Fickle Groups:
An Experimental Assessment of Time Preferences*

Zain Chaudhry and Karrar Hussain†

November 3, 2022

Abstract

Groups with potentially heterogeneous time preferences, in households or firms, regularly make intertemporal decisions jointly related to consumption, savings, education, and investment. While there is theoretical work on groups intertemporal preferences, it has yet to be fully empirically tested. This paper uses reduced-form and structural methods to study the empirical relationship between individual and group time preferences. Unlike previous work, (i) we measure time preferences through the allocation of costly tasks over time, not monetary methods, (ii) use randomly created groups, (iii) and know the time preferences of both groups as well as their constituent individuals. We find that groups are much more present-biased than individuals. Connecting group behavior with individual members' behavior, we find that individuals with higher present bias drive group decisions within groups. Further, we find that groups exhibit greater present bias when the difference in discount rates within-group is larger. Finally, we find that present bias in the group decisions is reduced when bargaining power in the group is less symmetric.

JEL Classification: D12, D15, C91, D81.

*We are grateful to Michael Callen, Asim Khwaja, Aprajit Mahajan and Charlie Sprenger for their advice and support. We are grateful to the Center for Economic Research Pakistan (CERP), Sohaib Athar, Zara Salman and Mehroz Alvi for excellent logistical support. We are indebted to Dr. Turab Hussain and Muhammad Hussain for championing this project. Rao Hashim and Danish Raza provided excellent research assistance. We received Institutional Review Board approvals from Harvard and UC San Diego.

†Chaudhry: Department of Economics, University of Heidelberg, zain.chaudhry@awi.uni-heidelberg.de; Hussain: Department of Economics, FAU Erlangen-Nuremberg, karrar.hussain@fau.de

1 Introduction

Intertemporal choices—decisions for which costs and benefits are spread out over time—are an important part of day-to-day decision-making for households, policy makers, and managers. They are relevant to such important areas of economic life as consumption, saving, and investment. A variety of important real-life outcomes are strongly associated with individuals' time preferences, including health status (Chabris et al. 2008, Bradford et al. 2017, Khwaja et al. 2006), educational attainment (Cadena and Keys 2015, Castillo et al. 2011), savings (Finke and Huston 2013, Laibson 1997, Beshears et al. 2008), physical exercise (DellaVigna and Malmendier 2006), labor-market earnings (Golsteyn et al., 2014), and take-up of beneficial programs, such as health screenings or financial education (Meier and Sprenger 2013, Picone et al. 2004). Because of these far-reaching effects, intertemporal choices lead not only to divergent individual-level outcomes but also differences at the macroeconomic level (Rae 1905, Sunde et al. 2022), as consumption and savings are important determinants of economic growth (Mankiw et al., 1992). Therefore, understanding intertemporal choice, using theory and data, has been a major focus of economists (Samuelson 1937, Koopmans 1960, Laibson 1997, O'Donoghue and Rabin 2001, Gul and Pesendorfer 2001, Fudenberg and Levine 2006, Jackson and Yariv 2015, Andreoni and Sprenger 2012a, Noor 2011).

A rich theoretical and empirical literature has substantially advanced our understanding of intertemporal decision-making since the early work of Samuelson (1937).[1] However, nearly the entirety of this literature focuses on individual decision-making, even though many dimensions of intertemporal choice are better modeled at the group level. For instance, educational, health, and savings decisions are typically made at the household level between partners, and allocations of budgets over time are made by finance committees within firms and legislatures. Often, such groups tend to have heterogeneous time preferences, which can lead to tension in important collective decision-making.[2] That preference heterogeneity

[1] A few seminal examples from the empirical literature, which mostly use structural models to estimate the level and shape of discounting, are Hausman (1979), Lawrance (1991), Warner and Pleeter (2001), Laibson et al. (2007), Harrison et al. (2002), Andersen et al. (2008), Andreoni and Sprenger (2012a), and Andreoni and Sprenger (2012b). The literature is reviewed in detail by Ericson and Laibson (2019) and Frederick et al. (2002).

[2] Even in the context of individual choice, one can consider the existence of multiple selves with distinct

exists within most groups is evident, for example, from the facts that women and men have different life expectancies and that age gaps in partnerships exist, which together mean that partners have different horizons . Similarly, other decision-making groups, such as committees in firms, exhibit substantial differences in gender, age, and cognitive ability. All these factors have been shown to be determinants of time preferences (Dohmen et al. 2010, Bortolotti et al. 2021, Frederick 2005, Andreoni et al. 2019), which suggests that such groups would have within-group differences in discount rates.

This paper goes beyond the assumption that groups act as a single representative agent and asks: are randomly formed groups present biased, and how do their individual members' time preferences determine their own time preferences?

To answer this question, we conduct a field experiment with 244 university students in Pakistan to measure individual- and group-level time preferences in an effort-allocation task over three weeks. We ask participants to allocate effort to the task of taking photos of a book using an app developed by the research team. The task was conducted by individuals working by themselves or as a group, where both group formation and the determination of individual or group work were random. On the first day of the experiment (Day 1), each individual made the following decisions: allocation of effort for exactly one week (Day 8) and two weeks (Day 15) later. Each decision was made for three different task rates: $R \in \{0.8, 1, 1.2\}$. A task rate of 1:0.8 , for example, would mean that every task the participant allocated to the present reduced the number of tasks allocated to the future by 0.8. The participants were asked to make the same choice a week later (Day 8) before they attempted the task for that day. The same decisions were elicited from randomly formed groups as well. Hence, we elicited the same effort-allocation decisions from every individual and group. One of the eighteen decisions made by each participant was chosen to be implemented based on a rule (explained in Section 2) about which all participants were informed.

Theoretically, time inconsistency in groups can arise simply from the aggregation of heterogeneous preferences even when individuals on their own are time consistent. Such

personalities, rather than a single homogeneous decision-making unit. Thaler and Shefrin (1981) contrast the longsighted "planner" within us to the shortsighted "doer," while Metcalfe and Mischel (1999) contrast our "hot" and "cool" systems. More recent work also models multiple selves with competing sets of interests, such as Fudenberg and Levine (2006, 2011), Brocas and Carrillo (2008a,b), and Noor and Takeoka (2022). Such evidence supports the application of collective-choice models to characterize the behavior of individuals.

inconsistency may occur because of variations in individual discount rates and innovations in the Pareto weight summarizing the collective decision-making process (Marglin 1963, Feldstein 1964, Jackson and Yariv 2015, Gollier and Zeckhauser 2005). Further, for a uniform distribution of discount rates in an otherwise-homogeneous population, maximizing group utility in a nondictatorial way generates aggregate behavior that corresponds to hyperbolic discounting (Jackson and Yariv, 2015). As a result, all else equal, it is optimal to favor impatient members of the group in early periods and patient members in later periods.

