**Savings and Personal Discount Rates in a Matched Savings Program for Low Income Families**

**JEL codes: D91 Intertemporal Consumer Choice; I30 Welfare and Poverty**

*The ability to save for future needs is critical to family well-being and is especially challenging for low-income families with little extra income and limited access to institutional structures like employment- based retirement funds or low cost savings mechanisms. Many nonprofits and governments have created new savings vehicles to fill this void. The ability of families to succeed in these programs may depend on their personal discount rates (time preferences). In this paper, we use survey data from a matched savings program to test three methods of characterizing family time preferences in order to predict their influence on savings levels. We find that a single latent factor describing the level of discount rates (rather than other dimensions of time or amount inconsistency) best describes family differences and is significantly related to the ability of families to save within the program.*

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## I. Introduction

The empirical evidence on savings suggests that while poor families can and do save, lower income families are less likely to save and report lower rates of savings than do higher income families (Bucks, Kennickel, Mach, & Moore, 2009). Meeting the basic needs consumes most of a low-income family's household income. As a result, such families are more likely to save, if at all, only for very short-term goals (especially regular household needs) and for emergencies than are higher income households, who are more likely to be saving for retirement (Bucks et al., 2009; Dunham, 2001).

In the last ten years, advocates and community organizations in the U.S. have created new programs and policies intended to help low income families save and to build durable assets. Michael Sherraden effectively disseminated the model for asset building in his book, *Assets and the Poor* (1991) where he posited that poor families are impoverished not only by having very low incomes, but also by lacking the economic and social benefits of asset ownership. His prescription was the creation of opportunities like matched savings programs that support savings and wealth-building. These programs provide the institutional structure and incentives for families to save towards assets like education, home ownership, and small business development. Since then, federal, state, and local governments and nonprofits have all contributed toward creating Individual Development Account (IDA) matched savings programs. Experience with IDA programs suggests that, while they can provide some families with a vehicle for increasing savings, they are not a panacea for the difficulties in saving or for family disadvantage.

One rationale for matched savings programs is that the regular savings patterns they promote overcome a natural time inconsistency experienced by many individuals. An individual with time inconsistent preferences may want to save, but when the time comes to actually put money away, the desire for current consumption trumps her previous commitment to save. While higher income families have access to the commitment mechanisms offered by employer-based retirement savings, direct deposit, and home mortgages, lower income families often lack similar opportunities. Hence participation in matched savings programs may provide a self-commitment mechanism to help low income individuals save. Understanding how time preferences are related to savings behaviors can help inform the design of matched savings programs or other asset-building initiatives for low income individuals.

In this paper, we use data from a local matched savings program to assess the ability of low income families to save within an IDA program and, more specifically, the influence that individual time preferences have on savings. We approach the problem of measuring the latent construct of time preference with factor analysis and latent class analysis, which may offer a novel way of addressing concerns of confounding factors such as risk attitudes. We find that responses to survey questions designed to elicit discount rates (implicit interest rates for future consumption) are best summarized by a single latent factor and cannot easily be used to otherwise distinguish among subgroups of participants. We find no strong evidence that discount rates were much affected by experience in the matched savings program. Consistent with expectations, participants with higher discount rates saved less, on average, in the first year of the program and were less likely to complete the savings program.

## II. Literature Review

### *A. Time preferences and discount rates*

The basic choice to save implies trading off present for future consumption. Time preference is the desire for immediate over delayed consumption, and the discount rate measures the rate at which individuals are willing to make these intertemporal trade-offs. In spite of the importance of this parameter to the many intertemporal decisions we make – financial investing, education, our use of natural resources - until a decade ago there was little discussion in the economics literature about how discount rates are formed and whether and how they vary across individuals or over time. Frederick, Loewenstein, and O'Donahue (2002) note that early economic explanations of savings motives included a number of psychological factors that were ultimately collapsed into a single discount rate in the discounted utility model proposed by Paul Samuelson in 1937. This discount rate represents an individual's pure rate of time preference in trading off present for future consumption.

Work on time preferences has used a range of empirical methods, which can be broadly divided into techniques that infer discount rates from consumption or expenditure data, and techniques that elicit discount rates directly through laboratory experiments or survey questions. The common issues in both approaches are: 1) Whether discount rates reveal a short run present bias; 2) How much heterogeneity there is across individuals; 3) How sensitive the results are to experimental parameters, and 4) How well estimated or elicited discount rates predict actual behavior. Our study is one of the few to address all four issues in our analysis.

### *B. Present Bias*

Most recently, researchers have sought to test a key assumption of the traditional economic model of discounted utility—namely that people will discount future consumption at a constant rate independent of the time period and the amount of the potential changes in consumption (Frederick, Loewenstein, & O'Donoghue, 2002). Studies have generally rejected the notion of time consistent discount rates in responses to hypothetical questions (Andersen, G. W. Harrison, M. I. Lau, & Rutström, 2008; Anderson et. al, 2004; Anderson and Gugerty, 2009; Benhabib, Bisin, & Schotter, 2010; Benzion, Amnon Rapoport, & Yagil, 1989; Glenn W. Harrison, Morten I. Lau, & Williams, 2002; Loewenstein & Prelec, 1992; Praag & Booij, 2003; Thaler, 1981) or actual behavior (Gouskova, Chiteji, & Stafford, 2010; Lawrance, 1991; Shapiro, 2005; Warner & Pleeter, 2001; Wong, 2008). As alternatives, researchers have proposed models of hyperbolic or quasi-hyperbolic discount rates that assume lower discount rates for longer time periods, for periods further in the future (present bias), and for larger amounts of money or changes in consumption (magnitude bias) (Chabris, Laibson, & Schuldt, 2008). There is, however, some evidence that discount rates are not continuously hyperbolic, but rather are very sensitive to “front-end delays,” but somewhat independent of the time period after that. Initial work in Canada and the U.S. suggests premiums for consumption within a month of the decision time, after which discount rates flatten out (Eckel, Johnson, and Montmarquette, 2004; Coller, Harrison, and Rutstrom, 2003). Work in lower income countries, however, suggests that the relevant time threshold may be context dependent (Klemick and Yesuf, 2008; Anderson et. al, 2002).

### *C. Discount rate heterogeneity*

There is a growing empirical literature investigating the heterogeneity of discount rates across individuals or households. This literature both seeks to use heterogeneity to explain puzzles such as the considerable wealth inequalities across households with similar lifetime earnings (Hendriks, 2007; Krusell and Smith. 1998), or to uncover the socio-economic or demographic drivers of the variability. In their review of the historical writings on time preference, Becker and Mulligan (1997, 731) conclude that “patience seems to be associated with income, development, and education.” Lawrence (1991) found evidence of higher discount rates for low income individuals from estimating Euler consumption equations for a U.S. sample. Her results can be alternatively interpreted as impatience leading to poverty if individuals choose jobs with low and flat pay scales, or poverty breeding impatience from living at or near subsistence. In developing countries with fewer educational opportunities, the latter interpretation may apply more generally (Pender, 1996; Klemick and Yesuf, 2008). Holden et. al (1998), and Nielson (2001) also find a negative relationship between discount rates and income or wealth, including animal wealth (Klemick and Yusef, 2008). Income flows may also affect time preference.Adams, Einav and Levin (2007) show that, if not considered, real liquidity constraints may inflate elicited discount rates. If respondents, in reality, face de facto infinite interest rates for borrowing and smoothing consumption, it may shorten their time horizon and bias upward their elicited discount rates. Even with quite varied estimation approaches, the negative relationship between education levels and discount rates has been robust (Alan and Browning, 2010; Cagetti, 2003; Cadena and Keys, 2010). Causality, again, remains unclear: whether patient individuals self-select into educational opportunities, or whether education tempers discount rates – a question we explore in our study.

The literature on how discount rates vary with other individual characteristics and demographics is less clear cut. The findings have been inconsistent across studies for age and gender differences (Anderson and Gugerty, 2009; Ashraf, Karlan, & Yin, 2006; Anderson and Nevitte, 2006; Benzion et al., 1989; Glenn W. Harrison et al., 2002; Lawrance, 1991). Tanaka et al. (2001) found age was negatively related to discount rates, while in other developing and transition country studies age was insignificant (Pender, 1996; Nielson, 2001; Bauer, Chytilova and Morduch, 2008). A large study in the Netherlands found that women have higher discount rates than men (van Praag and Booij, 2003), contrary to findings by Coller and Williams (1999) that women are more patient. Anderson and Gugerty (2009) found that commonly held beliefs about gender and age influences did not hold once having children and rural versus urban residence were controlled for in samples from Russia and Vietnam. In a large sample of Canadians, results suggest a parenting effect: although men save less in general, having children elicits the same incremental change in savings behavior for women and men (Anderson and Nevitte, 2006).

*D. Experimental parameters*

All methods of measuring latent variables require trade-offs, beginning with understanding whether what is being measured is confounded with other latent variables such as risk attitudes, impulsivity, or values of thrift. Despite the ongoing debates over present bias and heterogeneity, econometric techniques using survey data often require assuming a functional form and the use of average values of discount rate parameters (Barsky, et. al, 1997). Likewise, experimental methods using direct questions and tasks to elicit discount rates are subject to criticisms over how sensitive respondents are to changes in experimental methods. The main issues in the literature concern whether or not “front-end delays” are used, whether actual payments are made to participants, censored responses in laboratory experiments, and whether risk aversion is controlled for.

Results suggest that using “front-end delays” (that is, having all possible options for payment time in the future), having real rather than hypothetical payments, providing market or relevant field interest rates for respondents in laboratory settings, and controlling for risk all decrease elicited discount rates (Eckel, Johnson and Montmarquette, 2004; Coller, Harrison and Rutstrom, 2003; Coller and Williams, 1999). These biases are important when estimating cardinal measures of discount rates, but because they appear systematically, are less likely to compromise comparisons of rates across individuals.

