about 20 percentage points) to drop-out (Table 2). A degree is both a cause *per se* as well as a signal of omitted causes. College classes likely teach some things that highlight the value of saving. At the same time, having invested in a degree signals personal traits (such as perseverance and future-orientation) that are themselves causes of greater saving. Knowing this, IDA programs might focus financial education on participants without a degree.

Employment is not associated with drop-out risk at the $p = 0.10$ level. The three “working” categories, however, all have less risk and smaller p-values than the three “non-working” categories. If this association is real, then it likely reflects omitted characteristics that cause both employment and low drop-out risk.

About half of IDA participants in ADD planned to save for home purchase, and they are much more likely to drop out than those planning for other matched uses. Two factors probably explain this. First, renters planned for home purchase, but renters have—on average—omitted characteristics that cause low saving (and hence high drop-out). Because the chief barrier to home ownership is saving for a down payment, renters are usually worse "savers" than homeowners are. Second, home purchase is difficult, requiring not only saving for a down payment but also committing to 30 years of mortgage payments. Thus, IDA participants planning for homeownership may be more likely to get discouraged than would, say, participants saving for retirement or post-secondary education where even small savings can be matched and put to good use. Knowing this, IDA programs might target up-front counseling to those who plan for home ownership and steer the least-prepared into other matched uses. Furthermore, programs can make sure that participants know that, even if they cannot save enough for home purchase, they can still make matched withdrawals for other purposes.

3.4 Income and receipt of public assistance

Do the poorest IDA participants—those with very low income or who received welfare—drop out more? Welfare use—whether Aid for Families with Dependent Children, Temporary Assistance for Needy Families, Social Security Disability Insurance, or Food Stamps—is not associated with drop-out.

The regression distinguishes between "recurrent" income (wages, retirement benefits, and welfare) and "intermittent" income (self-employment, child support, gifts, investments, and "other") because the propensity to save varies with the source of the income (Thaler and Shefrin, 1981). Recurrent income (the type least likely to be saved) was not linked with drop-out risk, and intermittent income (the type most likely to be saved) was only weakly linked. In the range from 0 to $2,000, $100 more intermittent income means 0.7 percentage points less drop-out risk. Given that monthly intermittent income averaged $216, this is not a strong association. Specifications that omit splines or lump recurrent and intermittent income together achieve less statistical significance. Controlling for other factors in the regression, income and welfare receipt are not associated with drop-out. Assets matter more than income for drop-out.

What does this mean for IDA programs? First, there is no *a priori* reason to exclude the poorest; some very poor people do save and build assets in IDAs. Second, IDA programs need not concern themselves with trying to inculcate "savings habits", for example, by requiring deposits each month or forbidding unmatched withdrawals. Any "bad habits" encouraged by welfare rules appear to be overwhelmed by the highly rewarding structure of IDAs (Sherraden, Schreiner and Beverly, 2003).

3.5 Participant assets and debts

The presence of assets (and the absence of debts) is linked with less drop-out. Three factors explain this. First, asset ownership signals omitted characteristics that cause both greater general saving and also greater IDA saving. For example, owners of checking accounts or financial investments tend to have greater financial sophistication and thus a fuller appreciation of the benefits of IDAs. Second, asset ownership signals greater ability to "reshuffle" existing savings into IDAs. For example, owners of bank accounts can transfer balances to IDAs. Third, ownership may directly facilitate IDA saving by reducing the transaction costs of making a deposit. For example, making deposits by mail (or automatic transfer) is simpler with a checking account. Likewise, getting to the bank to make a deposit is easier for participants with cars.

IDA participants with a checking account are less likely to drop out (Table 4). Checking accounts not only signal financial sophistication—balancing a checkbook and avoiding bounced checks requires math skills and perseverance—but also greater ability to "reshuffle" existing assets. Checking accounts also reduce transaction costs when making IDA deposits (by mail or automatic transfer). For drop-out, owning a passbook is like being unbanked, suggesting that checkbooks mostly signal financial sophistication. Beyond encouraging participants to open a checking account in parallel with IDAs, programs might teach checkbook management and/or target financial education on those who enroll without a checking account.

Bank-account balances—in contrast to their presence—are weakly related with drop-out risk. The non-intuitive pattern probably reflects data issues, as participants can report the presence of an account more accurately than its balance.

Owners of physical assets—homes, cars, and land or property (but not microenterprises)—have less drop-out risk, as do owners of financial investments. These assets are illiquid, so they are not easy to reshuffle into IDAs. Instead, they reflect greater financial sophistication and other omitted factors that make participants "savers" even without IDAs. The link with cars probably reflects transaction costs; the value of time spent walking or taking a bus to the bank can swamp the value of the deposit itself (Adams, 1995). Car ownership also decreases the cost of attending financial-education classes.