We analyze our data using both reduced-form and structural-estimation methods and document three main results.

First, using a two-limit tobit regression, we find that individuals making immediate, same-day choices allocate around 12% fewer tasks to the earlier task day than those making the same decision a week before the first task day. The corresponding figure for groups is 21%. The results suggest that the degree of time inconsistency is lower for individuals compared to groups, which is in line with previous research.

Second, we estimate a structural model. The structural estimate is close to our reduced-form result, which shows that the theoretical model under consideration is a good fit for the experimental data and corroborates the finding that groups are time inconsistent. Further, we compare individuals' and groups' decisions. While the estimate for the present-bias parameter shows the existence of present bias in effort choice for both individuals and groups, the present-bias estimate is lower for individuals compared to groups. Further, individuals' weekly discount-parameter estimate is less than groups' estimate. Hence, individuals and groups exhibit different present bias and discount factors.

Third, to better understand the connection between individual and group time preferences, we regress group-decision-estimated time-preference parameters on individual decisions in the group. Because we collect data both at the individual and group levels, we are able to use these within-group estimates of present bias. These results show that the weekly-discount-factor heterogeneity of individuals explains group present bias. We find that group present bias is mostly driven by the individual with greater present bias and that variance in the group members' discount rates and bargaining power explains group present bias. These results are in line with Jackson and Yariv's (2014) theoretical prediction that for a uniform distribution of discount rates in an otherwise-homogeneous population, group utility maximization generates aggregate behavior that corresponds to hyperbolic discounting, and if there is some fundamental heterogeneity in temporal preferences in the form of differing discount factors, then the only well-behaved collective utility functions that are both time consistent and respect unanimity are dictatorial.

Our results are important because we present both nonparametric and parametric characterizations of individual and collective intertemporal choice for the same set of participants, under experimentally controlled environments, based upon intertemporal allocations of effort.[3] We begin with an approach free of functional form using experimentally induced exogenous variation, then move to theory-based parametric analysis of time inconsistency on the individual and group levels. By adopting this approach, our subsequent parametric estimates thus result from restrictive parametric assumptions rather than from a failure of the underlying theoretical framework, which is free of functional form and related to an assessment of the degree of differences between these two kinds of decision environments. In the structural part of our empirical analysis, the preference structure associated with the discounted-utility approach is applied (without modification) to model group behavior. This is in line with the representative-agent modeling structure mostly used in macroeconomics. This unitary approach assumes the collective acts as a single decision-making unit and therefore can be treated as a rational individual.

While a few important papers have empirically tested group-level intertemporal choice (Schaner 2015, Mazzocco 2007), these papers use monetary-choice methods for measurement, study endogenously formed groups (and thus have no exogenous variation in intertemporal preferences at the group level) such as spouses, or elicit intertemporal preferences at the individual or group level but not both.

Our contribution to this literature is threefold. First, we explore intertemporal choice with a better measurement: we measure time inconsistency based on intertemporal allocation of effort (negative consumption), which has been shown to be a better method of eliciting time preference (Sprenger 2015, Cohen et al. 2020, Augenblick et al. 2015). Second, we study

[3]This occurs in the consumption-choice rather than monetary-choice domain. The monetary methods used typically confront several confounding factors in identifying and estimating the shape of time preferences, which we explain in detail later in this section.

exogenously formed groups because endogenously formed groups such as couples may self-select on time preference, risk preference, income level, and other personality traits. Further, as researchers usually collect data long after couples form, learning effects over time may have caused the individuals' preferences to become more aligned. If couples match assortitatively on the marriage market, there may also be no real differences in time preferences: the data may only show differences because of measurement error that is correlated with cognitive ability and financial literacy (Schaner, 2015). Third, we do not just measure time preferences for individuals or groups but both individuals and groups, which allows us to understand how individual behavior drives group behavior.

Finally, we use consumption-based measures of intertemporal choice because the assumptions necessary for using time-dated monetary payments to measure intertemporal choice are not always satisfied (Sprenger 2015, Cohen et al. 2020). For example, in violation of usual assumptions, participants may think of external financial decisions (that is, arbitrage opportunities outside the experiment) (Cubitt and Read 2007, Chabris et al. 2008), they may think of their external consumption choices, or they might not trust the research team enough to neglect future transaction costs and assume payment reliability.[4] Andreoni and Sprenger (2012a), Giné et al. (2018), and Andersen et al. (2008) document that when closely controlling for transaction costs and payment reliability, dynamic inconsistency in choices over monetary payments is virtually eliminated in the aggregate. All these challenges can create spurious dynamic inconsistencies as suggested by the fact that this literature has elicited an extremely wide variety of discount rates, ranging from less than 1% (Thaler 1981) to more than 1,000% (Holcomb and Nelson 1992).

The paper proceeds as follows. Section 2 presents the details of the experimental design. Section 3 provides an overview of the data we collected. Section 4 describes the reduced-form regression analysis, including two-limit-tobit and nonlinear-least-squares estimation , and Section 5 presents the structural-estimation results. Section 6 explores how individual-level preferences drive group-level preferences. Section 7 concludes.

[4]The main idea was originally raised by Thaler (1981), who, when considering the possibility of using incentivized monetary payments in intertemporal choice experiments, noted, "Real money experiments would be interesting but seem to present enormous tactical problems. (Would subjects believe they would get paid in five years?)."

2 Experimental Design

To understand dynamic inconsistency in the allocation of effort for individuals and groups, we conducted an experiment with 244 undergraduate students from different majors at Lahore University of Management Sciences (LUMS) over three weeks. LUMS is one of Pakistan's most prestigious universities and attracts the brightest from across the country (and because it boasts large, targeted programs for low-income families, it is not restricted to students from high-income families).

The research team asked participants to allocate effort on one kind of task in the real world with monetary incentives as an individual and as part of a (randomly chosen) group of two. On the first day of the experiment, each individual as well as each separately group made the following decisions: allocation of effort on Day 8 (exactly one week later) and allocation of effort on Day 15 (exactly two weeks later). The same choices were made one week later, on Day 8, but before the participants were supposed to perform the task. Each decision was made with three different task rates. One of the eighteen allocation decisions was randomly chosen for each participant based on a rule explained below, and they were given a monetary reward of $15 if the work was completed and $0 otherwise.

Timeline: On the first day of the experiment, Day 1, we gave participants detailed instructions on how the experiment would work. We told them that they would make decisions about effort allocation that day (Day 1) to undertake the task exactly one (Day 8) and two weeks (Day 15) later, and make the same decisions again exactly one week later (but before the task was set to be performed). They would make these decisions, as individuals and as groups, in sessions with the research team present. Whether a participant first made a decision as an individual or a group was randomized to avoid potential ordering effects.