*E. Predicting behaviors*

A few studies have directly estimated the influence of future orientation or discount rates on behaviors. Higher or more time inconsistent discount rates are associated with running out of food stamps (Shapiro, 2005), studying less for exams (Wong, 2008), illegal drug use, alcoholism, smoking, obesity, risky behaviors, and gambling addiction (Chabris et al., 2008a; Chabirs et al., 2008b; Kirby & Petry, 2004; Scharff, 2009).

The empirical links to savings or financial behaviors are less well documented. Closest to our study, Eckel, Johnson and Montmarquette (2004) find that short term discount rate elicitation can predict long term savings behavior among a relatively low-income population. Higher or more time inconsistent discount rates are associated with lower credit scores and higher loan default rates (Meier &

Sprenger, 2007). Also, those with lower discount rates were more likely to choose a restricted bank account that would not allow early withdraws of savings (Ashraf et al., 2006). This latter finding is consistent with the literature suggesting that "sophisticated" consumers may be aware of self control issues and choose devices to precommit themselves and counteract time inconsistent preferences (Ashraf et al., 2006; Scharff, 2009; Thaler & Shefrin, 1981; Wong, 2008 O'Donahue and Rabin, 1999) "*Naives*," by contrast, are unaware of their self-control problems or believe that they will be able to overcome their self-control problems in the future. These people would thus be less likely to seek out a program designed to commit them to future savings.

A sophisticated" but time inconsistent individual who desires to save must construct or find a mechanism to constrain herself from consuming instead of saving. Hence many researchers have argued that time inconsistency lies behind the prevalence of programs that commit individuals to future savings paths (Gugerty, 2001; Laibson, 1997; O'Donahue and Rabin 1999) such as store lay-away programs, Christmas clubs, employer-based retirement savings, and tax withholding beyond expected taxes. For example, the Save More Tomorrow program allowed employees to commit themselves to increase their savings rate each time they received a raise and participants had much higher savings rates than their non-program counterparts (Thaler and Benartzi, 2004).

On the whole, the empirical discount rate literature supports the idea that elicited discount rates are a reasonable measure of time preferences for individuals, that those preferences vary significantly across individuals, and that discount rates are predictive of certain behaviors. But to date, the asset building literature in the U.S. has not focused on how variation in time preference among individuals might affect the likelihood of joining a matched savings program, or whether participation in such a program affects an individual's discount rate. In this analysis we examine the factors associated with variation in measured discount rates and then investigate how that variation is in turn predictive of the ability to save within a community-based asset-building program designed to precommit families to saving for asset goals.

## III. Asset building and savings for low income families

Both of the classic economic savings theories, the life cycle and permanent income hypothesis**,** predict that rational individuals with stable well-defined preferences will borrow against future income if they expect higher future income or lower future consumption. According to the life cycle hypothesis**,** this borrowing will predictably occur during an individual's earlier years along with dissaving in later years (Ando and Modigliani, 1963). In the permanent income model, individuals save transitory income, the difference between estimates of their permanent income and actual income (Friedman, 1957).

After reviewing empirical papers on savings behavior, however, Knowles and Postlewaite [2003, p. 4] conclude that "there is non-trivial savings behavior heterogeneity among individuals that cannot be accounted for by differences in family or income circumstances...the evidence to date seems consistent with differing discount rates and with variation in some logically distinct “attitude toward saving”, as well as differences in ability to plan or carry out a plan.” Beverly et al (2008) build a general model of savings in which institutional constructs, economic resources, social networks, financial literacy, and psychological, variables are hypothesized as critical to the ability to build assets. Within the psychological variables that affect one’s willingness to save, they include future orientation (discount rates), motives for saving, and perceived ability to successfully save.

IDA programs have incorporated many of the commitment mechanisms identified by the literature on time inconsistency and the above savings model that help individuals to overcome self-control problems. Most programs offer:

- Pre-commitment by asking families to save a minimum amount per month
- Mechanisms to prevent casual withdrawals (a “locked” savings account) and
- Easy access to financial institutions to remove barriers to safe savings vehicles.

Significantly, most IDA programs also offer a crucial incentive for savings in the form of matching funds at a one-to-one or higher ratio. In addition, many programs provide financial training on strategies for generating savings (e.g., family budgeting) as well as case management to help families navigate financial institutions, plan family finances, and trouble-shoot credit problems. Most programs also provide additional training specific to the purchase of the targeted asset such as for home ownership or small business development.

Within IDA programs, many low income families have been able to save and to acquire new assets, though some studies suggest that the programs may have larger effects on the composition of assets than on the levels (Mills et al 2008a and 2008b; Nam, Ratckuffe, & McKernan, 2008). Most studies find that savings in IDA programs are greater for those with more education and greater financial literacy (Fry, Mihajilo, Russell, & Brooks, 2008; Grinstein-Weiss, Yeo, Despard, Casalotti, & Zhan, 2010; Schreiner & Sherraden, 2006; Zhan & Grinstein-Weiss, 2007). The effects of gender, race, income, and prior savings on savings rates are less consistent.

Both the take up of IDA programs and savings within the program are likely to be affected by an individual’s discount rate, an issue which has not yet received attention in the IDA literature. In this paper we add to the existing literature on IDAs by examining the relationship between stated discount rates and savings behavior among participants in a matched saving program run by the United Way in King County (Seattle metropolitan area), Washington. We have data only on those who entered the program so we are unable to examine the relationship between discount rates and participation, but we can observe whether those with higher stated discount rates save less or quit the program, and whether the activities associated with the program appear to shift individual discount rates.

## IV. Savings program and Sample

### *A. Program background*

In 2001, the United Way of King County brought together 13 community based organizations to collaborate on a matched savings program to serve low-income families in King County, Washington, which includes Seattle (DeMarco, Mills, and Ciurea, 2008).[1] As a group, the organizations serve a diverse population of families including many immigrant groups, and offer a wide array of services and programs including in home ownership, micro-enterprise, job training, and educational counseling. The collaborative developed a uniform program that initially matched family savings 3 to 1 up to a maximum of $8000 combined family and IDA funds to be used towards home purchase, small business expenses, or educational acquisition. Later, the match rate was lowered to 2 to 1. Program funding came from the federal Assets for Independence Act, the state (funding from Temporary Assistance for Needy Families and state general funds), and private foundations and donors.

Individuals were eligible for the program if their income fell below 200 percent of the federal poverty level, they had at least one household member with regular earned income, had less than $10,000 in assets (excluding a first car and home), and had a social security or taxpayer identification number. [2]

The program combined many of the standard features of IDA programs designed to increase savings: case management, general and asset-specific financial training, access to a secure bank account, strict limits on the ability to withdraw funds, and a required monthly deposit amount (in this case $50). To obtain matching funds, clients were required to complete their savings and purchase their asset within 5 years of being accepted to the program.[3]

In the spring of 2002, the organizations began offering the matched savings program and most clients were recruited from the existing organizational client bases, though some applied because of marketing by the United Way. By January 2009 when our data ends, the program had accepted about 800 people-- more than 760 had opened savings accounts, and about 300 had already purchased their asset.

[1] The State of Washington was and remains a supportive environment for asset-building: In 2002, it was ranked 7 among states based on asset outcomes in the CREF Assets and Opportunity Score Card, though had fallen to 19th in the 2009 rankings. http://scorecard.cfed.org/main.php?page=resources

[2] Households with incomes above 200% of the poverty level were still eligible if someone in the household was eligible for the federal Earned Income Tax Credit or for Temporary Assistance for Needy Families.

[3] Most participants save for homeownership, but those who save for education or small business ownership can withdraw savings and matching funds for authorized purchases and continue to save.

## B. *Research Sample*

The research in this paper is based on the IDA program clients who consented to be part of the research and who had opened a savings account—a sample of 603 clients.[4]

Table 1 shows descriptive statistics for our sample. About a quarter of the sample is male, 38 percent white, 40 percent black, and 11 percent Asian or Pacific Islander. English is a primary language for about two thirds of the sample. Participants range in age from 21 to 75 with an average age of 41. The group is highly educated compared to many low income samples: only 9 percent have less than a high school education and 70 percent have at least some college. About a third of respondents are married and three quarters have children at home.

At the start of the program, households averaged a little less than $3000 in assets and $8000 in liabilities, and average household income was about $18,000 per year. The program participants are only rarely unbanked (have no bank account); almost 90 percent have a checking account and three quarters have a non-IDA savings account. In addition, 57 percent have at least one credit card in the household.

The second panel of Table 1 shows descriptive statistics for savings and program outcomes. Participants saved an average of $128 per month in their first year of the program and $132 per month over their full time in the program. They made a deposit in about three quarters of the months over the first year and similarly over their full time in the program. Eighteen percent of participants completed the program in the first year and 34 percent had completed by 2 years. Almost 40 percent had completed by the end of our data collection. About 10 percent dropped out in the first year, 20 percent within 2 years, and 28 by the end of data collection.

The bottom panel of Table 1 describes our measures of discount rates which we discuss below.

# V. . Methodology

This study aims to understand the patterns in discount rates across individuals and over time, how those are explained by individual characteristics, and how the discount rates are related to later savings outcomes. To address these research questions, we created measures of discount rates for our sample, estimated models explaining the variation in discount rates, and then used the discount rate measures as predictors in models explaining variation in savings outcomes.

[4] A total of 670 of the 747 program participants consented to be part of the research. Sixty-seven of those had not opened a savings account (65) or had never made a deposit (2) and we dropped these people as they had no significant contact with the program.

In the initial program in-take survey and in follow up surveys, clients were asked to pick the amount of money they would be willing to pay back after 3 different loan periods (3 months, 6 months, and 1 year and for 3 loan amounts ($40, $200, and $1000). [Appendix A shows the survey questions.] These 9 responses serve as the basis for our discount rate measures. Our questions and method follow the general form of earlier work on discount rates (Thaler 1981; Benzion, Rapoport and Yagil 1989; Anderson *et al*. 2004). However, in response to requests from program staff to simplify the task, clients were given a set of 7 responses for each of the 9 time and loan combinations rather than asked for an open ended response.

We infer discount rates from the responses using the simple discrete present value equation:

$$DR = (P/L)^{1/t} - 1, \qquad (1)$$

where DR is the discount rate (implicit interest rate), P represents the dollar amount to be paid back, L is the loan amount, and t is the time until the loan is due.

