# TEMPORAL STABILITY OF TIME PREFERENCES

Stephan Meier and Charles D. Sprenger*

*Abstract*—The preferences assumed to govern intertemporal trade-offs are generally considered to be stable economic primitives, though evidence on this stability is notably lacking. We present evidence from a large field study conducted over two years, with around 1,400 individuals using incentivized intertemporal choice experiments. Aggregate choice profiles and corresponding estimates of discount parameters are unchanged over the two years and individual correlations through time are high by existing standards. However, some individuals show signs of instability. By linking experimental measures to administrative tax records, we show that identified instability is uncorrelated with both levels and changes in sociodemographic variables.

## I. Introduction

INDIVIDUALS are frequently faced with intertemporal decisions. From larger decisions such as how much to save for retirement and how much to borrow on credit cards or on payday loans, to smaller decisions such as whether to go to the gym or how much to study, individuals are required to make trade-offs over time. The preference parameters governing these decisions, intertemporal preferences, are generally assumed to be static economic primitives, fixed over time. Economic analysis effectively proceeds from this basis: if changes in intertemporal choice behavior are observed (e.g., if consumers borrow more this year than last), then relative prices or budget constraints must have changed but preferences remained the same.

It is necessary to know whether time preferences are indeed stable, such that an individual will make the same intertemporal trade-offs today as in one year's time.[1] Though unstable intertemporal preferences can be incorporated into theoretical models of economic decision making, empirical analysis is hampered by such instability. Unstable intertemporal preferences would imply that preference parameters have to be separately measured and accounted for in each time period. As such, it is difficult to pin down time-varying preferences and responses to changing economic incentives solely from time-varying behavior. In their seminal work on stable preferences, Stigler and Becker (1977) make the key point that attributing changes in behavior to changes in preferences leaves too many degrees of freedom to be economically interesting.

Despite its importance for economic research, relatively little is known about the stability of time preferences.[2] A few psychological and economic studies show correlation between experimental measures of patience and subsequent behaviors such as scholastic achievement (Mischel, Shoda, & Rodriguez, 1989), borrowing (Meier & Sprenger, 2010), and credit default (Meier & Sprenger, 2012). This evidence, however, is indirect in that stability is identified only under the assumption that a common set of preferences drives both experimental responses and later real-world behavior.

Contrary to the findings already noted, other research shows low (or no) correlation between measured time preferences and intertemporal decisions such as diet and exercise behavior (Chabris et al., 2008). Such low correlation in cross-situational behaviors has been interpreted by psychologists as evidence of instability in personality traits or preferences (Mischel, 1968; Ross & Nisbett, 1991).[3] Additionally, experimentally measured time preference parameters vary broadly. Frederick, Loewenstein, and O'Donoghue (2002) review the literature and find annual discount rates ranging from 0 percent to thousands of percent per annum. If subjects in different studies are truly similar, this suggests substantial instability in time preferences. However, the authors propose that at least part of the variance in findings is due to differing experimental methodology and differing sample selection. They also note that "no longitudinal studies have been conducted to permit any conclusions about the temporal stability of time preferences" (Frederick et al., 2002, p. 391). To our knowledge, the lack of longitudinal time preference studies persists to the present. A recent exception is Krupka and Stephens (2013), who use hypothetical discounting surveys in a longitudinal study collected in the mid-1970s. They show that hypothetical discount rates increase during a period of substantially rising inflation, suggesting a link between inflation and required rates of return.[4] In a study of present-biased preferences, Harrison, Lau, and Rutstrom (2005) obtain experimental time preference data for 97 Danish individuals that could be used

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* Meier: Columbia University; Sprenger: Stanford University.
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[1] Time preference stability as we investigate it is separate from the concept of dynamic consistency. Indeed, one can consider stable dynamically inconsistent preferences, as in the case of the often-used $\beta-\delta$ model (Strotz, 1956; Laibson, 1997; O'Donoghue & Rabin, 1999).

[2] Readers interested in the temporal stability of other preferences are referred to Andersen et al. (2008b), who analyze the stability of experimentally elicited risk preferences for a sample of 97 Danes and find evidence in favor of stable risk preferences. The stability of other-regarding preferences has been investigated, for example, by Benz and Meier (2008), de Oliveira, Croson, and Eckel (2012), and Volk, Thöni, and Ruigrok (2012).

[3] Low correlation between different indicators of time preference does not necessarily mean that time preferences are unstable. Decisions such as smoking and borrowing might be governed by a number of factors independent of time preferences.

[4] In a related cross-sectional study, Wang, Rieger, and Hens (2009) document little correlation between hypothetical discount rates and inflation.

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to explore this topic. Observation of the presented data is not suggestive of stability in elicited one-month discount factors.[5]

Our study begins to fill the gap with a longitudinal experimental research design. In consecutive years, we elicit the time preferences of around 1,400 adults from the same subject pool using identical incentivized experimental methods. The experimental methodology was designed to elicit potentially present-biased time preferences (Laibson, 1997; O'Donoghue & Rabin, 1999). This represents one of the largest incentivized studies of time preferences conducted to date.[6] The study investigates temporal stability of measured time preferences, which means that any temporal instability could be due to either instability of preferences or instability of measurement of those preferences. The size of the study provides power for hypothesis tests of stability. The study was conducted at a tax filing center, and individuals granted us access to their tax filing data. Thus, we obtain objective information on economically relevant changes in income, unemployment, and family composition. Changes in economic variables such as income have long been thought to affect time preference (Fisher, 1930).[7] Study participants are low income such that substantial proportional income changes are observed, and changes to employment and family composition may have important economic impacts. In addition, the tax data allow us to investigate the influence of future changes to liquidity on measured time preferences by analyzing the effects of changes in the magnitude of tax refund receipts.

Our analysis yields three results. First, the aggregate choice profiles over intertemporal payments are indistinguishable across the two years of the study. Resulting maximum-likelihood estimates accounting for stochastic decision error show stability in discounting, present bias, and decision error parameters over time. Given the wide historical variation in time preference parameter estimates from experimental studies (Frederick et al., 2002), this demonstrates that when rigorously controlling both the experimental methodology and the sample pool, one can obtain stable aggregate estimates over time.

Second, in individual-level panel analysis, we demonstrate a one-year correlation in choice behavior of around 0.5, high by both predictions generated from our aggregate estimates and existing psychological standards (Costa & McCrae, 1994). Supporting the analysis on the choice level, we also show that 43% of individuals exhibit identical switching points within a time frame and that 50% of individuals have monthly discount factors, $\delta_i$, within 0.025 of each other in the two years (40% have calculated present biased parameters, $\beta_i$, within 0.05 of each other in the two years). These panel results focus on a selection of subjects who participated in both years of the study. Hence, we present these correlational results taking as given any possible selection effects and attempt to analyze selection on observable characteristics.

The third contribution explores the degree of instability in measured preferences. Some subjects show variation in their choice behavior over time. We find that there exist few demographic correlates for this instability, and one cannot predict differences with economically relevant changes in income, unemployment, family composition, or future liquidity. This suggests that though one can obtain a stable distribution and high correlations at the individual level, there remains an instability in choice, largely independent of sociodemographics and situational changes, potentially attributable to error.

The remainder of the paper proceeds as follows Section II presents our methodology for experimentally eliciting time preferences and discusses design details. Section III presents results related to stable preferences over time at the aggregate and individual levels and discusses sources of potential instability. Section IV concludes.

## II. Empirical Methodology

### A. *The Setup*

Evidence in this paper comes from a field study conducted in collaboration with the City of Boston at a Volunteer Income Tax Assistance (VITA) site in Roxbury, Massachusetts. At the time of the study, there were 22 such VITA sites in Boston, providing free tax preparation assistance to low-to-moderate income (LMI) households in specific neighborhoods in order to help them claim valuable tax credits such as the earned income tax credit (EITC). The VITA site in Roxbury is Boston's largest and was established in 2001.

A total of 2,366 individuals received tax assistance in 2007 and 2008 from the VITA site on the days the experiment was conducted. In both years, VITA site intake material included identical, incentive-compatible choice experiments to elicit time preferences. The choice experiments were presented on a single colored sheet of paper and were turned in at the end of tax filing for potential payments. The experimental paradigm is presented as appendix A.2 in the online supplement.

The subject pool, though nonstandard, comes to the VITA site for reasons other than the experiment. This partially reduces the problem of subjects self-selecting into experiments (Levitt & List, 2007). Individuals may, of course, choose not to participate in the experiment once at the VITA site. Of all the individuals coming to the site, 71% elected to participate in the experiment and consented to the use of their data for research purposes.[8] This yields a data set of 1,684 individual-level responses to the choice experiments (890 in

[5] Interested readers are referred to figure 1C, data series *A* and *A** of Harrison, Rutstrom, and Williams (2005).

[6] This is in terms of total individuals, not necessarily in terms of choices, that is, number of individuals × number of choices.

[7] In addition, cross-sectional data show dramatic differences in the rate of time preference between wealthy and poor households (Lawrance, 1991).

[8] This includes accessing their tax filing data and combining tax filing data and choice experimental responses. We are able to measure selection into the experiments as all VITA site attendees consented to the use of their data for program evaluation purposes.