During all the training sessions, the research team ensured that participants within each group exchanged their email addresses and phone numbers.

Effort Allocations: To further motivate the intertemporal trade-off, an additional factor in the decision-making was the task rate. The decisions were made using the Convex Time Budget methodology proposed by Andreoni and Sprenger (2012a). The allocations were made in a mobile application with slider bars, where every slider bar corresponded to a specific task rate, to make it easy to visualize the decision (see Figure 1). We offered three task rates, $R \in \{0.8, 1, 1.2\}$, and a decision had to be made for each one. A task rate of 1:0.8 means that every task the participant allocated to the present (v_1) reduced the number of tasks allocated to the future (v_2) by 0.8. For ease of understanding, the task rates were always represented as $1 : R$, and the participants were fully informed of the value of $R \in \{0.8, 1, 1.2\}$ when making their decisions. Output exceeding v_1 targets on the first day was not transferable to v_2 . The participant's decision can be formulated as allocating tasks $(v_1, v_2) = f(R, V)$ over time, subject to the present-value budget constraint. v_1 and v_2 satisfy the intertemporal budget constraint:

$$v_1 + R \cdot v_2 = V.$$

In Figure 1, we show an image of the (translated) main page of the application (the original Urdu version is shown in Appendix Figure /ref).

To avoid corner solutions in allocation decisions, when an individual or a group decided to allocate all their tasks either to Day 8 or Day 15, the application automatically restricted the minimum number of pictures for the Day 8 task to twelve. With this limit, we observed corner-solution allocation decisions extremely rarely: only in 2.50% of the total 2,196 allocation decisions was $v_1 = 12$. Toward the end of the Day 8 session, all participants were informed which allocation had been (randomly) selected for them out of the eighteen total decisions that they recorded during the experiment. We explained to them at the outset how this decision would be selected. We called the selected decision the "decision that counts." On Day 1, two hours after the allocation-decision session, participants were asked to complete their "decision that counts" allocations in the specified period (21:30 to 22:30 Pakistan Standard Time).

Such intertemporal bonus contracts can be used to investigate intertemporal preferences. The allocations participants make, (v_1, v_2), convey information on their discount rates. Additional experimental variation permits us to identify an important behavioral aspect of intertemporal choice: the existence of present-biased preferences.

When participants made decisions on Day 8, we did not remind them of the Day 1 allocations. Importantly, on Day 1, participants were making decisions involving two future work dates (one and two weeks later), whereas on Day 8, they were making decisions for the same day and the week after. On Day 1, before any decisions were made, participants were told how allocations for the two future dates would function and that only one of the allocation decisions made by them would eventually be chosen for them to implement.

Tasks: The task was to take clear, legible pictures of any book of the participants' choice in one specific hour (21:30 to 22:30 Pakistan Standard Time), using the mobile application provided by the research team, and to upload the pictures to a server (all pictures were automatically geotagged and timestamped). To avoid sample-selection issues, we provided mobile phones and internet packages to all participants and taught them how to use the application and upload the data. The evening time was chosen to ensure that nobody had classes, family obligations, or religious obligations. This equalized outside options that could otherwise have contaminated the purity of the intertemporal choices. A complete practice run was conducted to ensure that everyone understood how the application worked. The target for the task was two hundred pages ($V = 200$) in the individual setting and four hundred pages ($V = 400$) in the group setting. If the page in a picture were not legible, the picture would not be counted as a completed task.

Recruitment, Selection, and Attrition: Two hundred forty-four students at LUMS took part in the experiment. The participants did not receive a show up fee but only a completion fee of $15 if all tasks were accomplished according to their selected allocation.

The Allocation That Counts: Participants were informed that three factors determined which allocation out of the eighteen they made would randomly be chosen for them to implement. First, the allocated task could be either from a Day 1 or a Day 8 decision according to 20% and 80% probabilities, respectively. Second, the allocated task could either be an individual or a group task according to 33% and 66% probabilities, respectively. Third, the allocated task could be from one of the three task rates, $R \in \{0.8, 1, 1.2\}$, which were all equally likely. This randomization process, which is follows Augenblick et al. (2015), ensured the incentive-compatibility constraint was satisfied for all decisions. The design choice to ensure that participants had a 20% chance of receiving a preference schedule of the v_1 and v_2 targets from Day 1 was made to allow and intimate to them that they potentially exhibited

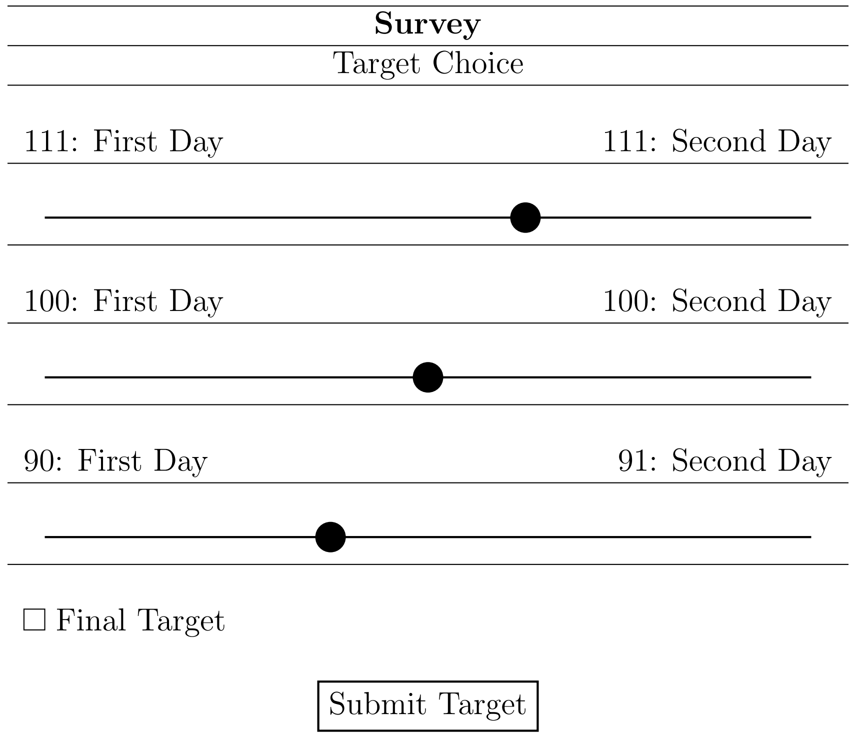

Figure 1: Slider Bar for Task Allocations

Notes: The above slider bars, a translation of the original app in Urud, show the individual task allocation decisions over the two weeks, i.e., $V = 200$. The blue letters in translate (literally) to "set target". The next lines (from left to right) translate to "First day: 111; Second day: 111" for slider bar 0.8, "First day: 100; Second day: 100" for slider bar 1, and "First day: 90; Second day: 90" for slider bar 1.2. The text next to the box translates to "finalize target" and the black letters on the bar translate to "set target".

present-bias.