**Figure 1** shows the mean discount rate responses to the 9 loan questions. The responses indicate that average elicited discount rates were higher the more proximate the time period, consistent with short run rates exceeding long run rates. Also consistent with previous results, for each loan period, discount rates were higher for smaller amounts of money.

Discount rates cannot be directly observed and any methodology to elicit them has some drawbacks. Three challenges especially salient to stated preference surveys of this type are “hypothetical bias,” question complexity, and validity. Hypothetical bias arises if the answers that individuals give do not accurately reflect actions they would take if real money were involved (Schwarz, 1999; List, 2001, Carson et al. 2000; Binswanger, 1980). How well the stated preferences predict real choices or behaviors is an empirical question which we are testing in this paper

Answering hypothetical questions can be cognitively challenging and respondents may either have difficulty formulating a valid answer, or they may get easily fatigued and give up. Studies offering open-ended responses must often make arbitrary decisions on cutoffs for discount rates that end up unrealistically low or high (Coller, Harrison and Rutstrom, 2003; Coller and Williams, 1999; Holcomb and Nelson, 1992; Thaler, 1981) Our choice to use an instrument with categorical choices was in response to program staff who anticipated that respondents would have difficulty giving meaningful responses otherwise, particularly given the circumstances in which the survey was administered (through multiple community based organizations serving many non-native English speakers). This is not an uncommon strategy, especially for populations or circumstances where simplicity is crucial (Barsky et. al. 1998).

Though we avoid some biases, we risk introducing others that arise with discrete choice answers if we are truncating the possible range of responses.

Finally, there is the challenge of disentangling discount rates from risk aversion, impulsivity, and other latent variables, which has been managed in other studies using risk-controlled time preference questions, joint elicitation of risk and time preference, and other techniques (Laury et. al, 2010; Anderson et. al. 2008; McLeish and Oxoby, 2007). A more empirically driven alternative, however, is to abstain from imposing any ex-ante categories on the attitudinal variables, and use the statistical patterns in the data that capture some underlying relationships. The resulting factors (that summarize these underlying relationships) likely represent some combination of what is usually classified as a time or risk preference, and perhaps importantly, distills some latent dimension that is important across all observations for responding to the choice questions. We used three alternative methods to characterize variations in discount rates for individuals: factor analysis, latent class analysis, and a set of indices derived from previous research. We use these to identify latent dimensions of the responses to the 9 indicators in order to more concisely describe what we will continue to refer to as discount rates (understanding that it is a measure derived from the multiple discount rate questions responses) for individuals and to subsequently predict savings behavior. The first two methods are more inductive and empirically driven; the last is based on deductive theories and previous studies of time preferences.

The first method, exploratory factor analysis (EFA), identifies possible latent factors common to a set of multiple survey items, in this case distilling down the responses to the 9 hypothetical loan repayment questions. This technique estimates one or more continuous factors that capture correlations in the multiple survey items and "loading factors" that describe how each of the survey items is related to each factor.[5] That allows us to potentially identify multiple components of discount rate functions such as present bias and magnitude bias and their strength within our sample. Factor scores give the estimated value of each latent factor for individual respondents and can be used as explanatory variables in later analyses of savings outcomes. We used a maximum likeliho od method to estimate factors and Anderson-Rubin factor scores (Fabrigar et al 1999).[6]

Latent Class analysis (LCA) identifies subgroups ("classes") that categorize individuals by their pattern of responses to a set of survey items (Reinecke 2010). We used LCA to group respondents into subgroups based on their 9 discount rate question responses.[7] For each respondent, the model estimates probabilities that they belong to each class, as well as an indentified most

[5] In contrast to principal components analysis, factor analysis is designed to assess the relationships between survey items (Fabrigar et al 1999, p. 275).

[6] An interative principal factor method found nearly identical results and the rotation method did not affect the results given we found only one factor.

[7] Latent Class Analysis can accommodate the categorical responses in our data, unlike the more common cluster analysis. We use LatentGold to estimate the model.

probable class. We use the class probabilities as explanatory variables to capture the effects of discount rates on savings outcomes.

As an alternative to the factor analysis and latent class analysis, we also created three summary measures of the discount rate responses: a discount rate "intercept" (the discount rate from the first question about a $40 loan for 3 months), a time "slope" that was the difference between the rate for the $40 loan for 3 months and the same loan for one year, and an amount slope that was the difference between the discount rate response for a $40 loan and a $1000 loan each for one month. Together, these three indicators capture many of the visible patterns in discount rate responses, as we show below.

We use Tobit analysis of the responses to the discount rate questions to explore how they vary by amount of loan, loan period, time in the program and individual and family characteristics. These models stack the discount rates associated with the responses to the 9 loan questions for individuals and allow us to test for magnitude bias (lower discount rates for greater loan amounts), present bias (lower discount rates for longer loan periods), and changing discount rates attributable to program activities (lower discount rates over time in the program). The Tobit model accounts for the responses of 0 for discount rates and we use clustered standard errors to model the correlations in responses by one individual. These models allow us to assess the determinants of discount rates over time, as the empirical results on age and education suggest that discount rates may be mutable. Although we don't have direct information on the amount of financial training individuals receive as part of the IDA program, the time in the program serves as a proxy for the influence of that training as well as of interactions with case managers, or habit building encouraged by the savings program.

To explore the effects of discount rates on the ability of families to save within the IDA program, we use OLS regressions of measures of average monthly deposits into the IDA saving accounts and the proportion of months in which they made a deposit. We also examine the effects of discount rates on the chances a family completed the program or dropped out prior to completion. Completing the program meant that they saved the maximum possible ($2000) or purchased a house with a smaller amount of money.[8] About 40 percent of the sample had completed and 30 percent had dropped by the time of our data collection. We expect that program participants with lower discount rates would be able to save more each month and, as a result would be more likely to complete the program and less likely to drop out.[9]

[8] Those saving for a small business or education could withdraw money and the matching funds, but continue to save for future investment up to the $2000 limit. We considered them to have completed when they reached the limit.
[9] There is some evidence that lower discount rates (less time inconsistent preferences) might allow individuals to complete education programs they start (Cadena and Keys 2010) and similarly lead to completing the IDA program.

We provide additional details on the multivariate models of discount rates and of savings outcomes below.

Our sample is made up of participants in a structured savings program which may affect the results in two ways. First, discount rates for our sample may be lower and less variable than those for a typical group of low income families. Most participants had already applied for and received some type of service from a community-based organization and all volunteered for the matched savings program. Thus, our sample may include families with better information and more motivation to save than would be representative of the population and this may be related to their discount rates. Second, the program is structured to encourage, facilitate, and force savings by contact with the case manager, a minimum monthly required savings amount of $50, the matching incentive, and the locked savings account requiring program permission for withdrawals and this may limit variation in savings levels for participants. The selected types of participants and the program structure may limit both the variation in discount rates and their impact on savings outcomes. But as we show below, there is still considerable variation in discount rate responses and it is related to savings outcomes.

## VI. **Results**

### *A. Factor analysis of Initial Discount Rates*

We use factor analysis to describe patterns in discount rate questions across participants. For our first analysis, we use responses to the discount rate questions collected prior to participation in the matched savings program.

**Table 2** shows the results of maximum likelihood estimation of the factor analysis for the 535 people who answered all 9 discount rate questions.

The factor analysis finds that cross sectional variation in discount rates is captured by a single latent factor which explains over 70 percent of the variation in the 9 survey questions. Responses on all 9 loan questions are highly correlated with this latent factor (.66 to .96) with the highest factor loadings for the $200 loan questions and for the longer loan periods (6 month and 1 year).

In short, the factor analysis suggests that the loan discount rate questions are highly correlated and are best described by a single continuous factor reflecting the levels of the discount rate responses. There is no evidence here of strong components of present or magnitude bias in the description of cross respondent patterns as these would show as separate factors.

For each respondent, we save the single factor score which serves as a continuous measure of discount rates and ranges between about -1 and 3

These scores serve as explanatory variables in our models explaining variation in savings levels.[10]

*B. Latent Class Analysis of Discount Rates*

We used Latent Class Analysis (LCA) to identify subgroups of respondents based on their responses to the discount rate questions on the pre-program survey. **Table 3** shows summary statistics for models identifying between 1 and 12 clusters of respondents. Researchers typically choose the number of clusters based on additional clusters no longer providing additional statistical explanatory power (p>.05) or on the lowest Bayesian Information Criterion (BIC).

LCA typically distills multiple indicators down to a smaller number of subgroups of respondents and, unlike other types of cluster analysis is appropriate for categorical indicators. However, for the 9 discount rate questions, the BIC continued to drop through 10 clusters and indicated significance beyond 20 clusters. To keep the number of clusters manageable, we chose to use 4 clusters because each contained more than 10 percent of observations and they were clearly distinguishable.

**Figure 2** shows average discount rates for each loan amount and time period combination for the four clusters. The first cluster contains the 30 percent of the cases where respondents answered that they were willing to pay back only the loan amount for all 9 questions (the lowest line on the figure). [**Appendix B** has the frequencies for responses to each discount rate question by cluster.]

The second and third clusters contain 28 and 23 percent of respondents, respectively. In both clusters, individuals start with moderate discount rates for each loan amount and discount rates fall with longer time periods and larger amounts, consistent with the empirical findings of present bias and magnitude effects in other studies. Discount rates for the third cluster fall more from the initial question for a $40 loan for 3 months than do those for the second cluster. The fourth cluster includes about 20 percent of cases, starts with the highest discount rates (well over 100 percent) and has the greatest decreases with loan periods and amounts.

Each respondent has a predicted probability of being in each cluster and we use these as 4 explanatory factors in our savings models.

Figure 3 shows the relationship between average monthly savings, the discount factor from the factor analysis, and the classes from the Latent class analysis. There is no clear pattern in average savings over the range of the discount rate factor (X axis) before controlling for other influences. However, the results of the latent class analysis and the factor analysis track closely as the classes (colors) are tightly clustered along the X axis. This suggests that both methods are

[10] We also estimated factor scores for surveys after the initial survey and similarly found that each set was best described by a single factor.

capturing the overall level of discount rates, rather than primarily present bias, magnitude bias, or some other aspect of the choice.