In contrast to assets, the presence of debts is associated with greater drop-out. This makes sense; assets produce income (and reduce expenses, see Sherraden, 1989) and so increase cash available to save, but debts must be repaid and so decrease cash available to be saved. Owners of cars or land who were free-and-clear of their mortgages were less likely to drop-out than those with mortgages (Table 4). Furthermore, participants with credit-card debt were 4.7 percentage points more likely to drop-out (Table 5). The signs on other types of debt are consistent with this interpretation, although the estimated coefficients are not statistically significant.

What does this mean for IDA programs? The point is not to make participants owners—IDAs already try to do that—but rather to find factors correlated with ownership that policy might influence. In the case of assets, IDA programs can seek to increase financial sophistication (by targeting financial education to the least-sophisticated) and to decrease the transaction costs of making a deposit (perhaps by helping participants sign up for automatic transfer or providing them with deposit-by-mail slips). IDA programs might also provide matches for car purchase. In the case of debt, IDA programs might review credit status with all enrollees rather than only those planning for home purchase. They might advise some participants to focus first on repaying their debts; after all, saving is optional, but debt repayment is obligatory.

3.6 Aspects of IDA design

Unlike participant characteristics, IDA design directly influences drop-out. Just as important, policy can influence IDA design. Aspects of IDA design are strongly correlated with drop-out, providing several powerful policy levers.

Matches are central to IDAs. Higher match rates decrease drop-out by increasing its opportunity cost (Schreiner, 2004). Compared with participants in ADD with 1:1 match rates, participants with 2:1 match rates were 8.9 percentage points less likely to drop out, and participants with match rates of more than 2:1 were 15.8 percentage points less likely to drop out (Table 6). Given the overall drop-out rate of 48 percent, these are huge effects. One simple—if costly—way to decrease drop-out from IDAs is to increase match rates.

Higher match caps—that is, higher limits on matchable deposits—should help prevent drop-out for two reasons. First, higher match caps increase the possible match and so increase the opportunity cost of drop-out. Second, participants may interpret the match cap as the amount that wiser minds believe that they "should" save (Choi, Laibson, and Madrian, 2004; Thaler and Sunstein, 2003; Bernheim, 2002). Indeed, IDA programs in ADD explicitly exhorted participants to "max out" their IDAs by saving up to the match cap. Thus, IDA participants may mentally turn the match cap into a savings target (Beverly and Sherraden, 1999). In ADD, however, match caps are not strongly related with drop-out risk.

ADD participants who use automatic transfer to their IDAs are much less likely (16.7 percentage points) to drop out. Like ownership of a checking account, the use of automatic transfer could signal financial sophistication that causes greater saving. Automatic transfer can also directly reduce drop-out by reducing transaction costs, by removing the recurrent need to make a deliberate choice to save, and by helping participants “pay themselves first”. How can IDA programs use this knowledge? At the least, financial-education classes can discuss the advantages of automatic transfer. Instructors might walk participants through the initial paperwork or ask them to check with employers about direct deposit of paychecks. Some IDA programs might even require the use automatic transfer, helping unbanked enrollees set up a bank account into which they make deposits (perhaps direct deposits of paychecks) and from which the IDA receives automatic transfers. This “liquid” account would complement the “illiquid” IDA, perhaps providing the silken handcuffs that can help participants mentally commit to long-term saving while still providing access to funds in an emergency. Finally, classes could also cover basic account management to reduce the risk of overdrafts when using automatic transfer.

Finally, longer time caps (months available to make matchable deposits) are associated with less drop-out risk. This makes sense, as more time with an IDA increases the chances that an “up” spell will make saving easier. Also, participants with distant deadlines who have saved little so far may get less discouraged because they know that they still have time to catch up.

4. Profiling participants at-risk of drop-out

Increasing match rates, using automatic transfer, and lengthening time caps all help prevent drop-out, but at a cost. One way to control costs is to target prevention only to the most at-risk participants. But who are they?

Statistical profiling identifies at-risk participants based on their characteristics. It is triage, focusing effort where it should have the greatest impact. Profiling is used in the social services, for example, to identify hard-to-employ people in welfare-to-work programs (Eberts, 2001) and claimants likely to exhaust unemployment insurance benefits (Black *et al.*, 2004).

Profiling uses Probit regression, but—unlike the analysis in this paper so far—the goal is not to identify relationships between characteristics and drop-out risk but rather to use those relationships to predict drop-out. In ADD, several participant characteristics and aspects of IDA design are strongly associated with drop-out. Does this mean that the Probit regression will accurately identify at-risk participants? Not necessarily; statistically significant coefficients need not imply anything about predictive power (Breiman, 2001; Greene, 1993).

This section uses three tools—a generalized “confusion matrix”, the Kolmogorov-Smirnov statistic, and a “lift chart”—to compare predicted drop-out risk to actual drop-out. These are common tools in the credit-scoring literature.