Monetary Reward: The monetary reward was based on individual or group performance depending on which allocation decision was randomly chosen for each individual. The reward was $15 for completing the task in line with the (randomly chosen) allocation decision. Any deviation, even of one page, meant the task would be deemed incomplete and carry no reward. In the group task, the reward was a total of $30, equally split between the two group members irrespective of their contribution to the task. No instructions were given about how to divide the work for the group task.

3 Data and Measurement

During the first session (Day 1), we collected data on a variety of participant characteristics. We collected demographic and educational information such as age, ethnicity, major, part-time employment status, family income, whether they had a savings account, used study plans, and knew their paired partner. Following Callen et al. (2015), we collected data on personality using a modified Big Five survey (Barrick and Mount 1991, Van der Linden et al. 2010, John et al. 2008)[5] and survey-based trust in strangers . The Big Five survey consisted of sixty questions and was developed in Urdu and validated for use in Pakistan by the National Institute of Psychology at Quaid-i-Azam University, Islamabad, Pakistan.

Table 1: Summary Statistics

	# of Obs	Mean	Standard Deviation	Minimum	Maximum
Demographic					
Age	244	20.32	1.75	17	27
Male	244	0.61	0.48	0	1
No on-campus job	244	0.91	0.28	0	1
No savings account	244	0.73	0.44	0	1
No savings account	244	0.62	0.48	0	1
Group-mate acquaintance index	244	3.04	1.28	1	5
Acquaintance time duration (months)	244	13.84	21.56	0	60
Big Five Survey					
Openness	212	3.30	0.45	2.17	4.42
Conscientiousness	212	3.43	0.52	1.75	4.92
Extroversion	212	3.25	0.33	2.16	4.44
Agreeableness	212	3.44	0.46	2.33	4.58
Neuroticism	212	2.82	0.57	1.25	4.67

Notes: This table reports summary statistics for our respondent population. We have a full sample of 244 students, though some students were not able to fill the Big Five survey. The group mate acquaintance index is. We use a 60-question Big Five survey developed in Urdu and validated for use in Pakistan by the National Institute of Psychology at Quaid-i-Azam University, Islamabad, Pakistan. Its variables were recorded on a 1-5 Likert scale.

We describe our sample of participants in Table 1. The mean participant age was 20.3 years, and 39% of the sample were women. Sixty-two percent had no access to a formal savings account at the time of the experiment, but 73 percent had access sometime in the past. This is relevant because the behavioral-economics literature has used savings accounts to predict the degree of patience or present bias. As explained above, individuals were randomly paired together. The mean of the group-mate acquaintance index indicates that

[5]The Big Five personality traits, according to the Five Factor Model, are five dimensions of human personality that were designed to be descriptive and non-overlapping. These traits are agreeableness, emotional stability, extroversion, conscientiousness, and openness.

individual members knew each other at the start of the study (the index ranges from zero - just met - to five years of acquaintance). The mean time duration of acquaintance is around thirteen months. In the structural analysis, we explicitly control for the duration of acquaintance. In this experiment, this variable tries to capture the effect of group dynamics such as coordination externalities at the stage of intertemporal task allocation.

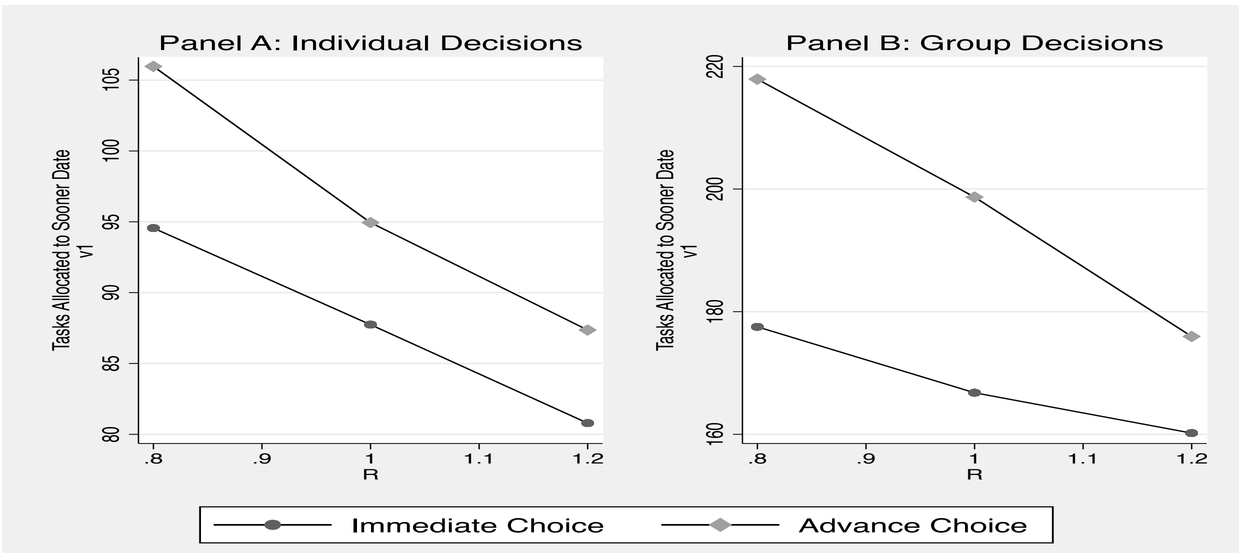

Figure 2: Discounting Behavior

Notes: Mean behavior in Individual and Group task allocated to sooner date combined.

4 Results: Reduced Form

In this section, we present a reduced-form analysis to test whether individuals and groups are time consistent. We run a two-limit tobit regression to analyze the effect on time preferences based on all the experimental variation. The advantage of reduced-form analysis is that we do not have to make any assumptions about the functional form of time preferences.

In Table 2, our outcome variable is the natural log of v_1 (task allocation for Day 8). In all our regressions, we control for the experimentally induced variations in R by including its natural log. As we set a minimum of twelve tasks to avoid corner solutions in allocation decisions, we use a two-limit tobit regression, which corrects for censoring (Wooldridge, 2002).