### *C. Summary measures of Discount rates*

Our final set of proxies for future orientation are the discount rate "intercept" ($40, 3 month loan discount rate), loan period slope (3 month discount rate minus 6 month rate for $40 loan) , and loan amount slope ($40 minus $1000 discount rate for 3 months). As shown above in **Figure 1**, average discount rates start high and fall with both loan period and amount. The latent class analysis (**Figure 2)** shows, however, that these three measures differ significantly for subgroups of observations. These three measures correspond both to the patterns in the latent class analysis, as well as to previous studies showing significant present bias and magnitude bias (rather than consistent discount rates over time and amounts).

For each respondent we calculated the three the measures (discount rate intercept, loan period slope, and time slope) and used them as explanatory measures in the savings models.

### *D. Demographic and time effects on Discount rates*

To assess the associations of discount rates with individual factors and time in the program, we used the discount rate responses as the outcomes in a multivariate analysis. We use a Tobit analysis with a lower limit of 0 for the discount rate because, as the latent class analysis revealed, about 30 percent of respondents reported being willing to pay only the loan amount back (a discount rate of 0).

We first use a model limited to the pre-program discount rate responses and including the loan period, loan amount, an interaction between loan period and loan amount, demographics (*Demog)*, pre-program family finances (*Fin)*, and a set of indicators for the community based agencies where clients accessed program services (*Agency)*.

$$DR = \beta_0 + \beta_p Period + \beta_a Amount + \beta_{pa} Period * Amount + + Fin\beta_f \, Demog\,\beta_d + Agency\beta_f + \delta_i + \varepsilon \quad for \quad DR^* > 0$$

$$DR = 0 \quad for \quad DRscore^* \leq 0$$

DR* is a latent variable that we only observe for those reporting positive scores on the survey.

Given the empirical literature, we expect discount rates to be lower for longer loan periods ($\beta_p$ <0) and larger loan amounts ($\beta_a$<0). We also allow for an interaction of the loan period and loan amount ($\beta_{pa}$).

The literature suggests that discount rates will vary with age, gender, and income so we include regressors for these characteristics. We control for the agency at which an individual applied for the program because surveys were usually administered by one case manager at each agency who may have influenced participant responses.

We know whether individuals have credit cards, presumably indicating the absence of a liquidity constraint. If discount rates are associated with liquidity constraints, then models looking at the relationship of individual characteristics to discount rate levels will be misspecified if variations in credit access are omitted but correlated with discount rate variation. Similarly, we do not have a measure of risk aversion for respondents, which means that discount rates may be overstated (Andersen et. al., 2008). Since we are looking for variations within our sample and their association with savings, however, this is less of an issue.

The responses for each of the 9 discount rate questions were stacked for respondents so each person had up to 9 observations. Because individual variation in the responses may not be not accounted for with model covariates, the model is estimated with robust standard errors clustered for an individual ($\delta_i$).

In addition, the finding that education is the most robust predictor of discount rates suggests that though some level of time preference may be innate, discount rates can change in response to external factors (Alan and Browning, 2010; Anderson and Nevitte, 2006; Cagetti, 2003). Accordingly, we explore whether responses change over time in the program because of financial training, contact with case managers, or successful experience with saving – something that the cross-sectional studies have not allowed for. To assess this, we also estimate the model with the discount rate responses for both the initial survey and any follow up surveys. For this analysis, each participant has up to 27 separate observations (9 questions x 3 surveys).

$$DR = \beta_0 + \beta_t Time + \beta_p Period + \beta_a Amount + \beta_{pa} Period * Amount + \beta_{ta} Time * Period + Demog\beta_d + Fin\beta_f$$

$$+ Agency\beta_f + \delta_i + \varepsilon \quad for \quad DR^* > 0$$

$$DR = 0 \quad for \quad DR^* \leq 0$$

This model adds a variable for the number of months since the respondent was accepted into the IDA program (*Time).* We expect that discount rate responses will be lower over time in the program ($\beta_t$<0) and that effect could differ for different loan amounts so we include an interaction of time in the program and loan amount. [Similar models with interactions of program time and loan period were not able to converge.]

**Table 4** shows the results of the Tobit analysis of discount rate responses from the initial survey (Model 1) and all surveys combined (Model 2).[11]

For both the initial survey and all surveys, discount rates are lower for longer loan periods and larger loan amounts, consistent with previous research. Discount rates are lower by about 3 percentage points for each month in the loan period and by about 2 percentage points for each $100 more in the loan amount, though the positive coefficient on the interaction between loan amount and period means the predicted drops are somewhat smaller for larger amounts and longer loan periods.

The amount of time in the program also attenuates the negative effect of loan amount, but doesn't have a direct effect on discount rates (Model 2 all surveys). This is contrary to the idea that financial education and experience with savings within the program would lead to a greater future orientation.

The effects of family demographics and finances are very similar for initial and follow up surveys. Discount rates are lower for respondents who are black, non-native English speakers, older, and have more than a high school education. Contrary to expectations, families with children have higher average discount rates as do those with higher household incomes and those who have a non-IDA savings account (all surveys only). The discount rates also differ significantly across the local agencies (coefficients not shown) which could reflect unobserved differences in the client populations or differences in guidance given during the survey by case managers. Differences in discount rate by agency could potentially be capturing differential effectiveness in changing future orientation through the program, however, this seems unlikely since the agency coefficients are mostly very similar in size and significance in the model for initial (pre-program) responses compared to the model that includes later responses.

Overall, these models show systematic differences in discount rates by family demographics and financial status, as well as by loan amount and loan period. However, there is no evidence that the program itself affects discount rates other than the variation across the community based agencies.

### *E. Savings and discount rates*

From a programmatic or asset building perspective, the most critical question is whether and how discount rates are related to how much families can save. We have data from monthly bank statements on the amounts and frequency of deposits into the accounts for the matched savings program. We model the savings outcomes as a function of our three alternative discount rate measures as well as other individual and family characteristics that might affect the ability and motivation to save.

[11] We also tried models that dropped all the family financial variables except income because financial status could result from the effects of discount rates. The results for those models were nearly identical to those shown in Table 4.

$$DEP = \beta_0 + \beta_1 DRscore + \beta_{drmiss} DRmiss + Demog\,\beta_d + Fin\beta_f + \varepsilon$$

$$DEP = \beta_0 + \beta_{c2} DRcluster2 + \beta_{c3} DRcluster3 + \beta_{c4} DRcluster4 + \beta_{drmiss} DRmiss + Demog\,\beta_d + Fin\beta_f + \varepsilon$$

$$DEP = \beta_0 + \beta_{DRInter} DRIntercept + \beta_{drtime} DRtimeslope + \beta_{dramt} DRamtslope + \beta_{drmiss} DRmiss + Demog\,\beta_d + Fin\beta_f + \varepsilon$$

Where *DEP* is the natural log of average deposits and is regressed on one of the three sets of discount rate measures: the discount rate factor score (*DRscore*), the predicted probabilities of being in three of the four latent classes (with the first cluster of 0 discount rates as the reference categories), or the set of discount rate intercept, loan period slope, and loan amount slope. Each model also has an indicator of cases in which the discount rate questions had missing values ( $DRmiss$ ).

Other factors in the regressions include a set of demographic characteristics similar to those in the discount rate models above (gender, race, English language at home, age, age squared, education, marital status, number of adults in household, children present) and family finances at time of program entry (total assets, total liabilities, monthly income, checking account, a non-IDA savings account, credit card). As in our models predicting discount rates, we also include a set of indicators for the 13 community based agencies where clients applied for the program. [12]

We estimate the effects of discount rates and other factors on deposits over the first year in the program and over the entire time in the program. To assess the robustness of our findings, we also estimate similar models for the frequency of deposits (percentage of months with any deposit) in the first year and over time in the program.

We expect that higher discount rate levels and greater responsiveness to loan period and loan amount will be associated with lower savings. So we expected lower average savings for those with higher discount rate scores, those in the latent classes other than cluster 1 with 0 discount rates, and those with higher discount rate intercept or greater slopes for the loan period or loan amount.

In addition to the savings outcomes, we use a competing risks hazard analysis to assess the effects of discount rates on the length of time until a participant completes or drops out of the program.

$$\log h_{comp}(t) = \alpha_{comp}(t) + \beta_{compDR} DRscore + Demog\,\beta_{compDemog} + Fin\beta_{compFin}$$

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[12] We also tried models without the family financial variables other than income in case they were too closely related to discount rates, but the coefficients and significance levels for the discount rate indicators hardly changed. We also tried models which included indicators of year accepted to the program to further account for economic changes. A couple of these indicators had significant coefficients, but including them did not change the size or significance of the other coefficients.

$$\log h_{drop}(t) = \alpha_{drop}(t) + \beta_{dropDR} DRscore + Demog\,\beta_{dropDemog} + Fin\,\beta_{dropFin}$$

Using a Cox proportional hazard model allows us to estimate the effects of explanatory factors on program completion or drop out while accounting for the changing risk of leaving the program over time in the program. It accounts for censoring of the data because of the end of data collection as well as for censoring due to the competing risk, that is, our inability of observing time to complete for those who drop out and vice versa. The model does not estimate the underlying pattern of probability of completing or dropping over time, but controls for that in estimating the influence of the explanatory factors.

We expect that people with higher discount rates will have a lower probability of completing the program at each time point and will have a higher probability of dropping out of the program ($\beta_{compDR} < 0$, $\beta_{dropDR} < 0$). The equations show only the models using the discount rate factor score, but as with the savings outcomes, we estimate alternative models with each of our alternative sets of discount rate measures.

**Table 5** shows the regression results for the first year of average deposits for each of the three sets of discount rate measures: the factor score (Models 1 and 2), the cluster probabilities (Models 3 and 4), and the discount rate intercept, time slope, and amount slope (Models 5 and 6). For each set, the first column shows a model that includes only the discount rate variables; the second model adds in other family characteristics and the agency indicators (not shown in table).