Figure 2 is a generalized “confusion matrix” that measures accuracy for all possible targeting policies (Hand, 1994). Suppose ADD programs target preventive assistance to a given share of participants with the highest predicted drop-out risk. Figure 2 compares the share of all participants targeted (horizontal axis) with the share of drop-outs and stayers correctly (or mistakenly) targeted (vertical axis). Targeting improves as a curve bends away from the diagonal. (This is an in-sample test; an out-of-sample test would have somewhat lower accuracy.)

If ADD gave preventive assistance to the 30 percent of participants with the highest predicted drop-out risk, then it would successfully target 50 percent of drop-outs and mistakenly target 12 percent of stayers. That is, for each five participants targeted, there would be four drop-outs and one stayer.

The curves in Figure 2 are the cumulative distribution functions of stayers and drop-outs with respect to predicted risk. One measure of predictive accuracy is the Kolmogorov-Smirnov statistic, that is, the maximum vertical distance between the two curves (Hollander and Wolfe, 1998). For the Probit regression, this is 0.44, occurring at the 43rd percentile of predicted risk. According to Mays (2000), profilers are "good" if Kolmogorov-Smirnov exceeds 0.4.

The "lift chart" in Figure 3 depicts the concentration of drop-outs among those targeted versus among all participants. For example, the concentration of drop-outs among the 30 percent of participants with the highest predicted risk was 1.62 times the overall concentration; drop-outs were 78 percent of targeted participants but 48 percent of all participants.

In sum, the three measures of predictive accuracy examined here all suggest that the Probit regression would work well as a profiling tool to focus (costly) preventive assistance on those IDA participants most at-risk of drop-out.

5. Concluding discussion

The only sustainable road out of poverty is saving and asset-building. But while the United States subsidizes almost all major types of assets for the non-poor, it does little to encourage asset-building by the poor. Individual Development Accounts are a new way to include the poor. IDAs provide matches for savings for home purchase, post-secondary education, and microenterprise. IDA programs also provide financial education and encouragement.

Matches and labor-intensive support, however, are costly, especially if an IDA participant drops out. What factors predict drop-out? And what can be done to prevent it? This paper relates drop-out with participant characteristics and aspects of IDA design for IDA participants in the American Dream Demonstration.

The broad lessons are that assets matter more than income and that IDA design is strongly linked with drop-out. Drop-out risk was lower for IDA participants who enrolled with human capital (college degrees or age), financial assets (checking accounts or no debt), physical assets (homes or cars), or social assets (marriage). At the same time, drop-out risk is not linked with income or welfare receipt. Asset ownership is both a direct cause of reduced drop-out and a signal of omitted characteristics that cause reduced drop-out. As a direct cause, existing assets such as cars or checking accounts reduce the transaction costs of making deposits. Furthermore, existing assets can be reshuffled into IDAs. As an indirect cause, existing assets signal the presence of omitted characteristics (such as financial sophistication) that reduce drop-out.

In terms of aspects of IDA design, drop-out risk was lower when participants had higher match rates, when they used automatic transfer, and when they had a longer time available to save. This provides policy with several levers to influence drop-out.

Besides adjusting IDA design, programs might try to reduce the transaction costs of making deposits, perhaps by helping participants sign up for automatic transfer, encouraging them to use direct deposit from their employer, giving them deposit-by-mail slips, and/or helping them open a parallel checking account. IDA programs might also increase financial sophistication by targeting financial education to at-risk participants, including credit counseling for those in debt and for those planning for home purchase. Classes might also focus on checkbook management.

In sum, low saving is not only predictable but also potentially preventable, as it depends partly on factors that IDA programs can influence. While prevention efforts are costly, they can be targeted to the most at-risk participants.

These results for IDAs in ADD suggest that, when it comes to saving and asset-building, the poor are not so different from the non-poor. Like the mostly non-poor participants in Individual Retirement Accounts and 401(k) plans, poor IDA participants respond strongly to changes in match rates (Clark *et al.*, 2000; Clark and Schieber, 1998; General Accounting Office, 1997; Bayer, Bernheim, and Scholz, 1996). Perhaps the poor participate less in Individual Retirement Accounts and 401(k) plans (Joulfaian and Richardson, 2001) not because they are insensitive to incentives but because—being in low tax brackets—they have no incentives.

Automatic transfer holds great promise for IDAs. It takes effort for anyone—poor or non-poor—to choose take cash out of his or her pocket and put it into a savings account rather than spend it on some more immediate need. But deposits taken straight from paychecks (or checking accounts, or tax refunds) exact no such psychological cost. In the case of 401(k) plans, employers must make direct deposits for participants *by law*. Willpower is no longer a recurrent issue. The 6 percent of ADD participants who use automatic transfer are much less likely to drop out. Why don't more IDA participants use automatic transfer? After all, banks and employers usually like to help set up automatic transfer, as it reduces their operating costs (and they believe it increases savings balances). The barrier is probably financial sophistication; IDA participants do not think about the automatic-transfer option, or they fear overdrawing the source account. This is a job for financial education. In the case of direct deposit of paychecks, IDA participants may dislike putting all their pay in an IDA, as they must withdraw most of it—and receive embarrassing inquiries from program staff checking up on unmatched withdrawals—for monthly expenses. Just as saving (in IDAs and in general) would be easier if people could split tax refunds between a check and direct deposits, IDA saving would be easier if participants could split their pay between a check and direct deposits (Beverly, Schneider, and Tufano, 2004). Of course, employers already do this routinely, for participants in 401(k) plans.