Table 2: Two-Limit Tobit Regression Analysis

Dependent variable:	Log of Tasks Allocated to the 1st Day			
	(1)	(2)	(3)	(4)
β_1 : Log Task Rate	-0.46***	-0.46***	-0.46***	-0.46***
	(0.08)	(0.08)	(0.08)	(0.08)
β_2 : Immediate Decision	-0.15***	-0.21***	-0.14*	-0.20**
	(0.04)	(0.05)	(0.07)	(0.08)
β_3 : Individual Decision		-0.75***		-0.75***
		(0.02)		(0.02)
β_4 : Immediate Individual Decision		0.09**		0.09**
		(0.04)		(0.04)
β_5 : Individual Decision First			-0.04	-0.04
			(0.06)	(0.06)
β_6 : Immediate Individual Decision First			-0.02	-0.02
			(0.08)	(0.08)
β_0 : Constant	4.70***	5.20***	4.72***	5.23***
	(0.03)	(0.03)	(0.04)	(0.04)
# of Obs	2196	2196	2196	2196
# of Groups	122	122	122	122
F-stats	23.68	326.64	13.36	219.78
Hypothesis (*p-values*)				
$H_0 : \beta_2 = 1$	0.00			
$H_0 : \beta_2 + \beta_4 = 1$		0.00		
$H_0 : \beta_2 + \beta_6 = 1$			0.00	
$H_0 : \beta_2 + \beta_4 + \beta_6 = 1$				0.00

Notes: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The table presents the effect of Immediate Decision and its interactions with other experimentally induced variations using the Two-Limit Tobit Regression technique. The first presents results with aggregated decisions. The second column captures the estimates of the Immediate Decision for the groups and individuals separately. The third column shows results of the effect of decision ordering and its interaction with Immediate Decision. The fourth column includes all previous variables. We cluster standard errors at the group level.

In column (1), we regress v_1 on a dummy variable, *Immediate Decision*, which takes the value of 1 when the allocation decision is immediate, i.e. an allocation made on Day 8 for tasks to be performed that very day. Here we combine both individual and group decisions (also illustrated in Figure 2). We show that participants allocate significantly fewer tasks to v_1 when R increases and when the allocation decision is immediate. This means that when the task rate is high (that is, it is more expensive to complete earlier tasks), participants allocate fewer tasks to earlier periods compared to when the task rate is low. This shows that our participants understand the trade-offs involved and make rational choices. Further, we find that on average 15% fewer tasks are chosen on the first day of task completion (Day 8).

In the second column, we add a dummy for decisions made by individuals only and a dummy where we interact *Individual Decision* with the *Immediate Decision* dummy variable.

We find that individual participants making immediate choices allocate around 12% fewer tasks to v_1 than those making the same decision a week before the first day of task completion. The corresponding figure for groups is 21%. This shows that that time inconsistency is lower for individuals compared to groups as the *Immediate Decision* dummy estimate interacted with the *Individual Decision* dummy increases by 9%. The estimate for *Individual Decision* is negative because of the variation between individuals and their groups in the total number of tasks over the two-week period (the total number of tasks is two hundred and four hundred in for individuals and groups respectively). The negative estimate signifies that participants allocate fewer tasks to earlier dates as individuals than as a group.

These findings differ from recent findings (for example, Carbone and Infante 2015; Denant-Boemont and Loheac 2011) that groups are less present biased and more time consistent compared to individuals. We attribute this difference to three factors we explained earlier. First, these studies use monetary methods to elicit time preferences, which, as noted earlier, are imperfect measures of time preference because many variables confound identification of the shape of time preferences (Sprenger 2015; Cohen et al. 2020; Augenblick et al. 2015). Second, these studies conduct the experiments with couples, which are endogenously formed groups, unlike our exogenous groups. Third, group present-bias estimates could be higher than individual estimates (for exactly the same people) because of the underlying bonus structure. Since our tasks are relatively easy to perform and are perfect substitutes, the coordination externality may be an important factor. Later, we explore these issues in more detail by putting some theoretical structure on the estimates.

Finally, in the third column, we analyze the effect of the order in which task-allocation decisions are taken. The order does not have any significant effect on behavior in either the individual or group setting. The estimates of the *Individual Decision First* dummy and its interaction with the *Immediate Decision* dummy are statistically insignificant. This, along with the nonchanging *Immediate Decision* estimate and its interaction with the *Individual Decision* dummy estimates in the last column, indicates the robustness of our finding. In the appendix, we also provide results controlling for demographic variables and show that all our results qualitatively remain the same.

5 Results: Structural Analysis

5.1 Nonlinear Regression Analysis

Next, we use a structural model to estimate time-preference parameters. We assume quasi-hyperbolic discounting, with subjects allocating effort for a task to an earlier date, v_1, or a later date, v_2. Under the assumptions that the cost-of-effort function is quadratic and that individuals and groups discount the future quasi-hyperbolically (Laibson 1997, O'Donoghue and Rabin 1999), the participants' preferences can be written as follows:

$$b_1 v_1^2 + \beta^{\mathbf{1}_{d=1}} \delta^k \ b_2 v_2^2$$

Normalizing $b_2 = 1$ and therefore dividing the intertemporal effort-cost function by b_2 (to remove scaling effects), the above cost function can be rewritten as follows:

$$\gamma v_1^2 + \beta^{\mathbf{1}_{d=1}} \delta^k \ v_2^2$$

Here, v represents a task performed on a given day (either an earlier or later day), $\gamma > 0$ and $\gamma = 1$ imply that the effort-cost function is stationary over time, and k captures delay length, which in this experiment was fixed at seven days (the gaps between first decision and first task day and between first task day and second task day). The indicator $\mathbf{1}_{d=1}$ captures whether the decision is made immediately or in advance of the first day of task performance. The parameters β and δ encapsulate individual or group discounting, with β capturing the degree of present bias, active for participants who make immediate decisions; that is, $\mathbf{1}_{d=1} = 1$. If $\beta = 1$, the model nests exponential discounting with the discount factor δ, while if $\beta < 1$ the decision-maker exhibits present bias, being less patient in immediate decisions than advance decisions.

When modeling group decisions, we assume the group members are characterized by individual preferences and that the group acts as a decision-maker, similar to an individual, whose time-preference parameters can be measured independently of its members' preferences. This modeling technique is in line with the representative-agent setup mostly used in macroeconomic modeling. This unitary approach assumes that the collective acts as a single decision-making unit and therefore can be treated as a rational individual.