2007 and 794 in 2008). Of the participants in 2007, 250 again participated in 2008. That is, we obtain two observations for these individuals.

### B. Eliciting Time Preferences

Individual time preferences are elicited using identical incentivized multiple price lists in both years of the study (for similar approaches to elicit time preferences, see Coller & Williams, 1999; Harrison, Lau, & Rutstrom, 2002; McClure et al., 2004; Dohmen et al., 2006; Tanaka, Camerer, & Nguyen, 2010; Burks et al., 2009; Benjamin, Choi, & Strickland, 2010; Ifcher & Zarghamee, 2011). Individuals were given three multiple price lists and asked to make 22 choices between a smaller reward, $X$, in period $t$ and a larger reward, $Y > X$, in period $t + \tau > t$. We keep $Y$ constant at \$50 and vary $X$ from \$49 to \$14 in three time frames. In time frame 1, $t$ is the present, $t = 0$, and $\tau$ is one month. In time frame 2, $t$ is the present, and $\tau$ is six months. In time frame 3, $t$ is six months from the study date, and $\tau$ is again one month. The order of the three time frames was randomized. Appendix A.2 provides the full set of choices.

In order to provide an incentive for truthful choice, 10% of individuals were randomly paid one of their 22 choices (for comparable methodologies and discussions, see Harrison et al., 2002). This was done with a raffle ticket, which subjects took at the end of their tax filing and indicated which choice, if any, would result in payment. To ensure credibility of the payments, we filled out money orders for the winning amounts on the spot in the presence of the participants; put them in labeled, prestamped envelopes; and sealed the envelopes. The payment was guaranteed by the Federal Reserve Bank of Boston, and individuals were informed that they could always return to the head of the VITA site (the community center director) where the experiment was run to report any problems receiving payment. Money orders were sent by mail to the winner's home address on the same day as the experiment if $t = 0$, or in one, six, or seven months, depending on the winner's choice. All payments were sent by mail to equate the transaction costs of sooner and later payments. The payment procedure therefore mimicked a front-end-delay design (Harrison et al., 2005b).[9] The details of the payment procedure of the choice experiments were kept the same in the two years and participants were fully informed about the method of payment.

The multiple price list design yields 22 individual-level decisions between smaller, sooner payments $X$ and larger, later payments $Y$. We term the series of decisions between $X$ and $Y$ a *choice profile*. Choice profiles can be compared over time at both the aggregate and individual levels. We make one restriction on admissible choice profiles: that the choices satisfy monotonicity within a price list. That is, individuals do not choose $X$ over $Y$ and $Y$ over $X'$ if $X' < X$. This restriction is equivalent to focusing on individuals with unique monotonic switch points and individuals without any switch points in each price list. Roughly 86% of our sample, or 1,446 individuals, satisfy this restriction (796 in 2007 and 650 in 2008). Of the monotonic participants in 2007, 203 again participated and were monotonic in 2008.

The level of nonmonotonicity obtained in our data compares favorably to the level obtained in other multiple price list experiments with college students, where around 10% of individuals have nonunique switch points (Holt & Laury, 2002) and is substantially below some field observations where as many as 50% of individuals exhibit nonunique switch points (Jacobson & Petrie, 2009). For nonmonotonic subjects, we are unable to have a complete record of their choices as we measure only their first switch point and whether they switched more than once. Price list analysis often either enforces a single switch point (Harrison, Lau, Rutstrom, 2005) or eliminates such observations. We begin by focusing on the 1,446 individuals who satisfy monotonicity and enforce monotonicity by taking the first switch point as the relevant choice for the remainder as a robustness test.

### C. Estimating Time Preferences

The choice profiles in our decision environment over the two years of the study allow for several different analyses of the data. In addition to comparing full choice profiles, decisions can be used to estimate intertemporal preference parameters, which can then be compared over the two years of the study. This further provides an opportunity to compare our estimated parameters with the body of parameter estimates obtained in the literature.

As the experimental design permits the identification of dynamically inconsistent preferences, we begin by positing a quasi-hyperbolic $\beta - \delta$ discounting function (Laibson, 1997; O'Donoghue & Rabin, 1999) with linear utility.[10] The parameter $\beta < 1$ represents present bias, active during $t = 0$ decisions, while $\delta$ represents pure time discounting. The quasi-hyperbolic model nests standard exponential discounting as the case where $\beta = 1$. It is important to note that the quasi-hyperbolic model is often motivated with immediate decisions and primary rewards. As such, our small front-end delay where checks are mailed at $t = 0$ may be too late to capture the effects of immediacy. The quasi-hyperbolic model is offered as a simplification of a true hyperbola. However, we provide estimations of a hyperbolic function in appendix table A1.

[9] The use of this small front-end delay, though designed to equate transaction costs, may in principle limit the amount of elicited present bias in experimental responses as no choices truly involve the present. For additional discussion, see Andreoni and Sprenger (2012).

[10] Though this linear utility formulation is chosen, we note that responses in time preference experiments may be affected by utility function curvature (Anderhub et al., 2001; Frederick et al., 2002; Andersen et al., 2008a). We do not have complementary risk experiments as in Andersen et al. (2008a) or convex budgets as in Andreoni and Sprenger (2012) to account for curvature. We do, however, ensure that our results are maintained when accounting for a survey measure of risk attitudes previously validated in a large representative sample (see section IIIE).

Under our formulation, the utility of a larger reward, $Y$, obtained in $\tau$ months when viewed from $t = 0$ is $u(Y) = \beta\delta^{\tau}Y$. The utility of some undiscounted reward, $X$, obtained at $t = 0$ is $u(X) = X$. The present bias parameter, $\beta$, plays no role in time frame 3 ($t = 6, \tau = 1$) decisions as $u(Y) = \beta\delta^{t+\tau}Y$ and $u(X) = \beta\delta^{t}X$, and the common $\beta\delta^{t}$ can be eliminated.

In order to estimate utility parameters and obtain a measure of stochastic decision error, we introduce a probabilistic choice function following Holt and Laury (2002) and Andersen et al. (2008a). Given utility values, $u(Y)$ and $u(X)$, we establish the probability that an individual chooses the larger later payment, $Y$, in any given decision between $X$ and $Y$ as

$$Pr(Choice = Y) = \frac{u(Y)^{\frac{1}{\nu}}}{u(X)^{\frac{1}{\nu}} + u(Y)^{\frac{1}{\nu}}}, \tag{1}$$

where the parameter $\nu$ measures stochastic decision error. The analysis assumes that all individuals have the same preference parameters and that all heterogeneity is assumed to come from decision error. When $\nu$ tends to 0, choices are deterministic, and when $\nu$ tends to infinity, choices are random. Given this probability function, maximum likelihood methods are easily employed to estimate present bias, $\beta$, a monthly discount factor, $\delta$, and decision error, $\nu$ (for a helpful manual on estimating utility parameters from experimental choice data, see Harrison, 2008). In addition, maximum likelihood estimates of stochastic decision error suggest an appropriate level of individual choice correlation over time. That is, if decisions are effectively random even if preferences are stable, zero intertemporal correlation should be expected. If decisions are deterministic and preferences are stable, correlation should be 1. We will come back to this benchmark when analyzing individuals' choices over time (section IIIC).

### D. *Sample*

Table 1 shows summary statistics for the 1,446 study observations with monotonic choice profiles. Column 1 shows that 2007 nonreturnees earned, on average, approximately \$16,000 per year. They were around age 37, female, African American, with less than a college education, and had around 0.5 dependents. Around 10% of participants collected unemployment at some time during the previous calendar year (and so reported for tax filing purposes). Unlike individual tax return data, which are precisely measured, participants' gender, race, and college experience were collected from an auxiliary demographic survey. A nonnegligible proportion of observations has at least one of these values missing. Missing values for the indicator variables related to gender, race, and college experience are coded as the value of the majority, and whether such values are missing is controlled for in our analysis. In addition, we use tax filing information to obtain the postal code each individual used for his or her federal tax return. We calculate the direct line distance from the center of an individual's tax filing postal code to the center of Roxbury, Massachusetts 02119, where the VITA site is located. We also note whether an individual uses a post office box as opposed to a street address for tax filing purposes.

There are 22 VITA sites around Boston, each one local to a specific neighborhood. VITA site attendee demographics are therefore similar over time. Columns 1 and 3 of table 1 show summary statistics for nonreturnee participants in 2007 and 2008 (column 6 provides $p$-values of $t$-tests for differences in means). Comparing the observable characteristics shows that individuals are slightly older, earn less, and have lower federal refund values and that slightly more participants are African American and have missing demographic information in 2008 relative to 2007. The slightly higher age, lower income, and lower refund values in 2008 are likely due to the 2008 stimulus payments, which provided \$300 rebates to older social security recipients who would normally not file taxes. Ten percent of 2008 participants were over the age of 65 compared to only 4% of 2007 participants.