Overall, the results provide some evidence of lower average monthly deposits for people with higher discount rates (as expected), but the effects are smaller and not always significant after controlling for family characteristics.

The models without other covariates show lower logged average deposits for those with higher discount rate factors from the factor analysis (Model 1) and for those with higher probabilities of being in the classes with higher discount rates from the latent class analysis (Model 3), but no significant effects of the discount rate intercept, time and amount slopes (Model 5). In each of those models, respondents who were missing discount rate responses had lower average deposits. After controlling for family characteristics and agency, the higher factor scores were still significantly associated with lower savings, but in the model with the cluster probabilities, only the cluster with the highest discount rates was significantly associated with lower savings. The coefficients on the set of discount rate intercept and slopes remained insignificant.

Converting from a log scale, average monthly deposit was lower by about 12 percent or about $16 for a standard deviation change in the factor score in Model 2 (with covariates).[13] Similarly, people with an estimated probability of 100 percent of being in the highest class of discount rates (Class 4) had average

[13] This is .89*(exp(.15)-1) =.14

monthly deposits lower by about $49 compared to those with 0 percent probability (Model 4). [14]

Beyond the discount rate influence, average deposits were higher for families with non-native English speakers and those who had a checking account prior to joining the IDA program. None of the other family demographic or financial characteristics significantly affected savings rates.

**Table 6** summarizes the effects of discount rates on savings for all of the savings outcomes and each set of discount rate proxies (a total of 6 outcomes x 3 sets of discount rate measures for 18 analyses). Each model also included the demographics, family and financial characteristics, and agency indicators as did the models above, though these are not shown in the table.

To preview, the results suggest that people with higher discount rates have lower average deposits in the first year and are less likely to complete the program. Discount rates do not significantly affect deposit frequency or drop out risk, though those who did not answer the discount rate questions make fewer deposits.

The first column mirrors the results of the models with covariates shown in Table 5. The second column shows similar models for average deposits over the entire participation time in the program rather than just the first year. The results here are similar to those of the first year of participation though the effects are not as large or statistically significant. So, it seems that discount rates matter most for savings levels in the first year of the program, rather than for the entire program time beyond that year.

There is, in contrast, very little evidence that discount rates affect the frequency of deposits either in the first year or for the program duration (Columns 3 and 4), except that participants who did not answer the discount rate questions had a smaller proportion of months with deposits. The signs for the coefficients on the discount rate factor scores and clusters are negative as expected, but none of them is statistically significant.

Columns 5 and 6 shows the results of the Cox proportional hazard analysis of the competing risks of completing the program (Col. 5) and dropping out of the program (col. 6). The table gives the hazard ratios which provide the relative risks of the outcome; values below 1 show lower risks of completing or dropping out in each time period and values over 1 show higher risks. Most of the discount rate measures show that respondents with higher discount rates are less likely to complete the program (Col. 5), but are not more or less likely to drop out of the program (Col. 6).

Those with higher discount rate factor scores are at lower risk to complete the program as are those not in the lowest discount rate class (the reference group made up of those unwilling to pay interest for any of the amounts or periods).

[14] Most of the individual predicted probabilities for clusters were very close to 0 or to 1.

The relative odds of completing the program are 14 percent higher for those with discount rates factor scores higher by 1 standard deviation ( the SD is .90*(1-.85)=.14). Those in the higher classes are all about 40 percent less likely to complete that those in the lowest discount rate class.

The final column reports the results for the drop out hazard model. The only significant coefficient is that on cluster 2, suggesting that those individuals have a lower drop out risk relative to the lowest discount rate cluster.

On the whole, the results in Table 6 provide additional support for the idea that individuals with lower discount rates will find it easier to save. Lower discount rates are associated with higher first year savings, and higher probability of completing the program.

## VII. Conclusions

The evolving literature on discounts rates suggests that people discount future consumption at lower rates for periods further in the future and for larger dollar amounts. A growing number of studies have linked the levels and structure of discount rates to financial and non-financial behaviors. To these literatures we add evidence on the shape, correlates, and outcomes associated with discount rates elicited from participants in a structured savings program. The results here suggest that cross-sectional variation in discount rates can be captured by a relatively simple set of questions and that variation in initial rates is significantly predictive of early success in a matched savings program.

We find that discount rates decrease for longer loan periods and larger loan amounts, consistent with the literature on time preferences. We do not find that discount rates are systematically lower for people with more experience in the savings program. This suggests that discount rates might be resistant to change even after the potential influence of case managers, financial training, and experience with the savings program. We also find evidence of demographic differences: discount rates are lower on average for respondents who are black, non-native English speakers, older, have education beyond high school, do not have children, and have lower incomes. Some of our findings, such as those of education and age, are consistent with previous empirical studies, but we find that many previous correlates of discount ratesare not significant in our analysis, perhaps because of the selective nature of our sample.

Our findings suggest that people with lower discount rates saved more in the first year of the savings program and had higher rates of completion. This is consistent with theories about the influence of time preferences on ability to save and the small literature on the effects of discount rates on financial outcomes. These findings imply that, even among those self-selecting into a matched savings program (or similar self- commitment mechanisms), some participants may need additional help in order to succeed in saving toward goals. Given the relatively high rate of program drop out (28 percent), there may also be some families who are not ready to save given current demands on income or fluctuations in earnings or other income. Those families might benefit from looser requirements or longer time frames for saving.

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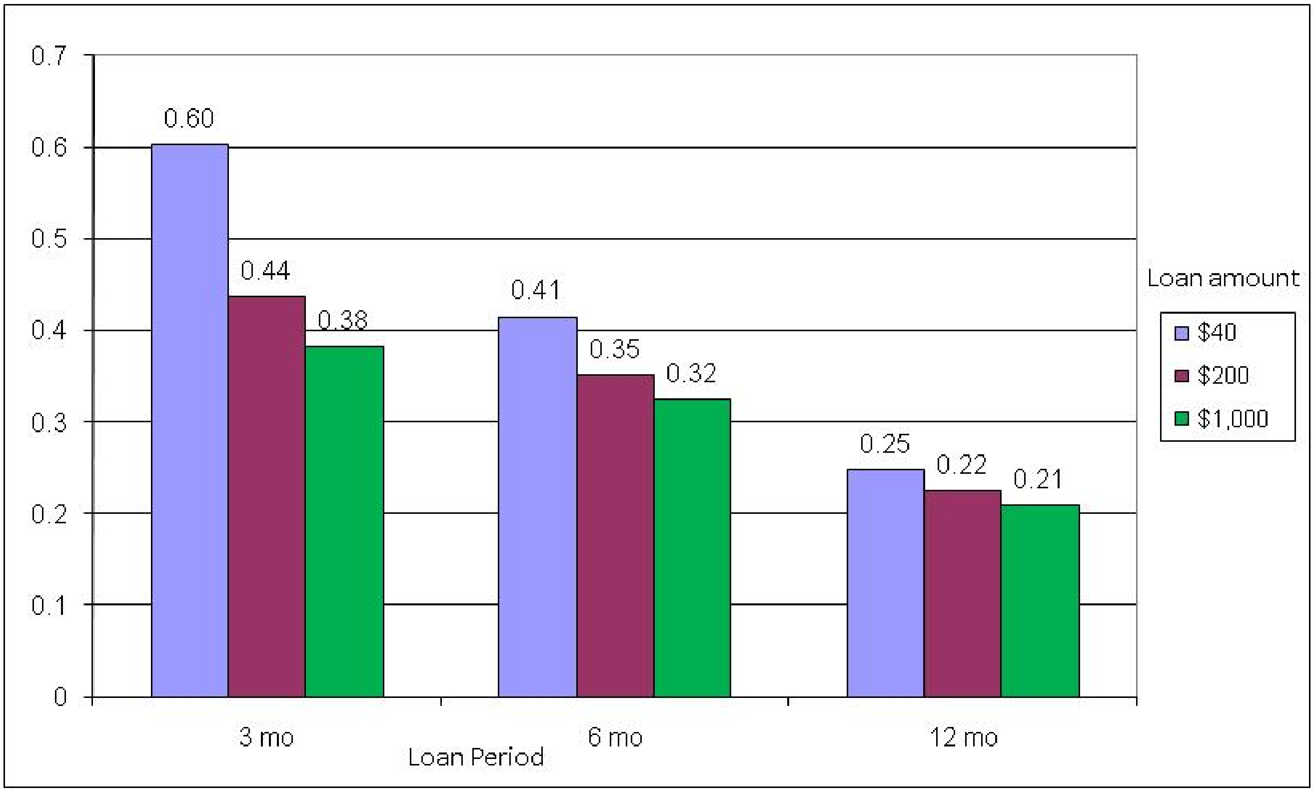
## Table 1: Descriptive Statistics