Minimizing discounted costs subject to an intertemporal budget constraint yields the following intertemporal Euler equation:

$$\gamma v_1^* R = \beta^{\mathbf{1}_{d=1}} \delta^k v_2^* \tag{1}$$

Here v_1^* and v_2^* are the optimal tasks performed on Day 1 and Day 8. This tangency condition implies that when individual or group preferences are dynamically consistent, the optimal $(\frac{v_1^*}{v_2^*})$ does not depend on the parameter $\beta^{\mathbf{1}_{d=1}}$ but only depends on the task rate R and the delay length k. Using the Euler equation with the intertemporal budget constraint and rearranging the equations yields the solution function for the optimal v_1^*:

$$v_1^* = \left(\frac{\beta^{\mathbf{1}_{d=1}} \delta^k V}{\gamma R^2 + \beta^{\mathbf{1}_{d=1}} \delta^k} \right)$$

and

$$\boldsymbol{v_1^*} = \begin{cases} \left(\frac{\beta^{\mathbf{1}_{d=1}} \delta^k V}{\gamma R^2 + \beta^{\mathbf{1}_{d=1}} \delta^k} \right) & d = 1 \\ \left(\frac{\delta^k V}{\gamma R^2 + \delta^k} \right) & d = 0. \end{cases}$$

The above equation implies that v_1^* is a nonlinear function of R, $\mathbf{1}_{d=1}$, k, and V.[6] If we assume that allocation decisions satisfy the above equation subject to an additive error term, ϵ, we arrive at the nonlinear regression equation:

$$v_{1it}^* = f(V, R_{it}, \mathbf{1}_{d=1}, k) + \epsilon_{it}. \tag{2}$$

The parameters β (present bias), δ (discount factor), and γ (curvature-of-cost function) can be estimated using a nonlinear-least-squares estimation at the individual or group level (see Appendix 8 for details). We present these estimates in Table 3. Throughout, we cluster standard errors at the group level.

In the first column, we pool all decisions together and show combined results. We show

[6]For this class of effort-cost function, both relative risk aversion and intertemporal elasticity of substitution are functions of v.

that our main parameter of interest, β, the present bias in effort provision, is 0.78 in the aggregate ($s.e. = 0.05$), which means that participants are not time consistent. This estimate is close to the reduced-form result of Table 2, which shows that the theoretical model under consideration is a good fit for the experimental data. The weekly discount factor, δ, averages around 0.98. Finally, we find that for the cost-parameters ratio, γ, we cannot reject the null hypothesis of a stationary cost-of-effort function; that is, the intertemporal effort-cost function is stationary over time.

Table 3: Non-Linear Least Squares Analysis

Dependent Variable:		v_{1it}^*			
Combined		*Ind. Vs. Group*		*Decision Order*	
$\beta_{Combined}$	0.78***	β_{Ind}	0.82***	$\beta_{IndFirst}$	0.77***
	(0.05)		(0.06)		(0.05)
$\delta_{Combined}$	0.98***	δ_{Ind}	0.96***	$\delta_{IndFirst}$	0.98***
	(0.04)		(0.03)		(0.06)
$\gamma_{Combined}$	1.07***	γ_{Ind}	1.00***	$\gamma_{IndFirst}$	1.17***
	(0.23)		(0.22)		(0.39)
		β_{Group}	0.71***	$\beta_{IndSecond}$	0.0.79***
			(0.06)		(0.10)
		δ_{Group}	1.01***	$\delta_{IndSecond}$	0.95***
			(0.04)		(0.03)
		γ_{Group}	1.23***	$\gamma_{IndSecond}$	0.85***
			(0.29)		(0.19)
# Observations	2196	# Observations	2196	# Observations	2196
# Groups	122	# Groups	122	# Groups	122
RMSE	0.54	RMSE	0.54	RMSE	0.54
Hypothesis					
$\beta_c = 1$, *p-value*:	0.00	$\beta_I = 1$, *p-value*:	0.00	$\beta_{IF} = 1$, *p-value*:	0.00
$\delta_c = 1$, *p-value*:	0.48	$\beta_G = 1$, *p-value*:	0.00	$\beta_{IS} = 1$, *p-value*:	0.03
$\gamma_c = 1$, *p-value*:	0.76	$\beta_I = \beta_G$, *p-value*:	0.03	$\beta_{IF} = \beta_{IS}$, *p-value*:	0.91

Notes: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The table presents structural estimates of intertemporal hyperbolic discounting model using non-linear least squares estimation. The dependent variable is the amount of optimal tasks performed on Day 8 or Day 15 of the experiment. The first column presents combined individual and group decision estimates for β, δ, and γ. The second column presents the structural estimates of the model for the individuals and groups separately. The third column presents the structural estimates based on the effect of decision ordering (either individual allocation decision taken first or second). We use cluster standard errors at the group level.

In the second column, we compare individuals' decisions and groups' decisions. The estimate for the present-bias parameter shows present bias in effort choice exists for both individuals and groups (which confirms our reduced-form results). However, the present-bias estimate is lower for individuals compared to groups. Further, individuals' weekly discount parameter is less than the groups' parameter estimate. Comparing the individual parameter estimate of present bias with the corresponding group estimate, the null-hypothesis test of

$\beta_I = \beta_G$ is rejected, as is the $\delta_I = \delta_G$ hypothesis. Hence, individuals and groups do indeed exhibit different present bias and discount factors. These results are similar to those of our nonparametric-analysis, in which the degree of time inconsistency is, on average, greater in group decisions compared to individual decisions but, at the same time, groups are more patient than individuals. The discount-factor estimates and their individual-versus-group differences are consistent with Milch et al. (2009), who find that participants discount more as individual decision-makers than they do as members of groups. The finding that groups are more patient also shows that the discount factors for groups are in line with market interest rates, unlike the discount factor for individuals.

Finally, comparing the cost-parameter estimates between individuals and groups, we observe that the estimate of γ is higher for groups compared to individuals, but $\gamma_I - \gamma_G$ has a coefficient of -0.23 with a p-value of 0.13, which indicates that the difference is not statistically significant. The individual decisions' estimated cost-parameters ratio $\gamma_I = 1.00$ ($s.e. = 0.21$). The null hypothesis of a stationary cost-of-effort function cannot be rejected, since the $\chi^2(1)$ test has a p-value of 0.99. For groups' estimated cost-parameters ratio $\gamma_G = 1.23$ ($s.e. = 0.29$), under the null hypothesis, groups' stationary cost-of-effort function also cannot be rejected, since the $\chi^2(1)$ test has a p-value of 0.43. These results indicate that the underlying cost-of-effort functions for both individuals and groups are stationary over time and are statistically not different from each other.

In the third column, the time-preference parameters are estimated for an ordering effect using the full sample of decisions; that is, we test whether making an individual decision first or second makes any difference. While the coefficients of *Individual Decision First* and *Group Decision First* differ, the difference is statistically insignificant. The same holds true for the discount factor. Hence, we find no support for ordering effects. These results also confirm results from the nonparametric reduced-form estimation shown in Table 2.