### E. *Returnees*

Because the free tax preparation service is valuable, individuals return in subsequent years for further tax preparation assistance. Of the 796 study participants in 2007 with monotonic choice profiles, 203 returned to participate again in 2008 and were again monotonic in their choice profiles.[11] We created a panel for these 203 individuals, allowing us to correlate individual choice behavior over time and to observe whether changes to income, unemployment status, family composition, or future liquidity correlate with changes in measured preferences.

Table 1 reports summary statistics for returnees and examines differences in various characteristics between returnees and nonreturnees. Substantial differences between returnees and nonreturnees exist along the axes of income, age, race, education, distance, and incomplete demographic survey information. (Column 5 provides $p$-values of $t$-tests for difference in means.)

The panel of returnees is clearly a selected sample. For the purposes of this study, selective attrition would be problematic if it was correlated with the stability of time preferences. In section IIIE, we analyze selection along two dimensions: returning to the VITA site and choosing to participate. This analysis should be thought of only as suggestive. Without clear exogenous variation in any of our key determinants of attrition, we cannot firmly extrapolate from our findings out-of-sample. The findings presented here should be thought of as point estimates for the sample in question.

[11] Of the 890 participants, including those with nonmonotonic choice profiles in 2007, 250 returned and participated again in 2008. Nonreturnees did not file taxes in a VITA site in Boston ($N = 386$), filed in another VITA site in Boston ($N = 186$), or filed taxes in the Roxbury VITA site, but did not participate again in the experiment ($N = 88$).

TABLE 1.—SUMMARY STATISTICS FOR 2007 AND 2008 SAMPLES

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | 2007 | | 2008 | | *t*-Test | *t*-Test |
| | *Nonreturnees* | *Returnees* | *Nonreturnees* | *Returnees* | (1) versus (2) | (1) versus (3) |
| *A: Sociodemographics* | | | | | | |
| Adjusted Gross Income | 15,789.08 | 20,551.66 | 13,438.25 | 22,003.28 | $p < 0.01$ | $p < 0.01$ |
| | (13,638.42) | (13,977.67) | (13,978.2) | (15,708.38) | | |
| Number of dependents | 0.51 | 0.44 | 0.43 | 0.47 | $p = 0.35$ | $p = 0.14$ |
| | (0.85) | (0.74) | (0.82) | (0.79) | | |
| Age | 37.26 | 41.56 | 42.67 | 42.56 | $p < 0.01$ | $p < 0.01$ |
| | (14.9) | (14.97) | (16.74) | (14.97) | | |
| Federal refund | 1,210.29 | 1,315.93 | 907.38 | 1,389.98 | $p = 0.39$ | $p < 0.01$ |
| | (1,512.47) | (1,495.71) | (1,488.91) | (1,954.66) | | |
| Unemployment (=1) | 0.10 | 0.10 | 0.10 | 0.10 | $p = 0.76$ | $p = 0.90$ |
| | (0.30) | (0.31) | (0.30) | (0.31) | | |
| Male (=1) | 0.34 | 0.36 | 0.31 | 0.36 | $p = 0.69$ | $p = 0.26$ |
| | (0.48) | (0.48) | (0.46) | (0.48) | | |
| African American (=1) | 0.75 | 0.82 | 0.79 | 0.82 | $p < 0.10$ | $p < 0.10$ |
| | (0.43) | (0.39) | (0.4) | (0.39) | | |
| College degree (=1) | 0.10 | 0.19 | 0.09 | 0.18 | $p < 0.01$ | $p = 0.53$ |
| | (0.3) | (0.39) | (0.29) | (0.39) | | |
| Gender imputed (=1) | 0.06 | 0.01 | 0.13 | 0.01 | $p < 0.01$ | $p < 0.01$ |
| | (0.24) | (0.12) | (0.34) | (0.12) | | |
| Race Imputed (=1) | 0.07 | 0.03 | 0.12 | 0.03 | $p < 0.05$ | $p < 0.01$ |
| | (0.25) | (0.17) | (0.33) | (0.17) | | |
| Education imputed (=1) | 0.10 | 0.03 | 0.15 | 0.03 | $p < 0.01$ | $p < 0.05$ |
| | (0.3) | (0.18) | (0.36) | (0.18) | | |
| Less than 2 miles | 0.66 | 0.73 | 0.68 | 0.67 | $p < 0.10$ | $p = .569$ |
| | (0.47) | (0.45) | (0.47) | (0.47) | | |
| PO box (=1) | 0.02 | 0.01 | 0.02 | 0.02 | $p = 0.97$ | $p = 0.39$ |
| | (0.12) | (0.12) | (0.15) | (0.14) | | |
| Number of observations | 796 | | 650 | | | |
| | 593 | 203 | 447 | 203 | | |

The table shows the means of sociodemographics for individuals with admissible choice profiles. Standard deviations are in parentheses. Column 4 shows *p*-values of *t*-tests for equal means between columns 1 and 2. Column 5 shows *p*-values of *t*-tests for equal means between columns 1 and 3.

## III. Results

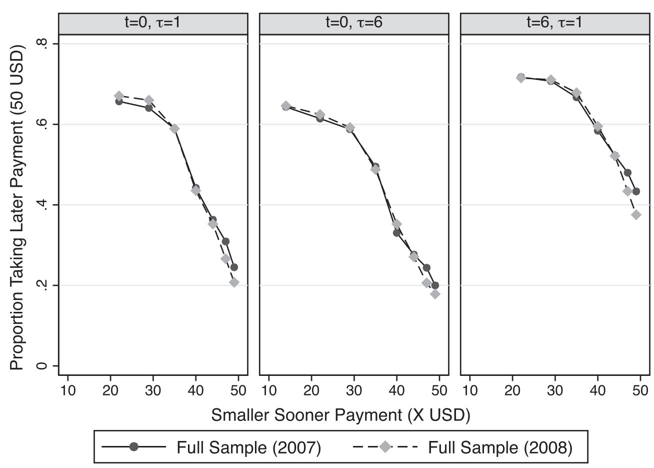
The results are presented in the following five sections. First, we analyze aggregate choice profiles over the two years of the study. Second, we present corresponding aggregate estimates of time preferences and error parameters. Third, we restrict our attention to the 203 returnees to discuss the extent to which individual choices, choice profiles, and resulting discounting calculations correlate over time. Fourth, we explore potential sources of instability. Fifth, we present robustness tests and additional analyses for selective sample attrition, individuals with nonmonotonic choice profiles, and risk attitudes.

### A. *Temporal Stability in Aggregate Choice Profiles*

When examining a group of people through time, stability in the aggregate distribution of choices is a necessary condition for the measurable stability of preferences. If the aggregate distribution of behavior is unstable, then individual preference parameters either cannot be fixed or are measured with sufficient error to make them practically unstable.

Because the sample pools are similar in the two years of the study, we examine the profile for all 1,446 study observations. Given the wide historical variation of time preference parameters obtained from different sample pools, this is a relevant avenue of exploration.

FIGURE 1.—CHOICE PROFILES THROUGH TIME




The figure shows choice profiles for the aggregate samples. For each of the different time frames (with $t$ = earlier date and $\tau$ = delay), the figure plots the proportion of the sample in 2007 and in 2008 that takes the larger, later payment for each sooner payment. The delay time, $\tau$, differs between time frames (i.e., between the panels in the figure) so does the implied monthly interest rate.

Figure 1 plots choice profiles over time for the aggregate sample. The proportion of participants choosing the larger later payment of Y = \$50 is graphed against the smaller sooner payment, X. Figure 1 illustrates several broad features of individuals' choices in the two years. First, the proportion of individuals choosing Y is decreasing in the value of

Table 2.—Temporal Stability of Preference Parameters

| | Full Sample | | Nonreturnee Sample | | Returnee Sample | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Present bias parameter: $\beta$ | 0.712 | 0.690 | 0.683 | 0.700 | 0.792 | 0.672 |
| | (0.024) | (0.047) | (0.027) | (0.050) | (0.034) | (0.090) |
| $Year_{2008}$ (=1) | −0.006 | 0.012 | −0.000 | 0.021 | −0.040 | −0.051 |
| | (0.030) | (0.038) | (0.037) | (0.041) | (0.047) | (0.064) |
| Adjusted gross income/10K | | 0.052*** | | 0.040** | | 0.079*** |
| | | (0.016) | | (0.016) | | (0.022) |
| Number of dependents | | 0.001 | | −0.009 | | 0.052 |
| | | (0.021) | | (0.021) | | (0.057) |
| Age | | −0.002** | | −0.002** | | −0.001 |
| | | (0.001) | | (0.001) | | (0.002) |
| Monthly discount factor: $\delta$ | 0.954 | 0.973 | 0.954 | 0.973 | 0.953 | 0.981 |
| | (0.004) | (0.012) | (0.006) | (0.012) | (0.006) | (0.021) |
| $Year_{2008}$ (=1) | 0.000 | 0.001 | −0.003 | −0.001 | 0.007 | 0.009 |
| | (0.007) | (0.008) | (0.008) | (0.009) | (0.010) | (0.013) |
| Adjusted gross income/10K | | 0.000 | | 0.003 | | −0.007* |
| | | (0.003) | | (0.003) | | (0.004) |
| Number of dependents | | 0.006 | | 0.005 | | 0.007 |
| | | (0.005) | | (0.006) | | (0.009) |
| Age | | −0.001** | | −0.001** | | −0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| Stochastic decision error: $\nu$ | 0.591 | 0.573 | 0.608 | 0.587 | 0.541 | 0.542 |
| | (0.032) | (0.028) | (0.039) | (0.035) | (0.050) | (0.054) |
| $Year_{2008}$ (=1) | −0.039 | −0.011 | −0.029 | 0.008 | −0.045 | −0.052 |
| | (0.043) | (0.045) | (0.051) | (0.059) | (0.069) | (0.073) |
| Number of observations | 31,812 | 31,812 | 22,880 | 22,880 | 8,932 | 8,932 |
| Number of clusters | 1,446 | 1,446 | 1,040 | 1,040 | 406 | 406 |
| Log likelihood | −20,490.403 | −20,374.52 | −14,746.98 | −14,671.31 | −5,715.49 | −5,671.04 |
| $H_0 : \gamma_{2008} = 0$ | $\chi^2(3) = 1.51$ | $\chi^2(3) = .14$ | $\chi^2(3) = 0.98$ | $\chi^2(3) = 0.38$ | $\chi^2(3) = 2.48$ | $\chi^2(3) = 1.63$ |
| | $(p = 0.68)$ | $(p = 0.99)$ | $(p = 0.81)$ | $(p = 0.95)$ | $(p = 0.48)$ | $(p = 0.65)$ |