Finally, drop-out is an issue only because IDAs are not permanent or universal. This is not the case for asset-building subsidies for the non-poor such as the home-mortgage interest deduction, Individual Retirement Accounts, and 401(k) plans.

The original IDA proposal called 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" Individual Retirement Accounts. Of course, not everyone would use their IDA at all times, but—as the time-cap results here suggest—permanent asset-building incentives would reach more people than time-limited incentives. The poor could save in IDAs at their own pace, and inclusion in asset-building policy would not depend on the time-pattern of saving. Permanent access would also increase accumulated sums. The non-poor tend to wait decades to start to save for retirement (Carroll and Samwick, 1997), but they do not forfeit their access to tax breaks because they did not save frequently or consistently.

As importantly, a universal, permanent IDA policy might make saving and asset-building for the poor a social norm. People would grow up knowing—without much conscious thought—that saving is a "good thing", just as they know now that home ownership is a "good thing". They could plan matched withdrawals for years or decades, buying different assets across the life cycle (Sherraden, 1991). Families at reunions and co-workers at water-coolers would discuss the pros and cons of saving strategies (Bernheim, 2002). Asset-building for the poor might become part of the

“American way of life”, something done and accepted as a “no brainer”. While such long-term social impacts of asset-building policy are nearly impossible to predict or quantify, America’s belief in them has been reinforced over and over, for the non-poor.

References

Adams, Dale W. (1995) “Transaction Costs in Decentralized Rural Financial Markets”, pp. 249–265 in Dina Umali-Deininger and Charles Maguire (eds.) *Agriculture in Liberalizing Economies: Changing Roles for Governments*, Washington, D.C.: World Bank, ISBN 0–8213–3354–2.

Bayer, Patrick J.; Bernheim, B. Douglas; and John Karl Scholz. (1996) “The Effects of Financial Education in the Workplace: Evidence from a Survey of Employers”, National Bureau of Economic Research Working Paper No. 5655, `http://www.nber.org/papers/w5655`.

Bernheim, B. Douglas. (2002) “Taxation and Saving”, pp. 1173–1249 in Alan Auerbach and Martin Feldstein (eds.) *Handbook of Public Economics, Volume 3*, North-Holland, ISBN 0–444–82314–X.

Beverly, Sondra G.; and Michael Sherraden. (1999) “Institutional Determinants of Savings: Implications for Low-income Households and Public Policy”, *Journal of Socio-Economics*, Vol. 28, No. 4, pp. 457–473.

_____; Schneider, Daniel; and Peter Tufano. (2004) “Refunds to Assets: Splitting Refunds and Building Assets”, `http://www.d2dfund.org/downloads/refunds_assets.pdf`.

Black, Dan. A; Smith, Jeffrey A.; Berger, Mark C.; and Brett J. Noel. (2004) “Is the Threat of Reemployment Services More Effective than the Services Themselves? Evidence from Random Assignment in the UI System”, *American Economic Review*, Vol. 93, No. 4, pp. 1313–1327.

Breiman, Leo. (2001) “Statistical Modeling: Two Cultures”, *Statistical Science*, Vol. 16, No. 3, pp. 199–231.

Carroll, Christopher D.; and Andrew A. Samwick. (1997) “The Nature of Precautionary Wealth”, *Journal of Monetary Economics*, Vol. 40, No. 1, pp. 41–71.

Choi, James J.; Laibson, David; and Brigitte C. Madrian. (2004) “Plan Design and 401(k) Savings Outcomes”, National Bureau of Economic Research Working Paper No. 10486, `http://www.nber.org/papers/w10486`.

Clark, Robert L.; Goodfellow, Gordon P.; Schieber, Sylvester J.; and Drew Warwick. (2000) “Making the Most of 401(k) Plans: Who’s Choosing What and Why?”, pp. 95–138 in Olivia S. Mitchell, P. Brett Hammond, and Anna M. Rappaport (eds.)

Forecasting Retirement Needs and Retirement Wealth, Philadelphia, PA: University of Pennsylvania Press, ISBN 0–8122–3529–0.

_____; and Sylvester J. Schieber. (1998) "Factors Affecting Participation Rates and Contribution Levels in 401(k) Plans", pp. 69–97 in Olivia S. Mitchell and Sylvester J. Schieber (eds.) *Living with Defined Contribution Pensions: Remaking Responsibility for Retirement*, Philadelphia, PA: University of Pennsylvania Press, ISBN 0–8122–3439–1.