6 Channels: Individuals vs. Groups

The results above lead to two obvious questions. First, what structural channels explain the connection between groups' greater present bias and their members? Second, could any confounding variables help explain groups' present bias? These questions are important for assessing the empirical validity of our theory and understanding what drives group decisions and dynamics. In this section, we present a theoretical model that connects groups' decision-making process to their members.

A natural assumption in many settings is that group members are heterogeneous, for example, households or committees comprise different types of agents. Given our finding that groups are more present biased than their members, we model group decisions based on individual decisions with the aim of connecting the individual decisions with the group-allocation decisions we observed.

6.1 Theory: Collective Decision Functions

We start by introducing a collective cost-of-effort function, which can be thought of as a planner's cost-of-effort function for a group. Examples include taking a weighted average of agents' cost-of-effort functions ($F[C](v) = \sum_i \omega_i C_i(v)$), where C is the cost function and v is the amount of effort provided. This is a utilitarian approach. A Rawlsian approach might consider the minimum of agents' cost-of-effort provision ($F[C](v) = min_i C_i(v)$).

In this experiment, we know $C = (\delta_1, \beta_1, \gamma_1; ..; \delta_n, \beta_n, \gamma_n)$. Thus, we consider an important class of collective cost-of-effort functions: those that are time separable. This class of functions exhibits a particular sort of time inconsistency or intransitivity[7]—namely, present bias — which matches our empirical evidence (Jackson and Yariv, 2015).

As postulated by Jackson and Yariv (2015), given that all the participants in the experiment are time consistent for any profile $(\delta_1, \gamma_1; ..; \delta_n, \gamma_n) \in C^n$, a time-separable group cost-of-effort function takes the form:

$$F[\delta_1, \gamma_1, ; ...\delta_n, \gamma_n](v) = \sum_t \tilde{\delta}_t C(v_t),$$

such that $\tilde{\delta}_t = \sum_i \omega_i \delta_i^t$. Such time-separable collective functions are standard in the literature. The standard utilitarian aggregation of individual utilities (or one that puts

[7]The intransitivity here is quite different from Condorcet's (1785) description of the voting paradox and Arrow's impossibility theorem (1963) because our collective-decision structure is quite different from the voting settings mentioned in these papers.

different weights on different individuals) is a special case. According to Jackson and Yariv (2015), for any profile $(\delta_1, \gamma_1; ..; \delta_n, \gamma_n) \in C^n$ such that for some k, j, $\delta_k \neq \delta_k$, a collective function of the form

$$F[\delta_1, \gamma_1, ; ...\delta_n, \gamma_n](v) = \sum_t \tilde{\delta}_t C(v_t),$$

such that $\tilde{\delta}_t = \sum_i \omega_i \delta_i^t$ for each t, and so

$$F[\delta_1, \gamma_1, ; ...\delta_n, \gamma_n](v) = \sum_i \omega_i C_i(v).$$

F is either dictatorial or present biased.[8] Before making group decisions, every participant in the experiment was asked to make unanimous decisions in the group since the bonus share was fixed for each group member. Therefore, the collective discount factor must be a weighted sum of the participants, and so it must correspond to a weighted utilitarian collective cost-of-effort function.

The proposition encompasses many formulations of time-inconsistent preferences. In our structural analysis, we assumed a quasi-hyperbolic formulation, which in this case corresponds to $\tilde{\delta}_1 = 1$ and $\tilde{\delta}_t = \beta\delta^{t-1}$ for all $t > 1$. As long as behavior has a separable structure and satisfies unanimity, the proposition shows that present bias is to be expected.

Using this proposition, a set of testable hypotheses can be generated. We use groups' time-preference estimates (specifically focusing on groups' present bias related to the present-bias estimate) and their members' structural estimates (including estimates of the discount-rate, present-bias, and effort-cost parameters) to empirically test the effects of theory-based heterogeneities on group present bias. These within-group heterogeneities include the differences in individual members' (i) discount factors, (ii) parameters governing the cost of effort, and (iii) bargaining position in the group.

For this last step, we have to mode bargaining power. In a utilitarian formulation, group decisions depend on the preferences of their members and the relative strengths of the members' weights in the group decisions, captured by Pareto (or bargaining) weights. A bargaining mechanism was introduced into empirical models of the group decision-making

[8] For detailed proofs, see Jackson and Yariv (2014) and Jackson and Yariv (2015).

process (Manser and Brown (1980), McElroy and Horney (1981)). Further, researchers have developed collective models, which assume that groups can achieve efficient decisions (Chiappori 1992; Browning and Chiappori 1998). Following Browning and Chiappori (1998), a group's intertemporal effort-cost function can be expressed as:

$$C_G = \omega_i C_i + \omega_j C_j.$$

where

$$\omega_i + \omega_j = 1. \ \ and \ \ (\omega_i, \omega_j) \geqslant 0.$$

These restrictions satisfy the unanimity condition in the group/collective decision-making process:

$$C_l = \ \gamma_l v_{1l}^2 + {\beta_l}^{\mathbf{1}_{d=1}} {\delta_l}^k \ v_{2l}^2 \quad and \quad l = \{G, i, j\}.$$

Here C_G is the group's intertemporal effort-cost function, C_i and C_j represent the intertemporal effort-cost function of members i and j, respectively, and ω_i and ω_j denote the bargaining power of members i and j, respectively, which measures how individual preferences are aggregated into groups' joint decisions. In our experimental setting, since we observe both individual and group decisions, we can estimate the extent to which each member influences a group's decisions. Using a multinomial logit model, we estimate ω_i and ω_j by running the following regression equation for each group :

$$v_{1G_p} = \omega_i v_{1i_p} + \omega_j v_{1j_p} + \epsilon_p,$$

$$s.t. \ \ \omega_i + \omega_j = 1. \quad and \quad p = \{1, 2, 3, ..., 122\}.$$

After estimating (ω_i, ω_j) for each group, we construct $|\Delta(\hat{\omega}_{_{IND}})|$, which is the absolute difference between the members' Pareto weights. Using these differences, we further construct $(|\Delta\hat{\omega}| \approx 1)_G (= 1)$, which is a dummy indicator for groups in which one of the members has virtually all the bargaining power. The summary statistics of these dummy indicators are presented in Section 7. The roles and effects of these variables on group present bias are described in Section 8.

6.2 Empirical Results

6.2.1 Summary Statistics

Now, we present empirical results to show how individual decisions are connected to group outcomes. In Table 4, we use the estimates of parameters for discounting, present-bias, and effort-cost parameters estimated using equation (2) and show summary statistics for groups and individuals separately. We report the median, fifth, and ninety-fifth percentiles, and the minimum and maximum values for individuals' and groups' annual discount rate ($\hat{\delta}$), present bias ($\hat{\beta}$), and cost parameter ($\hat{\gamma}$). While the median estimated weekly discount rate (0.92) and cost parameters (0.69) are the same for individuals and groups, the median individual present-bias estimate (0.97) is higher than the group median (0.90).