Maximum likelihood estimates with standard errors clustered on the individual year level in parentheses. Significant at $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

X, responding to increasing interest rates. However, even at the lowest and highest values of X, the choice proportions do not reach 0 or 1, respectively. This indicates substantial heterogeneity in behavior as roughly 40% of subjects choose either all sooner payments or all later payments in a given choice set. Second, the aggregate choices show both substantial impatience and a high degree of present bias. For example, around 55% of individuals prefer \$35 today to \$50 in one month, forgoing a monthly interest rate of 43%. However, only around 40% of individuals prefer \$35 in six months to \$50 in seven months, indicating present bias. Both of these observations from our data are consistent with a body of experimental research that tends to find both a high degree of impatience and present bias in monetary discounting experiments (Frederick et al., 2002).

Third, and most important for our research question, figure 1 illustrates the similarity of the distribution of choice profiles over time. The proportion of individuals choosing the later payment, $Y$, at any given $X$ is virtually unchanged over time. Because the sample is large by experimental standards, even small differences could be uncovered. Controlling for decision fixed effects, we are unable to reject the null hypothesis of equal behavior across years ($\chi^2(1) = 0.18,\ p = 0.67$).[12]

## B. Aggregate Parameter Stability

As discussed in section IIC, choice profiles can be used to estimate intertemporal preference parameters and stochastic decision error. As motivated by Andersen et al. (2008a), the implemented maximum likelihood procedure is useful for exploring changes in estimated preference parameters over time. One can estimate the linear relationship $\hat{\beta} = \hat{\beta}_0 + \hat{\gamma}_{2008} \times Year_{2008}$ where $\hat{\beta}_0$ captures 2007 present bias and $\hat{\gamma}_{2008}$ captures the difference over the two years under the assumption of homogeneous preferences within year. The null hypothesis $H_0 : \gamma_{2008} = 0$ is easily tested. In table 2, we employ maximum likelihood methods to estimate equation (1) and recover underlying aggregate utility and decision error parameters over time.

In column 1 of table 2, we estimate present bias, $\beta$, a monthly discount factor, $\delta$, and an error parameter, $\nu$, for each year of the study with the full sample of 1,446 observations. The results in column 1 show that for 2007, we estimate $\hat{\beta} = 0.712$, (SE. = 0.024), which is close to the often suggested value of 0.7 (Laibson, Repetto, & Tobacman, 2003), even without the true immediacy of the present.[13] We also estimate a monthly $\hat{\delta} = 0.954$, (0.004), implying an annual

[12] Test statistic from logit regression with choosing the later payment, *Choice* (=1), as the dependent variable and independent variables of 22 decision fixed effects and an indicator for $Year_{2008}$ (=1). Standard errors clustered on the individual level. The test statistic corresponds to null hypothesis of 0 coefficient for $Year_{2008}$ (=1).

[13] As this may suggest, behavior outside the quasi-hyperbolic model in the appendix reformulate the maximum likelihood procedure to estimate pure hyperbolic discounting of the form $u(X,k) = \frac{X}{1+\alpha \cdot k}$. Aggregate stability in the estimated hyperbolic parameter, $\alpha$, is documented. See table A1 for detail.

discount rate of around 75%. The 2007 error parameter is estimated to be $\hat{\nu} = 0.591$ (0.032), which is higher than that obtained in the parameter estimation exercises of Holt and Laury (2002) and Andersen et al. (2008a). Importantly, all estimated parameters are virtually unchanged over the two years. All coefficients of $Year_{2008}$ are small and insignificant. We fail to reject the null hypothesis of zero effect of time ($\chi^2_3 = 1.51$, $p = 0.68$). The results therefore suggest temporal stability of time preferences.

As mentioned above, the estimated stochastic decision error from our choice data are high relative to other studies. This can be due to at least two reasons: First, prior exercises either attempt to estimate fewer parameters, such as one parameter discounting functions (Andersen et al., 2008a) or have data, albeit between subjects, from a larger number of experimental conditions (Holt & Laury, 2002). Second, and more important, behavioral heterogeneity may cause differences between our estimates and prior work. For example, in the risk preference multiple price lists of Holt and Laury (2002), less than 10% of subjects lay at the edges of the distribution of elicited preferences. As figure 1 shows, many of our choice data lie at the edges in any choice set, being either extremely patient or extremely impatient. Indeed 23.4% of our sample never chose a later payment in 22 choices, and 16.3% of our sample never chose a sooner payment in 22 choices.[14] Attempting to fit a single set of homogeneous preference parameters to such heterogeneous behavior may increase the estimated error parameter in order to allow the model to match the empirical choice probabilities. In appendix table A2, we provide two exercises exploring this issue, demonstrating the extent to which the estimates of decision error are influenced by price list censoring and behavioral heterogeneity.

Because our sample is large relative to other studies, it may be of independent interest to examine the observable heterogeneity in preference measures based on demographic differences. In column 2 of table 2, we control for several covariates that are measured with precision from individual tax returns: adjusted gross income, the number of dependents, and age.[15] Higher income correlates with significantly less present bias, and present bias and impatience appear to increase with age. Such correlations are also presented in aggregate studies of preferences such as Harrison et al. (2002) and Tanaka et al. (2010). For comparison, Tanaka et al. (2010) find that older and wealthier individuals are more patient, and Harrison et al. (2002) find that more educated individuals are more patient. Tanaka et al. (2010) show virtually no correlation between present bias and demographic characteristics.

In columns 3 through 6 of table 2 we provide aggregate estimates separated by returnees and nonreturnees. Though some differences in parameter estimates exist between these subsamples, stability in aggregate estimates over time is documented for both. For both returnees and nonreturnees, we fail to reject the null hypothesis of zero effect of time, ($\chi^2_3 = 2.48$, $p = 0.48$) and ($\chi^2_3 = 0.98$, $p = 0.81$), respectively.

The aggregate choice profiles are stable over time, and there is no impact of the year of study on measured preferences or decision error. However, a stable distribution of responses and stable parameter estimates could be obtained without individual stability. In addition, the imposition of homogeneous preferences within year (or homogeneity within demographic groups) in the estimation procedure may be a difficult-maintained assumption. In the next section, we therefore focus our attention on the returnee panel of individuals who participate in the study twice and use those individuals to examine temporal stability at the individual level.

## C. *Temporal Stability in Individual Behavior*

In this section, we focus on the sample of 203 returnees. We explore stability at the individual level by comparing choices at two times one-year apart. We examine the one-year correlation in individuals' choices, choice profiles, and resulting parameter calculations, along with a benchmark for judging the size of these correlations.