Eberts, Randall W. (2001) "Targeting Welfare-to-Work Services Using Statistical Tools", *Employment Research*, Vol. 8, No. 4, pp. 1–3.

General Accounting Office. (1997) "401(k) Pension Plans: Loan Provisions Enhance Participation But May Affect Income Security for Some", GAO/HEHS–98–5.

Greene, William H. (1993) *Econometric Analysis: Second Edition*, New York, NY: MacMillan, ISBN 0–02–346391–0.

Hand, David J. (1994) "Assessing Classification Rules", *Journal of Applied Statistics*, Vol. 21, No. 3, pp. 3–16.

Hollander, Myles; and Douglas A. Wolfe. (1998) *Nonparametric Statistical Methods, Second Edition*, New York, NY: John Wiley and Sons, ISBN 0–471–19045–4.

Howard, Christopher. (1997) *The Hidden Welfare State: Tax Expenditures and Social Policy in the United States*, Princeton, NJ: Princeton University Press, ISBN 0–691–02646–7.

Johnson, Elizabeth; Hinterlong, James; and Michael Sherraden. (2001) "Strategies for Creating MIS Technology to Improve Social Work Practice and Research", *Journal of Technology for the Human Services*, Vol. 18, No. 3/4, pp. 5–22.

Joulfaian, D.; and D. Richardson. (2001) "Who Takes Advantage of Tax-Deferred Savings Programs? Evidence from Federal Income-Tax Data", *National Tax Journal*, Vol. 54, No. 3, pp. 669–688.

Massey, Douglas S.; and Nancy A. Denton. (1994) *American Apartheid: Segregation and the Making of the Underclass*, Cambridge, MA: Harvard University Press, ISBN 0–674–0182–14.

Mays, Elizabeth. (2000) *Handbook of Credit Scoring*, Chicago, IL: Glenlake, ISBN 0–8144–0619–X.

Oliver, Melvin L.; and Thomas M. Shapiro. (1995) *Black Wealth/White Wealth: A New Perspective on Racial Inequality*, New York, NY: Routledge, ISBN 0–415–91375–6.

Page-Adams, Deborah. (2002) "Design, Implementation, and Administration of Individual Development Account Programs", Center for Social Development, Washington University in Saint Louis, `http://gwbweb.wustl.edu/csd/Publications/2002/PageAdamsResearchReport2002.pdf`.

Rutherford, Stuart. (2000) *The Poor and Their Money*, Delhi: Oxford University Press, ISBN 0–195–65255–X.

Schreiner, Mark. (2004) "Match Rates, Individual Development Accounts, and Savings by the Poor", Center for Social Development Working Paper No. 04–02, Washington University in Saint Louis, `http://gwbweb.wustl.edu/csd/Publications/2004/WP04-02.pdf`.

_____; Sherraden, Michael; Clancy, Margaret; Johnson, Lissa; Curley, Jami; Grinstein-Weiss, Michal; Zhan, Min; and Sondra Beverly. (2001) *Savings and Asset Accumulation in Individual Development Accounts*, Center for Social Development, Washington University in Saint Louis, `gwbweb.wustl.edu/csd/Publications/2001/ADDreport2001/index.htm`.

Seidman, Laurence S. (2001) "Assets and the Tax Code", pp. 324–356 in Thomas M. Shapiro and Edward N. Wolff (eds.) *Assets and the Poor: The Benefits of Spreading Asset Ownership*, New York: Russell Sage, ISBN 0–87154–949–2.

Sherraden, Michael. (1991) *Assets and the Poor: A New American Welfare Policy*, Armonk, NY: M.E. Sharpe, ISBN 0–87332–618–0.

_____. (1989) "Poverty and Transaction Costs", Washington University in Saint Louis, `sherrad@wustl.edu`.

_____. (1988) "Rethinking Social Welfare: Toward Assets", *Social Policy*, Vol. 18, No. 3, pp. 37–43.

_____; Schreiner, Mark; and Sondra Beverly. (2003) "Income and Saving Performance in Individual Development Accounts", *Economic Development Quarterly*, Vol. 17, No. 1, pp. 95–112.

_____; Johnson, Lissa; Clancy, Margaret; Beverly, Sondra; Schreiner, Mark; Zhan, Min; and Jami Curley. (2000) *Saving Patterns in IDA Programs*, Center for Social Development, Washington University in Saint Louis, `gwbweb.wustl.edu/csd/Publications/2000/ADDreport2000/index.htm`.

Suits, Daniel B.; Mason, Andrew; and Louis Chan. (1978) "Spline Functions Fitted by Standard Regression Methods", *Review of Economics and Statistics*, Vol. 60, No. 1, pp. 132–139.