| Variable | Mean | Std.Dev. | Min. | Max. |
|---|---|---|---|---|
| **Demographics and Family Finances** | | | | |
| Male | 0.24 | 0.43 | 0 | 1 |
| White | 0.38 | 0.49 | 0 | 1 |
| Black | 0.41 | 0.49 | 0 | 1 |
| Asian/Pacific Islander | 0.11 | 0.31 | 0 | 1 |
| English is native language | 0.64 | 0.48 | 0 | 1 |
| Age | 41 | 10 | 21 | 75 |
| Age squared | 1732 | 815 | 441 | 5625 |
| Education: High School degree | 0.21 | 0.41 | 0 | 1 |
| Education: Some college | 0.48 | 0.50 | 0 | 1 |
| Education: College degree | 0.22 | 0.41 | 0 | 1 |
| Married | 0.36 | 0.48 | 0 | 1 |
| Number of Adults in household | 1.55 | 0.81 | 1 | 7 |
| Any Children | 0.76 | 0.43 | 0 | 1 |
| Assets for Household | $2,669 | $9,085 | -$57 | $186,006 |
| Liabilities for Household | $7,841 | $16,779 | $0 | $201,400 |
| Income for Household | $17,779 | $9,853 | $0 | $50,196 |
| Any checking account | 0.89 | 0.31 | 0 | 1 |
| Any non-IDA saving account | 0.76 | 0.43 | 0 | 1 |
| Any Credit Card | 0.57 | 0.50 | 0 | 1 |
| **Savings Measures** | | | | |
| Average IDA deposit per month (First 12 months) | $127.91 | $190.57 | $0.05 | $2,000.49 |
| Average IDA deposit per month (Full time in program) | $132.56 | $189.05 | $0.05 | $2,000.49 |
| Proportion of Months with a deposit (First 12 months) | 0.76 | 0.24 | 0.08 | 1.00 |
| Proportion of Months with a deposit (Full time in program) | 0.75 | 0.24 | 0.07 | 1.00 |
| Completed program by 12 months | 0.18 | 0.39 | 0 | 1 |
| Completed program by 24 months | 0.34 | 0.48 | 0 | 1 |
| Completed program by end of data collection | 0.39 | 0.49 | 0 | 1 |
| Dropped out by 12 months | 0.10 | 0.30 | 0 | 1 |
| Dropped out by 24 months | 0.20 | 0.40 | 0 | 1 |
| Dropped out by end of data collection | 0.28 | 0.45 | 0 | 1 |
| **Discount Rate Measures** | | | | |
| Discount rate questions missing | 0.18 | 0.38 | 0 | 1 |
| Discount rate Factor Score | -0.01 | 0.89 | -1 | 3 |
| Discount rate Cluster 2 | 0.24 | 0.41 | 0 | 1 |
| Discount rate Cluster 3 | 0.19 | 0.39 | 0 | 1 |
| Discount rate Cluster 4 | 0.15 | 0.35 | 0 | 1 |
| Discount rate Intercept | 0.52 | 0.85 | 0 | 4 |
| Discount rate Loan period slope | 0.31 | 0.66 | 0 | 4 |
| Discount rate Amount slope | 0.24 | 0.68 | 0 | 4 |

Note: n=603. Demographics and discount rates are measured by program start.

**Figure 1: Average Initial Discount rates by Loan Period and Loan Amount**




Note: Discount rates measured at program start.

## Table 2: Factor Analysis of Initial Discount Rates

**Total Variance Explained**

| Factor | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 6.899 | 76.660 | 76.660 | 6.586 | 73.179 | 73.179 |
| 2 | .840 | 9.329 | 85.989 | | | |
| 3 | .649 | 7.210 | 93.199 | | | |
| 4 | .276 | 3.062 | 96.261 | | | |
| 5 | .128 | 1.420 | 97.681 | | | |
| 6 | .088 | .974 | 98.654 | | | |
| 7 | .063 | .696 | 99.350 | | | |
| 8 | .032 | .358 | 99.707 | | | |
| 9 | .026 | .293 | 100.000 | | | |

Extraction Method: Maximum Likelihood.

**Factor Matrix(a)**

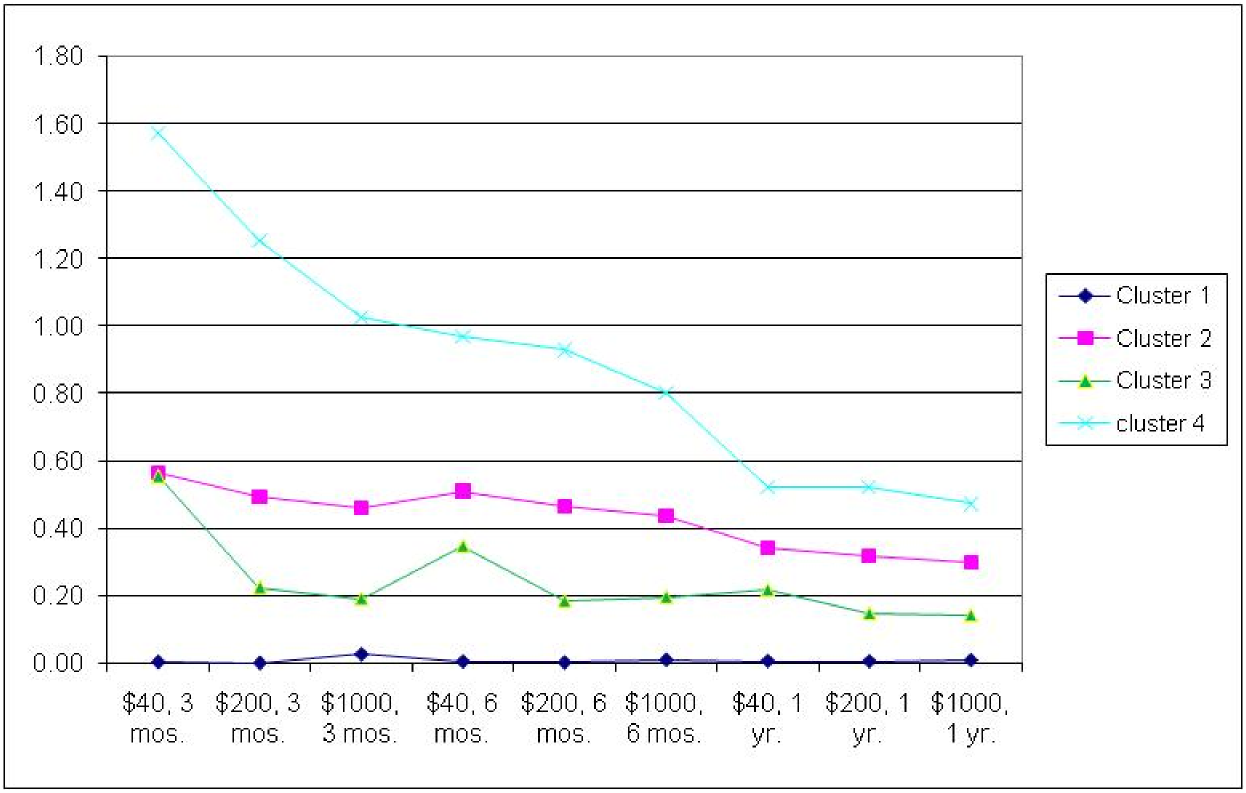
| | Factor |
|---|---|
| | 1 |
| future 40 dollars 3 month | .664 |
| future 40 dollars 6 month | .863 |
| future 40 dollars 1 year | .876 |
| future 200 dollars 3 month | .775 |
| future 200 dollars 6 month | .961 |
| future 200 dollars 1 year | .961 |
| future 1000 dollars 3 month | .720 |
| future 1000 dollars 6 month | .906 |
| future 1000 dollars 1 year | .920 |

Extraction Method: Maximum Likelihood.
a 1 factors extracted. 7 iterations required.

**Table 3: Latent Class Analysis Summary for 1 to 12 Clusters**

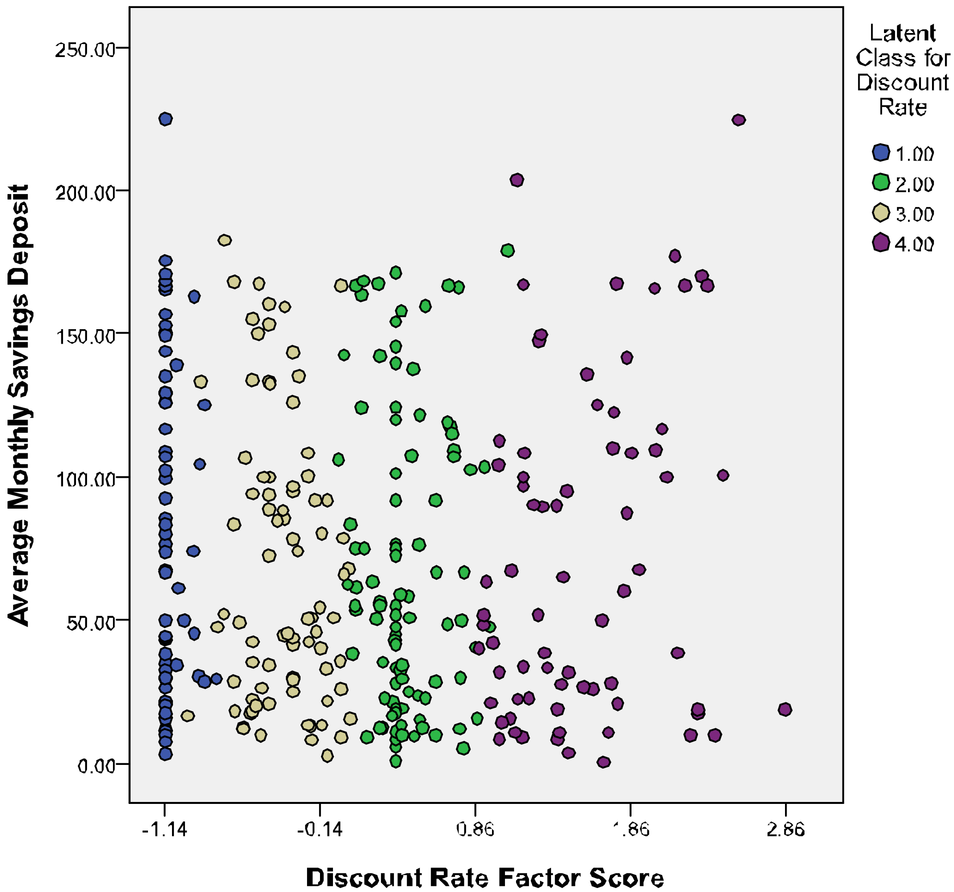
| | log likelikiood | BIC(LL) | Number of Parameters | L² | df | p-value | Class.Err. |
|---|---|---|---|---|---|---|---|
| 1-Cluster | -7520.68 | 15374.32 | 53 | 10374.87 | 482 | 1.30E-183 | 0 |
| 2-Cluster | -5901.10 | 12197.99 | 63 | 7135.71 | 472 | 4.20E-117 | 0.0068 |
| 3-Cluster | -5211.35 | 10881.31 | 73 | 5756.21 | 462 | 6.2e-900 | 0.0114 |
| 4-Cluster | -4912.16 | 10345.75 | 83 | 5157.83 | 452 | 3.2e-786 | 0.0182 |
| 5-Cluster | -4741.28 | 10066.81 | 93 | 4816.07 | 442 | 7.1e-724 | 0.0209 |
| 6-Cluster | -4622.88 | 9892.83 | 103 | 4579.26 | 432 | 2.2e-682 | 0.0328 |
| 7-Cluster | -4556.12 | 9822.13 | 113 | 4445.74 | 422 | 3.1e-661 | 0.029 |
| 8-Cluster | -4508.83 | 9790.38 | 123 | 4351.17 | 412 | 9.3e-648 | 0.0335 |
| 9-Cluster | -4441.06 | 9717.66 | 133 | 4215.62 | 402 | 3.2e-626 | 0.0446 |
| 10-Cluster | -4412.25 | 9722.87 | 143 | 4158.01 | 392 | 5.1e-620 | 0.0315 |
| 11-Cluster | -4317.81 | 9596.81 | 153 | 3969.14 | 382 | 5.3e-588 | 0.0355 |
| 12-Cluster | -4301.88 | 9627.77 | 163 | 3937.27 | 372 | 7.6e-587 | 0.034 |

**Figure 2: Average Discount rates for Latent Class Analysis 4 Clusters**




Note: Based on discount responses at program start.