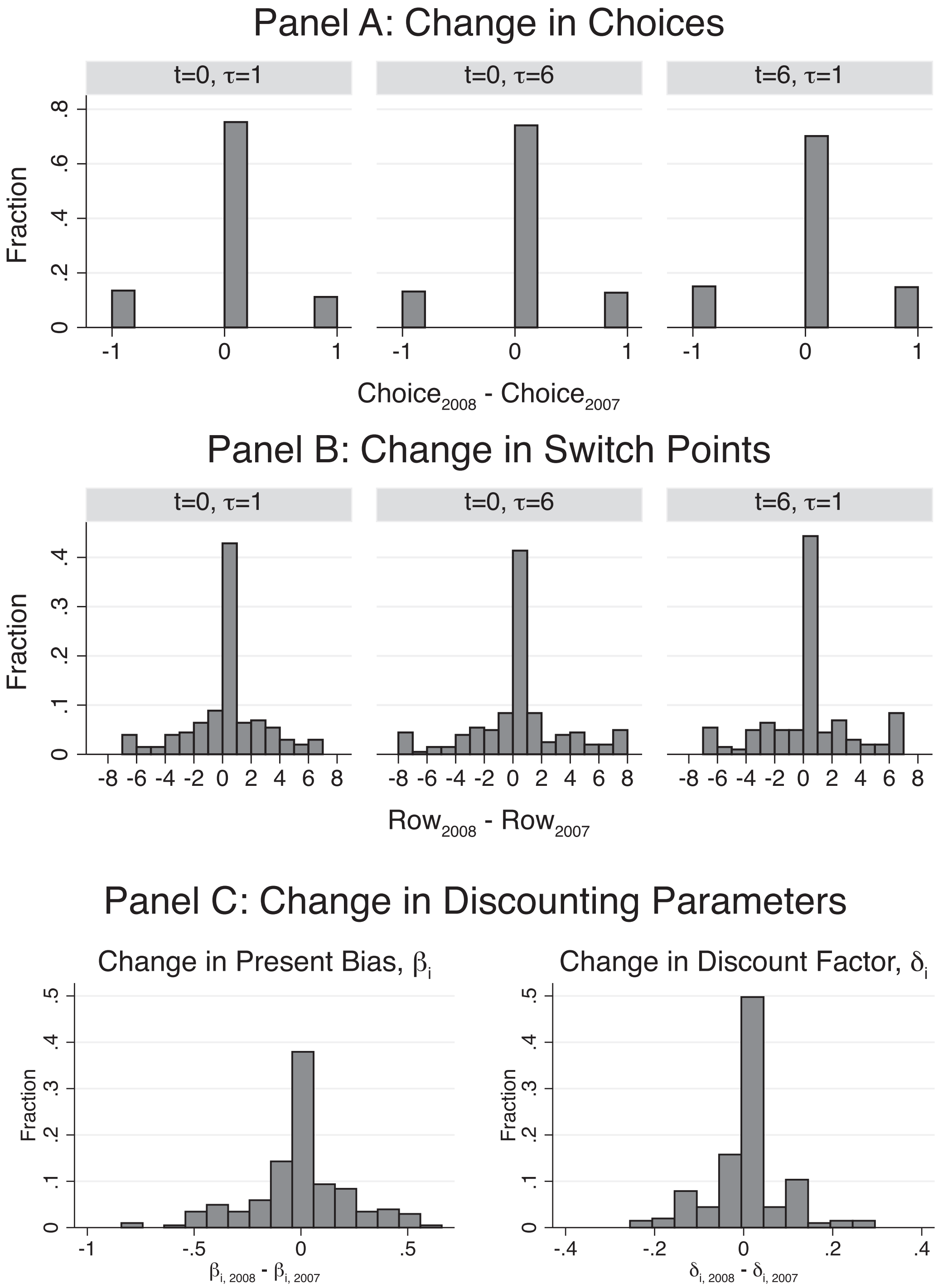
In order to explore individual stability, we first define the variables $Choice_{2007}$ and $Choice_{2008}$, which, for each of the 22 experimental decisions, take the value 1 if the later payment, $Y$, was chosen and the value 0 if the sooner payment, $X$, was chosen. Hence, $Choice_{2007}$ or $Choice_{2008}$ equal to 1 indicates a patient choice. By pairing $Choice_{2007}$ and $Choice_{2008}$, we can obtain a first impression of stability. Figure 2A presents a histogram for the difference between the two values, $Choice_{2008} - Choice_{2007}$, across our three time frames, $(t, \tau)$. The difference takes the value $1(-1)$ if in a given decision, the individual was patient (impatient) in 2008 and impatient (patient) in 2007. A difference of 0 indicates stable choice. Overall 73% of choices are stable within subject, and the raw one-year correlation between $Choice_{2007}$ and $Choice_{2008}$ is 0.464 ($p < 0.001$).

A high level of choice stability could arise without stability of time preference if experimental decisions lack the power to meaningfully distinguish between different levels of patience. For example, if subjects were asked our experimental questions and then an additional 100 repeated questions offering them either $50 at a later date or $0.01 at a sooner date, the stability at the choice level would be well above the documented 73.2%. Further, such apparent choice-level stability could occur even without stability of time preference. In our context, stability of time preference implies that individual choice profiles should be constant through time. That is,

[14] As in more straightforward methods for identifying utility parameters from price list switching points (Holt & Laury, 2002; Harrison et al., 2002), only one-sided bounds on utility parameters can be obtained for individuals who are censored by the price list. Maximum likelihood estimators focusing on such censored individuals do not converge.

[15] Further correlates from table 1 are not estimated for computational reasons as model results were found to be unstable.

FIGURE 2.—INDIVIDUAL STABILITY




The figure shows the proportion of stable and unstable choices in 2007 and 2008 for three levels of analysis: Panel A shows for each time frame $(t, \tau)$ stability of each choice of the smaller sooner payment relative to the large later payment of \$50. $Choice_{2007}$ and $Choice_{2008}$, for each of the 22 experimental decisions, take the value 1 if the later payment, $Y$, was chosen and the value 0 if the sooner payment, $X$, was chosen. Hence, $Choice_{2007}$ or $Choice_{2008}$ equal to 1 indicates a patient choice. $\text{Choice}_{2008} - Choice_{2007}$ indicates the difference between years. Panel B shows the stability of the row in the multiple price list at which an individual switches from preferring the sooner smaller payment to the later larger payment. Panel C shows the difference between calculated individual level discount factors, $\delta_i$, and presents bias parameters, $\beta_i$, between the two years.

the row at which an individual switches from preferring the sooner smaller payment to the later larger payment should be constant through time. To explore stability at this level, we define the variables $Row_{2007}$ and $Row_{2008}$, which take the value of the row at which an individual first preferred the later larger payment.[16] Figure 2B presents the histogram for the difference between the two switch points, $Row_{2008} - Row_{2007}$,

[16] This is either 1 to 7 for time frames $(t = 0, \tau = 1)$ and $(t = 6, \tau = 1)$ or 1 to 8 for the time frame $(t = 0, \tau = 6)$.

across our three time frames, $(t, \tau)$. Overall 43% of individuals exhibit identical values for $Row_{2007}$ and $Row_{2008}$ in a given time frame, and 29% of individuals exhibit identical values for $Row_{2007}$ and $Row_{2008}$ in all three time frames. The raw one-year correlation between $Row_{2007}$ and $Row_{2008}$ is 0.433 $(p < 0.001)$.

With significant correlations in hand at both the choice and choice pattern levels, we investigate individual-level intertemporal preference parameters and their stability. With a limited number of observations per person, parameter estimation of the sort conducted with the aggregate data is infeasible. However, some progress can be made with simple calculation. We maintain the assumptions of quasi-hyperbolic discounting and linear utility and consider the value of $X_{i,t,\tau}$ at which individual $i$ first switches from preferring the smaller sooner payment to the later larger payment in a time frame, $(t, \tau)$.[17] We assume that the relation

$$X_{i,t,\tau} = \beta_i^{\mathbf{1}_{t=0}} \delta_i^{\tau} Y$$

holds for each time frame and individual, where $\mathbf{1}_{t=0}$ is an indicator for the present and $\tau$ is the delay length in months. Hence, the system of equations

$$\log\left(\frac{\mathbf{X_{i,t,\tau}}}{\mathbf{Y}}\right) = \log(\beta_i) \times \mathbf{1}_{t=0} + \log(\delta_i) \times \boldsymbol{\tau}$$

is satisfied for each individual. Linear algebra provides the coefficient vector $[\log(\beta_i), \log(\delta_i)]$, which can be exponentiated to recover $\beta_i$ and $\delta_i$.[18] This simple calculation provides measures of discounting parameters summarizing the pattern of choices, which we can then compare through time. A key drawback is that we are unable to incorporate insights from stochastic decision error, effectively assuming a perfect representation of preferences in choice behavior.[19] Note that given the data limitations, we are also forced to ignore the interval nature of the data. The object of interest is whether, for a fixed definition of choice, temporal stability in calculated preference parameters is achieved.

We calculate $\beta_i$ and $\delta_i$ for each individual in the returnee sample in 2007 and 2008 to obtain $\beta_{i,2007}$, $\beta_{i,2008}$, $\delta_{i,2007}$, and $\delta_{i,2008}$.[20] Figure 2C graphs the difference between the measures through time. With regard to $\beta_i$, nearly 40% of subjects have calculated present bias parameters within 0.05 of each other in the two years (26% of subjects have identical calculated measures through time) with no clear directional trend through time. The one-year correlation between $\beta_{i,2007}$ and $\beta_{i,2008}$ is 0.364 $(p < 0.001)$. With regard to $\delta_i$, nearly 50% of subjects have calculated discount factor parameters within 0.025 of each other in the two years (30% of subjects have identical calculated measures through time) with no clear directional trend through time. The one-year correlation between $\delta_{i,2007}$ and $\delta_{i,2008}$ is 0.246 $(p < 0.001)$.