Thaler, Richard H.; and H.M. Shefrin. (1981) "An Economic Theory of Self-Control", *Journal of Political Economy*, Vol. 89, No. 2, pp. 392–406.

_____; and Cass R. Sunstein. (2003) "Libertarian Paternalism", *American Economic Review*, Vol. 93, No. 2, pp. 175–179.

Vonderlack, Rebecca M.; and Mark Schreiner. (2002) "Women, Microfinance, and Savings: Lessons and Proposals", *Development in Practice*, Vol. 12, No. 5, pp. 602–612.

Woo, Lillian G.; Schweke, F. William; and David E. Buchholz. (2004) "Hidden in Plain Sight: A Look at the $335 Billion Federal Asset-Building Budget", Washington, D.C.: Corporation for Enterprise Development, `http://content.knowledgeplex.org/kp2/cache/kp/24095.pdf`.

Table 1: Participant demographic characteristics

Independent variable	Mean	Prob.(Drop-out) Δ% pts.	p-value
Age			
14 to 20 (spline)	5.9	+7.3	0.01
20 to 70 (spline)	16	–0.5	0.01
Marital status			
Never-married	0.49		
Married	0.23	–7.9	0.05
Divorced or separated	0.28	–0.7	0.83
Widowed	0.03	–3.4	0.70
Gender			
Male	0.20		
Female	0.80	–6.8	0.04
Race/Ethnicity			
Caucasian	0.37		
African American	0.47	+2.3	0.49
Asian American	0.02	–20.3	0.04
Hispanic	0.09	–8.3	0.11
Native American	0.03	+5.0	0.50
Other race/ethnicity	0.03	–14.3	0.06
Household composition			
Adults (18 or older)	1.5	–2.4	0.25
Children (17 or younger)	1.7	+0.8	0.38
Location of residence			
Urban (pop. 2,500 or more)	0.87		
Rural (pop. 2,500 or less)	0.13	–2.4	0.68

Means taken over non-missing observations.

All tables pertain to a single Probit regression (N = 2,350).

Dependent variable is 1 for drop-outs, 0 for stayers.

Table 2: Education, employment, and planned use

Independent variable	Mean	Prob.(Drop-out) Δ% pts.	p-value
Education			
Did not complete high school	0.16		
Completed high school or GED	0.23	–4.6	0.26
Attended college but did not graduate	0.39	–6.3	0.12
Graduated 2-year college	0.04	–4.4	0.55
Graduated college, 2-year/4-year unknown	0.11	–18.3	0.01
Graduated 4-year college	0.07	–21.1	0.01
Employment			
Unemployed	0.05		
Homemaker, retired, or disabled	0.04	–2.2	0.79
Student, not working	0.06	+6.3	0.41
Student, also working	0.03	–14.4	0.11
Employed part-time	0.23	–6.5	0.27
Employed full-time	0.59	–7.0	0.23
Intended use of matched withdrawal			
Home purchase	0.48		
Home repair	0.09	–36.7	0.01
Post-secondary education	0.16	–17.7	0.01
Job training	0.02	–4.7	0.59
Retirement	0.06	–19.1	0.01
Small-business ownership	0.19	–16.0	0.01

Means taken over non-missing observations.

All tables pertain to a single Probit regression (N = 2,350).

Dependent variable is 1 for drop-outs, 0 for stayers.

Table 3: Income and receipt of public assistance

Independent variable	Mean	Prob.(Drop-out) Δ% pts.	p-value
AFDC or TANF before enrollment			
No	0.62		
Yes	0.38	–1.6	0.59
AFDC or TANF at enrollment			
No	0.90		
Yes	0.10	+4.2	0.41
SSI/SSDI at enrollment			
No	0.89		
Yes	0.11	–2.1	0.68
Food stamps at enrollment			
No	0.83		
Yes	0.17	–4.6	0.28
Recurrent income (monthly $)			
0 to $1,500 (spline)	1,000	+0.00003	0.41
$1,500 to $3,000 (spline)	155	–0.00003	0.52
Intermittent income (monthly $)			
0 to $2,000 (spline)	210	–0.00007	0.06
$2,000 to $3,000 (spline)	6	–0.00014	0.51

Means taken over non-missing observations.
All tables pertain to a single Probit regression (N = 2,350).
Dependent variable is 1 for drop-outs, 0 for stayers.