**Figure 3: Average monthly Saving Deposits**
**by Discount Rate Factor Score (X axis) and Latent Class (color)**



## Table 4: Tobit Analysis of Discount Rates for all and initial surveys only

| | Model 1: Initial Discount Rates | | | Model 2: Initial and Follow-up Discount Rates | | |
|---|---|---|---|---|---|---|
| | Coeff. | S.E. | p | Coeff. | S.E. | p |
| **Time in Program** | (omitted) | | | -0.0000728 | 8.81E-05 | 0.408 |
| **Loan Period** | -0.03 | 0.003 | 0.00 | -0.03 | 0.003 | 0.00 |
| **Loan Amount** | -0.0003 | 0.00004 | 0.00 | -0.0002 | 0.00003 | 0.00 |
| **Loan Period*Amount Interaction** | 0.00002 | 0.000004 | 0.00 | 0.00002 | 0.000003 | 0.00 |
| **Time in Program *Loan Period interaction** | (omitted) | | | 0.000011 | 0.000006 | 0.10 |
| **Male** | 0.04 | 0.06 | 0.54 | 0.03 | 0.06 | 0.65 |
| **White** | 0.01 | 0.09 | 0.88 | 0.03 | 0.10 | 0.80 |
| **Black** | -0.18 | 0.10 | 0.06 | -0.18 | 0.09 | 0.04 |
| **Asian/Pacific Islander** | -0.09 | 0.12 | 0.44 | -0.09 | 0.11 | 0.43 |
| **English is native language** | 0.15 | 0.07 | 0.03 | 0.15 | 0.06 | 0.02 |
| **Age** | -0.04 | 0.02 | 0.04 | -0.04 | 0.02 | 0.00 |
| **Age squared** | 0.0004 | 0.0002 | 0.03 | 0.0005 | 0.0002 | 0.01 |
| **Education: High School degree** | -0.19 | 0.10 | 0.07 | -0.21 | 0.10 | 0.03 |
| **Education: Some college** | -0.11 | 0.10 | 0.26 | -0.13 | 0.09 | 0.13 |
| **Education: College degree** | -0.12 | 0.12 | 0.32 | -0.16 | 0.10 | 0.11 |
| **Married** | 0.04 | 0.07 | 0.54 | 0.08 | 0.06 | 0.18 |
| **Number of Adults in household** | -0.02 | 0.04 | 0.54 | -0.02 | 0.03 | 0.54 |
| **Any Children** | 0.13 | 0.07 | 0.06 | 0.12 | 0.06 | 0.05 |
| **Assets for Household** | 0.000001 | 0.000001 | 0.38 | 0.000001 | 0.000002 | 0.54 |
| **Liabilities for Household** | 0.000001 | 0.000001 | 0.64 | 0.0000001 | 0.000001 | 0.91 |
| **Income for Household** | 0.000006 | 0.000003 | 0.05 | 0.000006 | 0.000002 | 0.02 |
| **Any checking account** | -0.09 | 0.09 | 0.37 | -0.03 | 0.08 | 0.69 |
| **Any non-IDA saving account** | 0.09 | 0.06 | 0.17 | 0.11 | 0.06 | 0.06 |
| **Any Credit Card** | -0.04 | 0.05 | 0.50 | -0.08 | 0.05 | 0.11 |
| **Constant** | 0.87 | 0.37 | 0.02 | 1.02 | 0.34 | 0.00 |
| **Sigma** | 0.67 | 0.03 | | 0.64 | 0.03 | |
| **Log pseudolikelihood** | | -4535.04 | | | -7739.53 | |
| **Sample Size (DR responses)** | | 4970 | | | 8685 | |
| **Left-censored observations** | | 1833 | | | 3136 | |
| **Uncensored observations** | | 3137 | | | 5549 | |

**Table 5: Average Monthly Deposit Regressions**

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | | Model 6 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coeff. | p | Coeff. | p | Coeff. | p | Coeff. | p | Coeff. | p | Coeff. | p |
| Discount rate Factor Score | **-0.21** | **0.00** | **-0.15** | **0.01** | | | | | | | | |
| Discount rate Cluster 2 | | | | | **-0.38** | **0.01** | -0.19 | 0.22 | | | | |
| Discount rate Cluster 3 | | | | | **-0.40** | **0.01** | -0.20 | 0.20 | | | | |
| Discount rate Cluster 4 | | | | | **-0.66** | **<.0001** | **-0.48** | **0.01** | | | | |
| Discount rate Intercept | | | | | | | | | -0.20 | 0.22 | -0.11 | 0.46 |
| Discount rate Loan period slope | | | | | | | | | -0.05 | 0.82 | -0.13 | 0.51 |
| Discount rate Amount slope | | | | | | | | | 0.17 | 0.22 | 0.20 | 0.12 |
| Discount rates missing | **-0.32** | **0.02** | -0.14 | 0.31 | **-0.65** | **<.0001** | -0.33 | 0.05 | **-0.37** | **0.01** | -0.19 | 0.19 |
| Male | | | 0.01 | 0.91 | | | 0.02 | 0.88 | | | 0.00 | 1.00 |
| White | | | 0.10 | 0.62 | | | 0.10 | 0.62 | | | 0.11 | 0.58 |
| Black | | | -0.10 | 0.60 | | | -0.11 | 0.59 | | | -0.07 | 0.71 |
| Asian/Pacific Islander | | | -0.12 | 0.64 | | | -0.12 | 0.64 | | | -0.09 | 0.74 |
| English is native language | | | **-0.37** | **0.01** | | | **-0.37** | **0.01** | | | **-0.39** | **0.01** |
| Age | | | 0.00 | 0.99 | | | 0.00 | 1.00 | | | 0.01 | 0.81 |
| Age squared | | | 0.00 | 0.92 | | | 0.00 | 0.93 | | | 0.00 | 0.77 |
| Education: High School degree | | | 0.01 | 0.96 | | | 0.01 | 0.97 | | | 0.03 | 0.89 |
| Education: Some college | | | 0.01 | 0.94 | | | 0.02 | 0.92 | | | 0.02 | 0.93 |
| Education: College degree | | | 0.08 | 0.71 | | | 0.09 | 0.69 | | | 0.09 | 0.69 |
| Married | | | 0.19 | 0.15 | | | 0.18 | 0.17 | | | 0.19 | 0.15 |
| Number of Adults in household | | | -0.07 | 0.38 | | | -0.07 | 0.38 | | | -0.07 | 0.34 |
| Any Children | | | 0.04 | 0.75 | | | 0.05 | 0.74 | | | 0.01 | 0.92 |
| Assets for Household | | | 0.000005 | 0.32 | | | 0.000005 | 0.40 | | | 0.000005 | 0.35 |
| Liabilities for Household | | | 0.000002 | 0.50 | | | 0.000002 | 0.48 | | | 0.000002 | 0.46 |
| Income for Household | | | 0.000003 | 0.56 | | | 0.000003 | 0.54 | | | 0.000003 | 0.57 |
| Any checking account | | | **0.30** | **0.08** | | | **0.29** | **0.08** | | | **0.31** | **0.07** |
| Any non-IDA saving account | | | -0.09 | 0.46 | | | -0.08 | 0.53 | | | -0.13 | 0.28 |
| Any Credit Card | | | 0.11 | 0.33 | | | 0.10 | 0.34 | | | 0.11 | 0.31 |
| Intercept | **4.23** | **<.0001** | **4.85** | **<.0001** | **4.56** | **<.0001** | **5.06** | **<.0001** | **4.32** | **<.0001** | **4.77** | **<.0001** |
| R squared | 0.03 | | 0.18 | | 0.04 | | 0.18 | | 0.02 | | 0.17 | |

Note: Models also include agency indicators. N=603 for each model.