The results on the individual level show that choice, choice profiles, and parameter calculations for the same individual between years correlate significantly. However, whether such correlations are high or low very much depends on the correlation in behavior over time that one expects. While there is substantial discussion in the psychological literature as to whether the researcher's prior should be zero or perfect correlation (Bem, 1972), such issues are not often discussed in economics. The intertemporal correlations in choice, choice profiles, and parameter measures are high by standards in psychology. Behavior in similar though slightly distinct situations rarely exceeds 0.2 to 0.3 (Mischel, 1968).[21] However, the correlation is far from 1, indicating that some instability in choice does exist.

The analysis of decision error in the previous section can give us guidance as to what temporal correlation in behavior to expect under stable preferences. As $\nu$ tends to infinity, $Pr(Choice = Y)$ tends to 0.5. All choices are random coin flips, leaving predicted temporal correlations in choice behavior of 0, even under stable preferences. Conversely, as $\nu$ tends to 0, decisions are deterministic and choice behavior should be perfectly correlated if preferences are stable. Given the parameter estimates from table 2, we can generate predicted choice probabilities for the aggregate behavior, $Pr(\widehat{Choice} = Y)$. Based on these predicted choice probabilities, one can simulate choice profiles under stable preferences and obtain their predicted correlations.

We generate 5,000 replicate data sets of 200 individuals. The simulated data are created in two steps. First, we use the aggregate estimates from table 2, column1 $(\beta = 0.712,$

[17] Top and bottom coding is conducted. An individual who always prefers the later larger payment has value $X = 50$. An individual who alway prefers the sooner smaller payment is given the lowest value of $X$ in the relevant time frame, either 22 or 14.

[18] In particular, define the vectors $\mathbf{1}_{t=0} = [1\ 1\ 0]', \boldsymbol{\tau} = [1\ 6\ 1]', \log\left(\frac{\mathbf{X_{i,t,\tau}}}{\mathbf{Y}}\right) = \left[\log\left(\frac{X_{i,t=0,\tau=1}}{Y}\right), \log\left(\frac{X_{i,t=0,\tau=6}}{Y}\right), \log\left(\frac{X_{i,t=6,\tau=1}}{Y}\right)\right]'$. The coefficient vector is calculated as $[\log(\beta_i), \log(\delta_i)] = ([\mathbf{1}_{t=0}, \boldsymbol{\tau}]'[\mathbf{1}_{t=0}, \boldsymbol{\tau}])^{-1}\left([\mathbf{1}_{t=0}, \boldsymbol{\tau}]' \log\left(\frac{\mathbf{X_{i,t,\tau}}}{\mathbf{Y}}\right)\right)$. Though this is the least squares linear algebra, with only three observations per person, we view this as only a calculation and avoid discussion of asymptotics or small sample parametric assumptions.

[19] We were unable to estimate equation (1) at the individual level or achieve a tractable fixed effects estimator.

[20] The mean value of $\beta_{i,2007}$ for the returnee sample is 0.837 (SD = 0.211), while the mean value of $\beta_{i,2008}$ is 0.827 (0.208). The difference is not significant, $(t = 0.592,\ p = 0.55)$. The mean value of $\delta_{i,2007}$ for the returnee sample is 0.946 (0.066), while the mean value of $\delta_{i,2008}$ is 0.950 (0.070). The difference is not significant, $(t = 0.582,\ p = 0.56)$.

[21] Such "low" cross-situational correlations were taken as evidence against trait stability by situational psychologists. It has been shown that aggregate measures built up from various separate behaviors can yield substantially higher cross-situational correlations (for discussion and examples, see Epstein, 1979; Benz & Meier, 2008). Because our experiment is identical in the two years, this is not necessarily a good benchmark against which to measure stability. In psychological personality trait studies, the temporal correlation of the Big Five personality characteristics is found to be as high as 0.6 to 0.8 (Costa & McCrae, 1994). However, measures for such traits are generally obtained from aggregating hundreds of survey questions. Similar to single cross-situational measures, on smaller subsets or individual questions, one could expect temporal correlations in the range of 0.2 to 0.3 (Block, 1971; Jessor, 1983). These relevant studies are discussed in Costa and McCrae (1994) and Epstein (1979), who provide excellent surveys of stability studies in psychology. Both cited studies present median intertemporal correlation coefficients over a number of single personality measures and find that the majority of correlations are around or below 0.3, specifically at longer time horizons.

$\delta = 0.954$, and $\nu = 0.591$) to generate decision-level choice probabilities for each of our 22 experimental decisions. Next, choice profiles are simulated from these choice probabilities. Imagine the probability that an individual chooses $Y$ over $X$ is 0.9. We draw a number from a uniform [0, 1] distribution. If the random number falls below 0.9, the simulated choice is $Y$; otherwise, the simulated choice is $X$. Every choice for every individual is simulated twice in such a way. Then the two simulated choice profiles are correlated.

Calculating the raw correlation from these simulated data sets provides a reference distribution for comparison. Conducting this exercise with the estimates of table 2, column 1, we predict an average correlation of 0.088 (SD = 0.015). Comparing this value to the true choice level correlation of 0.464 indicates that the implemented model underpredicts the observed stability in choice. This is likely due to the broadly heterogeneous behavior leading to increased aggregate decision error estimates. Interestingly, with lower levels of decision error closer to those of Holt and Laury (2002) and Andersen et al. (2008a), we obtain simulated choice correlations closer to our empirical findings. For example, with the discounting estimates of table 2, column 1 and an imposed error parameter of 0.175 we simulate an average correlation of 0.452 (0.013), close to our observed intertemporal correlation of 0.464.[22]

Importantly, models with stochastic decision error predict nonmonotonic choice profiles with relative frequency compared to our empirical findings. In our simulations, even with the lower value of $\nu = 0.175$, generally more than 99% of simulated individuals exhibited nonmonotonic choice profiles, while in the actual data, only 14% were nonmonotonic.[23] Because of these frequent nonmonotonicities, temporal correlations for simulated values based on the row of unique switch and corresponding discounting calculations are not possible. We can, however, provide the correlation for the simulated number of patient choices in each time frame.[24] For this measure, with $\nu = 0.175$ we obtain a mean correlation of 0.573 (0.024), which compares favorably with the correlation between $Row_{2007}$ and $Row_{2008}$ of 0.433.

Together these simulations give initial guidance for judging the size of the documented temporal correlations. With stochastic decision error in the range of prior findings (though far from our estimates), under stable preferences one would predict temporal correlations close to those documented.[25] We next investigate instability and its correlates in detail.

[22] Caution must be used when comparing decision error parameters across studies because they will be sensitive to experimental stakes. Andersen et al. (2008a) use substantially higher stakes, while Holt and Laury (2002) use a range of stake sizes varying from below to above our experimental values.

[23] These individuals are considered only in robustness tests and have not been discussed previously.

[24] For a monotonic subject, this is the simulation of $Row_{2007}$ and $Row_{2008}$.

[25] Naturally, providing a foundation for judging the size of the temporal correlation based on decision error suggests fundamental unpredictability. The researcher should not be able to predict instability based on observable characteristics or changes.

### D. *Individual-Level Instability*

While there is substantial correlation between choices over time, many individuals' choices change between years. Part of this instability might be related to instability in financial situation. Given the socioeconomic status of the sample, we observe individuals with substantial changes in income, numbers of dependents, unemployment, and refund values. The median change in income was around \$1,453, or around 7% higher income in 2008 compared to 2007. Around 27% (54 of 203) experienced income increases of at least 30%. Around 17% (35 of 203) of individuals experienced income decreases of at least 30%. With respect to unemployment status, 177 of 203 show no change in unemployment, while 13% (26 of 203) either cycle on or off unemployment in equal proportions. With respect to the number of dependents, 179 of 203 show no change in the number of dependents claimed on their tax filing, 5% (10) show a decrease in dependents, and around 7% (14) show an increase in dependents. Median changes in refund values are small—around 2.4% (\$14) more in 2008 versus 2007. Around 29% (59 of 203) of individuals experienced refund increases of at least 30%, while 26% (53 of 203) experienced refund decreases of at least 30%.[26]

In table 3 we explore the extent to which demographics and changes in financial situation relate to stability in measured time preferences. Raw differences in choices, choice profiles, and parameter calculations over the two years of the study are regressed on the demographics and changes in financial situation.[27] Unemployed individuals appear in some specifications to grow more patient between 2007 and 2008, and a quadratic relationship between changes in $\delta_i$ and income appears. Beyond these correlations, insignificant relationships between behavior and both the level and changes in financial situation are found throughout.[28] The predictive power of each model is limited, with $R^2$ values ranging from 0.028 to 0.083. Even with our rich panel of socioeconomic data, we have limited ability to predict the direction and extent of instability.

### E. *Robustness Tests*

In this section, we provide three additional analyses: we include individuals with nonmonotonic choice profiles in our aggregate estimates, analyze selection issues, and discuss and control for the impact of a survey measure of risk aversion.

First, in the main part of the paper, we restrict the analysis to individuals who exhibit monotonic choice profiles. The choice to focus the analysis on such subjects was largely driven by our data recording process. We recorded only

[26] Ten percent (20 of 203) of individuals had refunds of \$0 in 2007.

[27] The level for demographics is the 2008 level, and the changes are the measured value in 2008 minus the measured value in 2007.