Table 4: Participant Assets

Independent variable	Mean	Prob.(Drop-out) Δ% pts.	p-value
Passbook and checking accounts			
Both passbook and checkbook	0.38		
Checking only	0.26	–4.6	0.23
Passbook only	0.12	+12.8	0.01
Unbanked (no passbook, no checking)	0.23	+8.0	0.06
Passbook savings balance ($)			
0 to $400 (spline)	94	–0.00049	0.01
$400 to $3,000 (spline)	134	+0.00007	0.03
Checking balance ($)			
0 to $1,500 (spline)	198	–0.00012	0.01
$1,500 to $3,000 (spline)	21	+0.00010	0.33
Home ownership			
Renter	0.84		
Owned with mortgage	0.12	–9.5	0.04
Owned free-and-clear	0.04	–3.4	0.62
Car ownership			
None	0.36		
Owned with loan	0.24	–4.0	0.26
Owned free-and-clear	0.40	–11.3	0.01
Land or property ownership			
None	0.98		
Owned with mortgage	0.01	–55.4	0.07
Owned free-and-clear	0.01	–68.0	0.02
Financial investments			
No	0.87		
Yes	0.13	–12.8	0.01
Small-business ownership			
No	0.89		
Yes	0.11	+0.6	0.91

Means taken over non-missing observations.
All tables pertain to a single Probit regression (N = 2,350).
Dependent variable is 1 for drop-outs, 0 for stayers.

Table 5: Participant Debts

Independent variable	Prob.(Drop-out) Mean	Δ% pts.	p-value
Student loans			
No	0.83		
Yes	0.17	–3.4	0.34
Informal loans from family or friends			
No	0.82		
Yes	0.18	+3.7	0.27
Debt as overdue household bills			
No	0.72		
Yes	0.28	+1.2	0.68
Debt as overdue medical bills			
No	0.82		
Yes	0.18	+4.2	0.22
Credit-card debt			
No	0.67		
Yes	0.33	+4.7	0.10

Means taken over non-missing observations.
All tables pertain to a single Probit regression (N = 2,350).
Dependent variable is 1 for drop-outs, 0 for stayers.

Table 6: Drop-Out and IDA Design

	Prob.(Drop-out)		
Independent variable	**Mean**	**Δ% pts.**	**p-value**
Match rate			
1:1	0.28		
2:1	0.48	–8.9	0.07
>2:1	0.24	–15.8	0.03
Match cap			
Limit on matchable deposits ($/month)	41	–0.1	0.26
Use of automatic transfer to IDA			
No	0.94		
Yes	0.06	–16.7	0.01
Months to make matchable deposits			
24 or less	0.25		
25 to 35	0.19	–10.6	0.14
36	0.28	–8.7	0.36
37 or more	0.28	–19.5	0.01

Dependent variable is 1 for drop-outs, 0 for stayers.
All tables pertain to a single Probit regression (N = 2,350).
Means taken over non-missing observations.