## Table 6: Effects of Discount Rates on Savings and Program Completion or Drop out

| | Logged Average Monthly Deposit | | | | Deposit Frequency | | | | Completion Hazard | | Drop out Hazard | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) First year | | (2) Full program | | (3) First year | | (4) Full program | | (5) | | (6) | |
| | coeff | p | coeff | p | coeff | p | coeff | p | haz ratio | p | haz ratio | p |
| **Discount rate Factor Score** | **-0.15** | **0.01** | -0.09 | 0.10 | -0.01 | 0.23 | -0.01 | 0.43 | **0.85** | **0.05** | 0.91 | 0.44 |
| **Discount rates missing** | -0.14 | 0.31 | -0.19 | 0.17 | **-0.06** | **0.05** | **-0.05** | **0.09** | **0.55** | **0.01** | 1.27 | 0.27 |
| | *p=.03 $R^2$ =.18* | | *p=.10 $R^2$=.18* | | *p=.06 $R^2$=.13* | | *p=.18 $R^2$=.11* | | *p=.01* | | *p=.41* | |
| **Discount rate Cluster 2** | -0.19 | 0.22 | -0.14 | 0.37 | -0.02 | 0.59 | -0.01 | 0.81 | **0.60** | **0.01** | **0.52** | **0.02** |
| **Discount rate Cluster 3** | -0.20 | 0.20 | -0.16 | 0.29 | -0.02 | 0.63 | -0.02 | 0.48 | **0.62** | **0.03** | 0.77 | 0.33 |
| **Discount rate Cluster 4** | **-0.48** | **0.01** | **-0.32** | **0.06** | -0.04 | 0.24 | -0.03 | 0.40 | **0.63** | **0.05** | 0.82 | 0.54 |
| **Discount rates missing** | **-0.33** | **0.05** | **-0.33** | **0.05** | **-0.07** | **0.03** | **-0.06** | **0.07** | **0.38** | **0.00** | 0.93 | 0.80 |
| | *p=.06 $R^2$=.18* | | *p=.23 $R^2$=.18* | | *p=.25 $R^2$=.13* | | *p=.44 $R^2$=.11* | | *p=.01* | | *p=.12* | |
| **Discount rate Intercept** | -0.11 | 0.46 | -0.11 | 0.46 | -0.02 | 0.52 | -0.03 | 0.46 | 0.68 | 0.28 | 1.11 | 0.75 |
| **Discount rate Loan period slope** | -0.13 | 0.51 | -0.07 | 0.51 | -0.02 | 0.63 | -0.02 | 0.51 | 1.24 | 0.64 | 0.81 | 0.53 |
| **Discount rate Amount slope** | 0.20 | 0.12 | 0.18 | 0.12 | 0.02 | 0.42 | 0.03 | 0.12 | 1.22 | 0.33 | 1.17 | 0.41 |
| **Discount rates missing** | -0.19 | 0.19 | -0.22 | 0.19 | **-0.06** | **0.03** | -0.05 | 0.19 | **0.52** | **0.01** | 1.29 | 0.24 |
| | *p=.28 $R^2$=.17* | | *p=0.36 $R^2$=.18* | | *p=0.11 $R^2$=.13* | | *p=0.16 $R^2$=.12* | | *p=0.07* | | *p=0.60* | |

Note: Models also include family demographics, finances, and agency indicators as in Table 5. N=603 for each model. Under each model, p value for test of significance of set of discount rate variables (including indicator of missing discount rate) and $R^2$ for full model.

## APPENDIX A: Discount Rate Questions from Survey

**F: Future Orientation**

**Imagine that you could borrow some money. <u>Circle the largest amount that you would be willing to pay.</u>**

**1) Imagine that you borrow $40.** How much would you be willing to pay back

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| if you were paying in 3 months? | $40 | $44 | $48 | $52 | $56 | $60 | more |
| What if you were paying in 6 months? | $40 | $44 | $48 | $52 | $56 | $60 | more |
| What if you were paying in a year? | $40 | $44 | $48 | $52 | $56 | $60 | more |

**2) Imagine that you borrow $200.** How much would you be willing to pay back

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| if you were paying in 3 months? | $200 | $220 | $240 | $260 | $280 | $300 | more |
| What if you were paying in 6 months? | $200 | $220 | $240 | $260 | $280 | $300 | more |
| What if you were paying in a year? | $200 | $220 | $240 | $260 | $280 | $300 | more |

**3) Imagine that you borrow $1,000.** How much would you be willing to pay back

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| if you were paying in 3 months? | $1,000 | $1,100 | $1,200 | $1,300 | $1,400 | $1,500 | more |
| What if you were paying in 6 months? | $1,000 | $1,100 | $1,200 | $1,300 | $1,400 | $1,500 | more |
| What if you were paying in a year? | $1,000 | $1,100 | $1,200 | $1,300 | $1,400 | $1,500 | more |

## APPENDIX B: Latent Class Analysis for 4 Clusters

| Cluster size | Cluster1 | Cluster2 | Cluster3 | Cluster4 |
|---|---|---|---|---|
| | 30% | 28% | 23% | 19% |
| DR1_a | | | | |
| 0 | 0.99 | 0.26 | 0.27 | 0.08 |
| 0.46 | 0.01 | 0.47 | 0.48 | 0.27 |
| 1.07 | 0.00 | 0.20 | 0.19 | 0.24 |
| 1.86 | 0.00 | 0.06 | 0.06 | 0.21 |
| 2.84 | 0.00 | 0.00 | 0.00 | 0.03 |
| 4.06 | 0.00 | 0.00 | 0.00 | 0.11 |
| 4.07 | 0.00 | 0.00 | 0.00 | 0.06 |
| Mean | 0.00 | 0.57 | 0.55 | 1.53 |
| DR1_b | | | | |
| 0 | 0.98 | 0.04 | 0.11 | 0.00 |
| 0.21 | 0.02 | 0.20 | 0.33 | 0.02 |
| 0.44 | 0.00 | 0.43 | 0.44 | 0.12 |
| 0.69 | 0.00 | 0.20 | 0.10 | 0.15 |
| 0.96 | 0.00 | 0.10 | 0.02 | 0.31 |
| 1.25 | 0.00 | 0.01 | 0.00 | 0.22 |
| 1.26 | 0.00 | 0.01 | 0.00 | 0.18 |
| Mean | 0.00 | 0.50 | 0.36 | 0.95 |
| DR1_c | | | | |
| 0 | 0.94 | 0.03 | 0.13 | 0.00 |
| 0.1 | 0.06 | 0.05 | 0.15 | 0.00 |
| 0.2 | 0.00 | 0.17 | 0.30 | 0.01 |
| 0.3 | 0.00 | 0.30 | 0.28 | 0.04 |
| 0.4 | 0.00 | 0.21 | 0.09 | 0.12 |
| 0.5 | 0.00 | 0.13 | 0.02 | 0.47 |
| 0.6 | 0.00 | 0.10 | 0.02 | 0.36 |
| Mean | 0.01 | 0.34 | 0.22 | 0.51 |

| | Cluster1 | Cluster2 | Cluster3 | Cluster4 |
|---|---|---|---|---|
| DR2_a | | | | |
| 0 | 1.00 | 0.15 | 0.51 | 0.02 |
| 0.46 | 0.00 | 0.69 | 0.47 | 0.32 |
| 1.07 | 0.00 | 0.15 | 0.01 | 0.39 |
| 1.86 | 0.00 | 0.01 | 0.00 | 0.18 |
| 2.84 | 0.00 | 0.00 | 0.00 | 0.03 |
| 4.06 | 0.00 | 0.00 | 0.00 | 0.03 |
| 4.07 | 0.00 | 0.00 | 0.00 | 0.03 |
| Mean | 0.00 | 0.49 | 0.23 | 1.22 |
| DR2_b | | | | |
| 0 | 0.99 | 0.00 | 0.15 | 0.00 |
| 0.21 | 0.01 | 0.04 | 0.81 | 0.00 |
| 0.44 | 0.00 | 0.86 | 0.04 | 0.02 |
| 0.69 | 0.00 | 0.11 | 0.00 | 0.39 |
| 0.96 | 0.00 | 0.00 | 0.00 | 0.34 |
| 1.25 | 0.00 | 0.00 | 0.00 | 0.16 |
| 1.26 | 0.00 | 0.00 | 0.00 | 0.09 |
| Mean | 0.00 | 0.46 | 0.19 | 0.92 |
| DR2_c | | | | |
| 0 | 0.95 | 0.00 | 0.10 | 0.00 |
| 0.1 | 0.05 | 0.01 | 0.41 | 0.00 |
| 0.2 | 0.00 | 0.12 | 0.41 | 0.00 |
| 0.3 | 0.00 | 0.61 | 0.08 | 0.03 |
| 0.4 | 0.00 | 0.21 | 0.00 | 0.16 |
| 0.5 | 0.00 | 0.02 | 0.00 | 0.43 |
| 0.6 | 0.00 | 0.02 | 0.00 | 0.38 |
| Mean | 0.01 | 0.32 | 0.15 | 0.52 |

| | Cluster1 | Cluster2 | Cluster3 | Cluster4 |
|---|---|---|---|---|
| DR3_a | | | | |
| 0 | 0.94 | 0.24 | 0.61 | 0.06 |
| 0.46 | 0.06 | 0.59 | 0.38 | 0.37 |
| 1.07 | 0.00 | 0.16 | 0.02 | 0.38 |
| 1.86 | 0.00 | 0.01 | 0.00 | 0.17 |
| 2.84 | 0.00 | 0.00 | 0.00 | 0.00 |
| 4.06 | 0.00 | 0.00 | 0.00 | 0.02 |
| 4.07 | 0.00 | 0.00 | 0.00 | 0.01 |
| Mean | 0.03 | 0.46 | 0.19 | 1.00 |
| DR3_b | | | | |
| 0 | 0.95 | 0.01 | 0.19 | 0.00 |
| 0.21 | 0.05 | 0.22 | 0.71 | 0.02 |
| 0.44 | 0.00 | 0.61 | 0.09 | 0.21 |
| 0.69 | 0.00 | 0.15 | 0.00 | 0.32 |
| 0.96 | 0.00 | 0.01 | 0.00 | 0.28 |
| 1.25 | 0.00 | 0.00 | 0.00 | 0.10 |
| 1.26 | 0.00 | 0.00 | 0.00 | 0.07 |
| Mean | 0.01 | 0.43 | 0.19 | 0.80 |
| DR3_c | | | | |
| 0 | 0.91 | 0.00 | 0.15 | 0.00 |
| 0.1 | 0.09 | 0.05 | 0.40 | 0.00 |
| 0.2 | 0.00 | 0.26 | 0.38 | 0.03 |
| 0.3 | 0.00 | 0.45 | 0.07 | 0.15 |
| 0.4 | 0.00 | 0.17 | 0.00 | 0.23 |
| 0.5 | 0.00 | 0.04 | 0.00 | 0.31 |
| 0.6 | 0.00 | 0.03 | 0.00 | 0.29 |
| Mean | 0.01 | 0.30 | 0.14 | 0.47 |