[28] In table A3, two complementary analyses are presented. First, we examine the absolute value of differences between the two years. Second, we examine indicators for whether behavior or parameter estimates changed between the two years. Individuals with larger refunds, smaller numbers of registered dependents, and younger individuals appear more likely to be unstable. Cycling off unemployment is associated with increased instability.

TABLE 3.—CORRELATES OF INSTABILITY

| Dependent Variable | $\text{Choice}_{2008} - \text{Choice}_{2007}$ | | $Row_{2008} - Row_{2007}$ | | $\beta_{i,2008} - \beta_{i,2007}$ | | $\delta_{i,2008} - \delta_{i,2007}$ | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Adjusted gross income/10K | 0.031 | 0.020 | 0.224 | 0.147 | 0.001 | −0.012 | 0.014* | 0.014* |
| | (0.033) | (0.032) | (0.245) | (0.240) | (0.020) | (0.021) | (0.008) | (0.008) |
| $(\text{Adjusted gross income/10K})^2$ | −0.005 | −0.005 | −0.036 | −0.035 | 0.001 | 0.001 | −0.002** | −0.002** |
| | (0.003) | (0.003) | (0.024) | (0.024) | (0.002) | (0.002) | (0.001) | (0.001) |
| Federal refund/10K | 0.007 | −0.008 | 0.054 | −0.060 | 0.051 | 0.148 | −0.014 | −0.030 |
| | (0.108) | (0.221) | (0.802) | (1.645) | (0.087) | (0.168) | (0.034) | (0.055) |
| Unemployment (=1) | 0.210*** | 0.199* | 1.539*** | 1.457* | 0.059 | 0.075 | 0.034* | 0.030 |
| | (0.080) | (0.116) | (0.591) | (0.864) | (0.056) | (0.089) | (0.018) | (0.026) |
| Number of dependents | 0.035 | 0.054 | 0.258 | 0.394 | −0.010 | −0.023 | 0.015* | 0.017* |
| | (0.035) | (0.043) | (0.263) | (0.322) | (0.019) | (0.028) | (0.008) | (0.010) |
| Age | −0.014 | −0.013 | −0.099 | −0.092 | −0.010 | −0.008 | 0.001 | 0.001 |
| | (0.011) | (0.011) | (0.084) | (0.082) | (0.007) | (0.007) | (0.003) | (0.003) |
| $\text{Age}^2$ | 0.000 | 0.000 | 0.001 | 0.001 | 0.000 | 0.000 | −0.000 | −0.000 |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| Male (=1) | 0.072 | 0.086 | 0.525 | 0.629 | 0.035 | 0.039 | 0.017 | 0.017 |
| | (0.057) | (0.062) | (0.420) | (0.458) | (0.036) | (0.039) | (0.013) | (0.014) |
| African American (=1) | 0.079 | 0.094 | 0.580 | 0.688 | −0.018 | −0.008 | 0.018 | 0.018 |
| | (0.063) | (0.066) | (0.470) | (0.487) | (0.047) | (0.047) | (0.014) | (0.015) |
| College degree (=1) | −0.062 | −0.038 | −0.458 | −0.281 | −0.037 | −0.032 | −0.004 | −0.004 |
| | (0.058) | (0.063) | (0.428) | (0.465) | (0.042) | (0.049) | (0.017) | (0.019) |
| Δ (AGI/10K) | | 0.033 | | 0.242 | | 0.033 | | −0.001 |
| | | (0.034) | | (0.250) | | (0.025) | | (0.009) |
| Δ (Federal refund/10K) | | −0.002 | | −0.017 | | −0.151 | | 0.021 |
| | | (0.228) | | (1.694) | | (0.160) | | (0.056) |
| Δ Unemployment (=1) | | 0.015 | | 0.109 | | −0.021 | | 0.007 |
| | | (0.113) | | (0.839) | | (0.076) | | (0.021) |
| Δ Number of dependents | | −0.070 | | −0.511 | | 0.015 | | −0.002 |
| | | (0.067) | | (0.497) | | (0.051) | | (0.018) |
| Constant | 0.091 | 0.064 | 0.676 | 0.474 | 0.176 | 0.136 | −0.055 | −0.054 |
| | (0.223) | (0.218) | (1.654) | (1.619) | (0.153) | (0.161) | (0.057) | (0.058) |
| Time frame $(t, \tau)$ effects | Yes | Yes | Yes | Yes | – | – | – | – |
| Additional Demographics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 4,466 | 4,466 | 609 | 609 | 203 | 203 | 203 | 203 |
| Number of clusters | 203 | 203 | 203 | 203 | – | – | – | – |
| $R^2$ | 0.031 | 0.035 | 0.047 | 0.053 | 0.028 | 0.041 | 0.082 | 0.083 |

Coefficients of OLS regressions. Standard errors are clustered on the individual level or robust standard errors in parentheses. Additional demographic variables include indicator variables for whether race, gender, or education values are imputed. Level of significance: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

the first decision, where a subject switched from preferring the sooner smaller payment to the larger later payment in each time frame and whether the subject was nonmonotonic. Though for 86% of subjects, this collection process generated no data loss, for the 14% of subjects who were nonmonotonic, we are unable to know the full profile of choices beyond their initial switch from preferring the sooner smaller payment to the later larger payment. However, with appropriate caveats about imprecision, we can impose monotonicity on these choices and use them in estimation. That is, we can construct a choice profile that respects monotonicity around a subject's first switch point.[29] Table 4 provides analysis analogous to table 2 with the inclusion of nonmonotonic subjects. Virtually identical conclusions are reached for both the entire sample and subsamples of returnees and nonreturnees.

Second, in the main part of the paper, we abstracted from the possible selection to return to the tax site and participate in our study. We examine selection along these two dimensions in table 5. Of the 890 subjects who participated in our study in 2007, 250 returned and participated again in 2008, 88 returned and filed taxes at the Roxbury VITA site but did not participate, and 552 did not return to the Roxbury VITA site. In columns 1 and 2, we analyze the potential selection to return to the Roxbury VITA site with probit regressions where the dependent variable is an indicator for returning to the Roxbury VITA site. In column 1, we show that there exist important demographic differences along the axes of income, family structure, age, and race between individuals that do and do not return. One additional important determinant of return appears to be distance: individuals who live less than 2 miles from Roxbury are significantly more likely to return.[30] In column 2, we also include individual discounting measures from 2007.[31] Though marginally significant differences are obtained for $\beta_{i,2007}$, we cannot reject the null hypothesis of equal calculated discounting parameters for

[29] A subject who prefers $49 sooner over $50 later, then $50 later over $47 sooner, then $44 sooner over $50 later is an example of a nonmonotonic choice profile. Monotonicity is imposed by reversing the final choice. Intertemporal choice experiments similar to our own often enforce such monotonicity in design by requiring only a single price list switch point in each time frame (Harrison, Lau, Rutstrom, & Williams, 2005).

[30] From a mean return rate of around 36%, living less than 2 miles from Roxbury has a marginal effect of around 10 percentage points.

[31] Note that for this analysis, monotonicity is enforced for nonmonotonic subjects in the calculation of discounting parameters.

TABLE 4.—STABILITY OF PREFERENCE PARAMETERS, INCLUDING NONMONOTONIC SUBJECTS

| | Full Sample | | Nonreturnee Sample | | Returnee Sample | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Present bias parameter: $\beta$ | 0.756 | 0.748 | 0.730 | 0.751 | 0.822 | 0.769 |
| | (0.019) | (0.069) | (0.021) | (0.055) | (0.037) | (0.082) |
| $Year_{2008}$ (=1) | 0.007 | 0.025 | 0.017 | 0.039 | −0.027 | −0.022 |
| | (0.026) | (0.045) | (0.034) | (0.045) | (0.047) | (0.101) |
| Adjusted gross income/10K | | 0.041** | | 0.037** | | 0.037 |
| | | (0.019) | | (0.014) | | (0.031) |
| Number of dependents | | 0.001 | | −0.009 | | 0.048 |
| | | (0.042) | | (0.022) | | (0.078) |
| Age | | −0.002* | | −0.002** | | −0.001 |
| | | (0.001) | | (0.001) | | (0.003) |
| Monthly discount factor: $\delta$ | 0.959 | 0.980 | 0.961 | 0.988 | 0.955 | 0.955 |
| | (0.004) | (0.018) | (0.005) | (0.012) | (0.007) | (0.019) |
| $Year_{2008}$ (=1) | 0.005 | 0.006 | 0.004 | 0.007 | 0.010 | 0.007 |
| | (0.005) | (0.011) | (0.007) | (0.009) | (0.009) | (0.020) |
| Adjusted gross income/10K | | −0.000 | | 0.001 | | 0.000 |
| | | (0.003) | | (0.002) | | (0.006) |
| Number of dependents | | 0.003 | | −0.001 | | 0.010 |
| | | (0.012) | | (0.005) | | (0.014) |
| Age | | −0.001* | | −0.001*** | | −0.000 |
| | | (0.000) | | (0.000) | | (0.001) |
| Stochastic decision error: $\nu$ | 0.569 | 0.558 | 0.580 | 0.572 | 0.542 | 0.532 |
| | (0.028) | (0.026) | (0.029) | (0.032) | (0.046) | (0.048) |
| $Year_{2008}$ (=1) | −0.051 | −0.033 | −0.037 | −0.029 | −0.072 | −0.060 |
| | (0.037) | (0.039) | (0.042) | (0.049) | (0.061) | (0.064) |
| Number of observations | 37,048 | 37,048 | 26,048 | 26,048 | 11,000 | 11,000 |
| Number of clusters | 1,684 | 1,684 | 1,184 | 1,184 | 500 | 500 |
| Log-likelihood | −23,881.27 | −23,794.12 | −16,838.89 | −16,763.37 | −7,026.53 | −6,994.03 |
| $H_0 : \gamma_{2008} = 0$ | $\chi^2(3) = 2.16$ | $\chi^2(3) = 1.68$ | $\chi^2(3) = 0.92$ | $\chi^2(3) = 1.97$ | $\chi^2(3) = 2.97$ | $\chi^2(3) = 1.02$ |
| | $(p = 0.54)$ | $(p = 0.64)$ | $(p = 0.82)$ | $(p = 0.58)$ | $(p = 0.40)$ | $(p = 0.80)$ |