Figure 1: Age versus drop-out risk

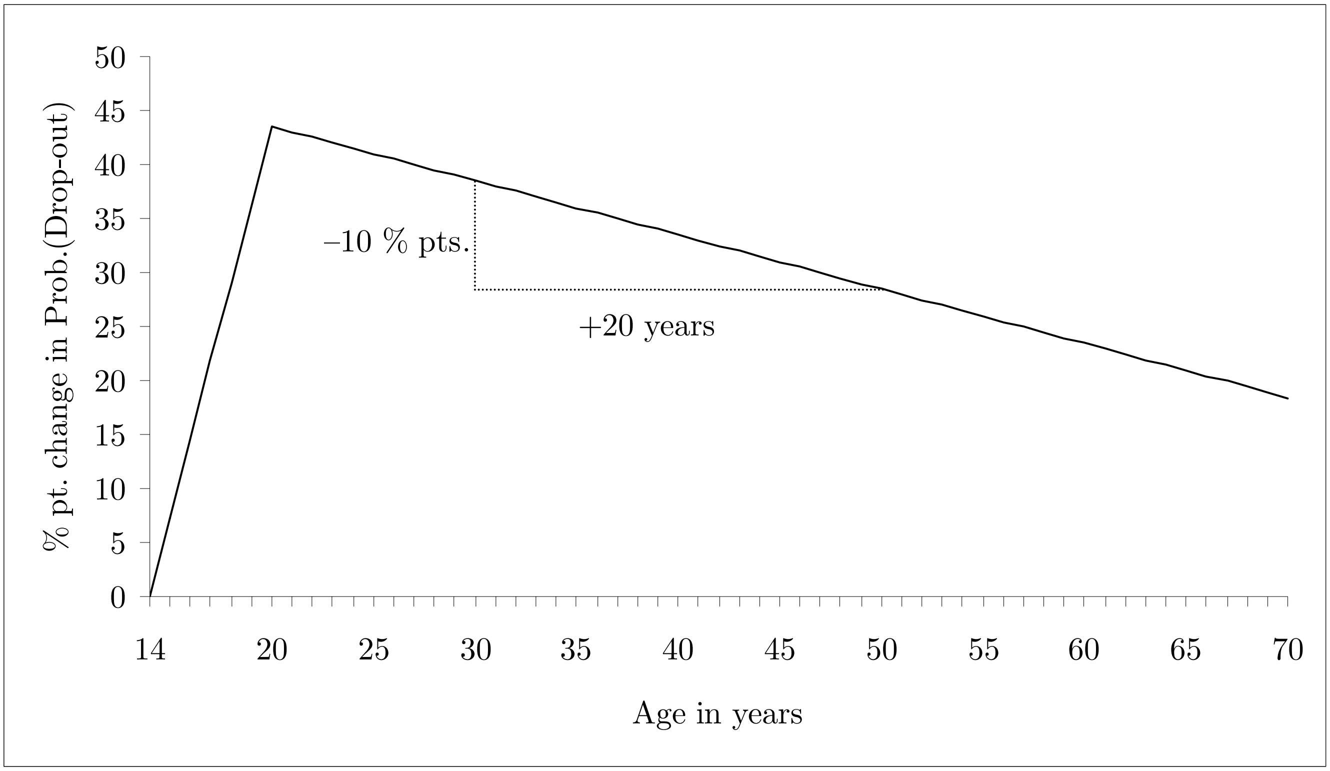

Figure 2: Generalized "confusion matrix"

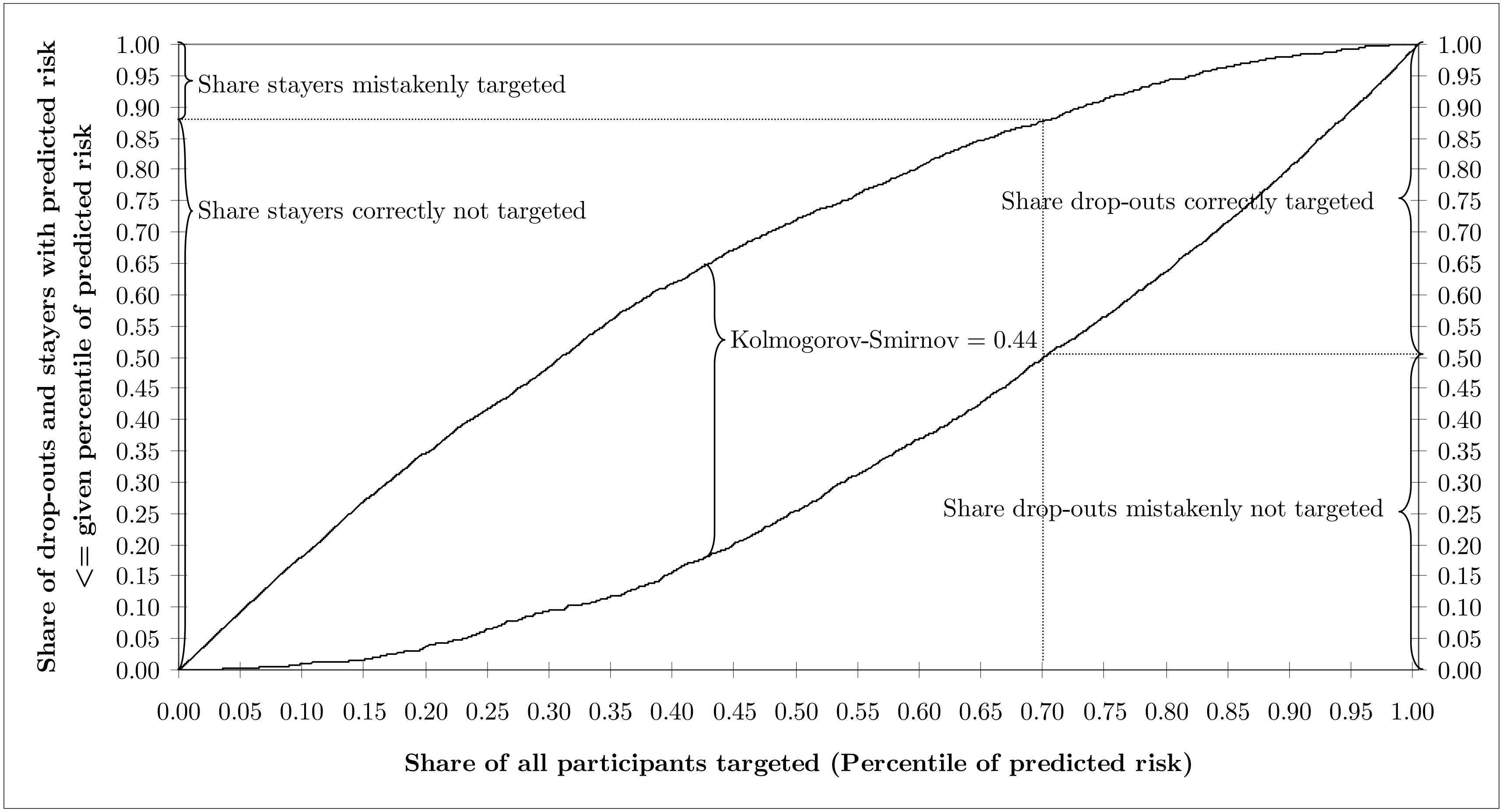

Figure 3: Lift chart