Maximum likelihood estimates with standard errors clustered on the individual year level in parentheses. Level of significance: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

people who do and do not return to the Roxbury VITA site, $\chi^2(3) = 5.98,\ p = 0.11$. Once they return to the VITA site, individuals decide whether to participate again in the study. Columns 3 and 4 analyze this avenue of selection with ordinary least squares regressions where the sample is subjects who returned to the Roxbury VITA site and the dependent variable is participation.[32] Virtually no observable differences are found between returning subjects who select into and out of the 2008 experiment. In addition, in column 4, we are unable to reject the null hypothesis of equal 2007 calculated discounting parameters for people who do and do not participate in 2008, $\chi^2(3) = 2.08,\ p = 0.56$.

It is clear from this analysis that the returning sample is selected on key observable characteristics. Once they have returned, however, we have limited ability to predict participation. Important for our analysis is the possibility that individuals select on the stability, or lack thereof, of their time preferences. Though we have no particular sign of selection on time preferences, without key exogenous variation in the probability of return and participation, we cannot confidently extrapolate out-of-sample from the results. Hence, we present the current findings as being estimates of stability on the selected sample at hand and note that care should be taken when attempting to relate our observed measures of stability to other environments.

Third, recent research has discussed the extent to which risk aversion or utility function curvature influences time preference responses (Anderhub et al., 2001; Frederick et al., 2002; Andersen et al., 2008a). Though we do not have complementary risk experiments as in Andersen et al. (2008a) or convex budgets as in Andreoni and Sprenger (2012) to account for curvature, we do have access to a survey measure of risk attitudes previously validated in a large representative sample as being predictive of risky choice (Dohmen et al., 2011). Participants answer the following question on an eleven-point scale: "How willing are you to take risks in general (on a scale from 'unwilling' to 'fully prepared')?" This risk measure is itself stable in our returnee sample for 113 returnees with monotonic choice profiles who responded twice, $\rho = 0.58$. Recognizing the limitations of our hypothetical risk measure (especially that it is not able to account directly for curvature), we can analyze the impact of this measure on observed correlations in choice behavior. The raw correlation between $Choice_{2007}$ and $Choice_{2008}$ for the 113 returnees with monotonic choice profiles is 0.493 ($p < 0.001$). Accounting for changing risk survey responses does not influence the observed correlation. When accounting for the absolute value of the change in risk response, $|\Delta|$ *Risk Survey*, the partial correlation between $Choice_{2007}$ and $Choice_{2008}$ is 0.495 ($p < 0.001$).

[32] Three subjects of 338 who returned to the Roxbury VITA site in columns 3 and 4 have their attrition completely determined by whether their gender was imputed. These observations are dropped, and hence these regressions feature 335 observations.

TABLE 5.—SELECTION: RETURNING AND PARTICIPATING

| Dependent Variable: Sample: | 2008 Return to Roxbury VITA 2007 Participants | | Participate in 2008 2008 Returned to Roxbury VITA | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Adjusted gross income/10K | 0.318*** | 0.307*** | 0.188 | 0.168 |
| | (0.091) | (0.092) | (0.157) | (0.159) |
| (Adjusted gross income/10K)$^2$ | −0.038** | −0.037** | −0.026 | −0.023 |
| | (0.016) | (0.016) | (0.027) | (0.028) |
| Federal refund/10K | 0.366 | 0.388 | 0.378 | 0.471 |
| | (0.462) | (0.467) | (0.758) | (0.763) |
| Unemployment (=1) | −0.227 | −0.245 | 0.539* | 0.581* |
| | (0.155) | (0.155) | (0.310) | (0.314) |
| Number of dependents | −0.183** | −0.195** | 0.067 | 0.065 |
| | (0.086) | (0.087) | (0.157) | (0.157) |
| Age | 0.021 | 0.024 | −0.033 | −0.036 |
| | (0.019) | (0.019) | (0.029) | (0.030) |
| Age$^2$ | −0.000 | −0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Male (=1) | −0.037 | −0.000 | 0.148 | 0.139 |
| | (0.098) | (0.100) | (0.171) | (0.174) |
| African American (=1) | 0.338*** | 0.334*** | −0.187 | −0.147 |
| | (0.114) | (0.114) | (0.213) | (0.214) |
| College degree (=1) | 0.195 | 0.172 | 0.007 | 0.006 |
| | (0.140) | (0.140) | (0.206) | (0.206) |
| Distance $\leq$ 2 miles | 0.279*** | 0.290*** | −0.031 | −0.048 |
| | (0.098) | (0.099) | (0.176) | (0.178) |
| PO box (=1) | −0.284 | −0.302 | −0.506 | −0.297 |
| | (0.337) | (0.332) | (0.495) | (0.489) |
| $\delta_{i,2007}$ | | 1.116* | | −1.388 |
| | | (0.654) | | (1.195) |
| $\beta_{i,2007}$ | | 0.314 | | 0.247 |
| | | (0.204) | | (0.366) |
| Nonmonotonic (=1) | | 0.030 | | −0.137 |
| | | (0.146) | | (0.231) |
| Constant | −1.700*** | −3.095*** | 1.079* | 2.277* |
| | (0.357) | (0.765) | (0.606) | (1.353) |
| Additional demographics | Yes | Yes | Yes | Yes |
| Number of observations | 890 | 890 | 335 | 335 |
| Pseudo-$R^2$ | 0.102 | 0.108 | 0.030 | 0.038 |

Coefficients of probit regressions. Robust standard errors are in parentheses. Additional demographic variables include indicator variables for whether race, gender, or education values are imputed. Three subjects of 338 in columns 3 and 4 have their attrition completely determined by whether their gender was imputed. These observations are dropped, and hence these regressions feature 335 observations. Level of significance: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

## IV. Conclusion

Economic analysis of intertemporal decisions is predicated on the notion that time preferences are stable primitives. Though time preference stability is a standard assumption, relatively little research in economics exists on the topic, and a large related literature in psychology disputes the notion that there are stable personality traits or preferences. In a large experimental study of time preferences, we test time preference stability at both the aggregate and individual levels. Using the same incentivized, intertemporal choice experiments and the same subject pool in two years, our results show that distributions of time preference parameters are stable over time, and the one-year individual-level correlations are high by both estimates generated from our aggregate analysis and standards in psychology. However, the one-year correlations are far from perfect. Notably, instability is found to be largely independent of sociodemographics and changes to income, unemployment, family composition, and future liquidity (all taken from individuals tax returns). This suggests that though one can obtain a stable distribution and high correlations at the individual level, there remains an instability in choice, largely independent of sociodemographics and situational changes.

Finding the degree of stability in experimentally elicited time preferences, we obtain support for two broad lines of economic research, one theoretical and one experimental. Much attention has been given to the low cross-situational correlation in behavior (Ross & Nisbett, 1991) and the wide variation in time preference parameter estimates resulting from experimental methods (Frederick et al., 2002). Our results indicate that when the sample pool and methodology are rigorously controlled, experimental procedures can yield stable aggregate parameter measures. This finding provides necessary support for theoretical developments based on aggregate assumptions of stable preferences. It also helps validate the current experimental trend toward correlating experimental time preference parameter measures with real-world behaviors (Ashraf, Karlan, & Yin, 2006; Meier & Sprenger, 2010, 2012). This line of research requires that experimentally measured preferences are stable enough to be usefully correlated with extraexperimental behavior. Given that these arguments rarely include precise estimates of marginal effects, significant correlation in measured choice behavior through time indicates that the obtained relationships may be more than just point-in-time correlations.

Finding the degree of instability we obtain also has implications for future research. First, we note that the multiple price list methodology may be particularly sensitive when attempting to obtain an estimate of stochastic decision error. A more precise experimental technique for eliciting time preferences would certainly be desirable if one wished to make further study of stability. Second, our results cannot rule out that there are some people with fundamentally unstable intertemporal preferences. Identifying these individuals, attempting to understand the source of their instability, and modeling their decisions are important next steps.

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