Table 4: Summary Statistics: Discounting, Present-Bias, and Effort Cost Parameter Estimates

	N	Median	5th Percentile	95th Percentile	Minimum	Maximum
Group						
$\hat{\delta}$	122	0.92	0.75	0.99	0.55	0.99
$\hat{\beta}$	122	0.90	0.18	2.32	0.02	10.8
$\hat{\gamma}$	122	0.69	0.19	1.33	0.14	2.80
Individual						
$\hat{\delta}$	244	0.92	0.76	0.97	0.66	1.00
$\hat{\beta}$	244	0.97	0.13	2.79	0.02	15.1
$\hat{\gamma}$	244	0.69	0.18	1.51	0.06	2.80

Notes: We use results from the non-linear squares (NLS) estimator used in Table 3. We show summary statistics for discounting, present-bias and effort cost parameter estimates for all groups and all individuals separately.

For most individuals and groups, the estimation strategy generates reasonable parameter estimates. However, extreme observations do exist. Figure 3 presents histograms of time-preference parameter estimates, $\hat{\beta}$, and discounting parameter estimates, $\hat{\delta}$. We can see that a large proportion of subjects have low discount rates and high present bias.

In Table 5, we use the fact that each group consists of two randomly paired individuals and calculate across-group estimates for the median, fifth, and ninety-fifth percentiles and the minimum and maximum discounting, present-bias, and effort-cost parameters for individuals.

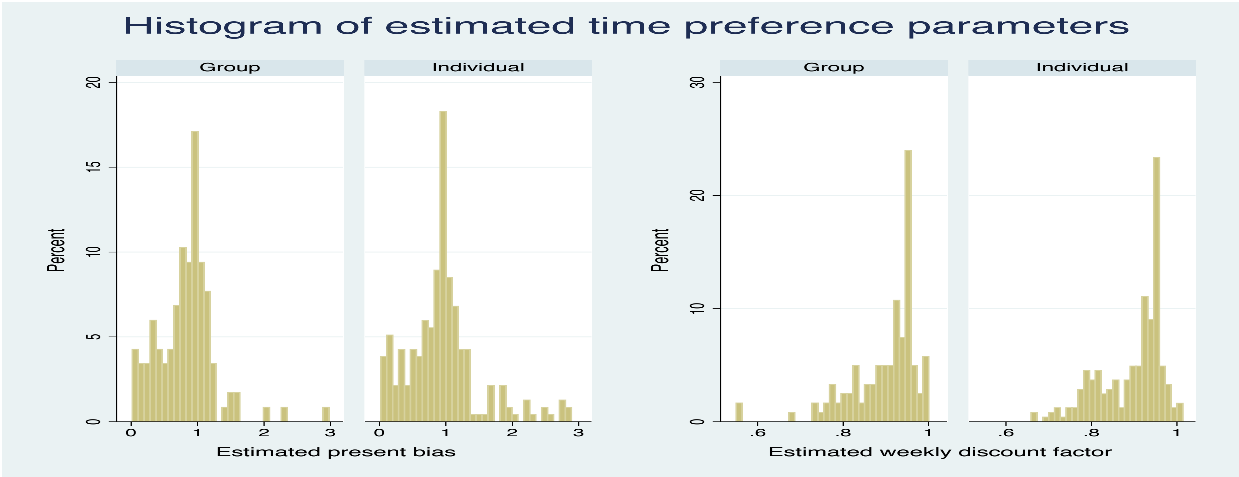

Figure 3: Estimates Histogram

This shows us the spread across the groups and allows us to compare the spread of our estimates for individuals (Table 4) with the spread of our estimates for groups (Table 5). We see that the group median parameter estimates in Table 4 are always greater than the minimum and less than the maximum of the median of the estimates presented in Table 5. The same is true for the fifth-percentile and ninety-fifth-percentile estimates of groups compared with their minimums and maxima. This finding is in line with Gollier and Zeckhauser's (2005) model of aggregation of time preferences, in which the rate of impatience of the representative agent is a weighted mean of individual rates of impatience, although this may not hold at the extreme points.[9]

In Figure 4, we see the distribution of time-preference parameters: the present bias and weekly discount factors for the minimum and maximum in the group along with its corresponding collective estimates. The figure visually highlights two important results. First, groups' time-preference estimates are bounded by their members' estimates. Second, the group present-bias estimates tend to be closer to the within-group minimum estimates. In other words, the group member with higher present bias dominates the group and drives the group present bias.

[9] Gollier and Zeckhauser (2005) also showed that heterogeneous individual exponential discounting yields collective hyperbolic discounting.

Table 5: Summary of Across-Group Min and Max Parameter Estimates

	N	Median	5th Percentile	95th Percentile	Minimum	Maximum
Minimum						
$\hat{\delta}$	122	0.88	0.72	0.95	0.66	0.95
$\hat{\beta}$	122	0.81	0.09	1.23	0.03	11.5
$\hat{\gamma}$	122	0.49	0.15	1.12	0.57	2.80
Maximum						
$\hat{\delta}$	122	0.95	0.79	0.99	0.75	1.00
$\hat{\beta}$	122	1.07	0.39	3.93	0.03	15.1
$\hat{\gamma}$	122	0.79	0.28	1.74	0.14	2.80

Notes: We use results from the non-linear squares (NLS) estimator used in Table 3. We calculate summary statistics for individuals across all groups dividing them up in the minimum constituent individual and the maximum constituent individual in each group and present summary statistics for discounting, present-bias and effort cost parameter estimates.

6.2.2 Relationship Between Individual and Group Parameters

The above stylized theoretical setup motivates another important hypothesis. Having constructed $\hat{\beta}^i_{min}$, $\hat{\beta}^i_{max}$, $\hat{\delta}^i_{min}$, and $\hat{\delta}^i_{max}$ for each randomly created group, we investigate how individual time preferences affect group time preferences. We employ a model in which a group's time-preference parameter is a linear function of its members' parameters:

$$\hat{\beta}_g = \alpha_1 + \kappa_1\hat{\beta}_{min} + \kappa_2\hat{\beta}_{max} + \epsilon_{1g} \qquad , \qquad \hat{\delta}_g = \alpha_2 + \eta_1\hat{\delta}_{min} + \eta_2\hat{\delta}_{max} + \epsilon_{2g}$$

First, we investigate whether there is a difference between individual and group decisions that is independent of individuals' time preferences. Specifically, we test the hypothesis that $\alpha_i = 0$ for $i = (1, 2)$ ($\alpha_i = 0$ would imply no relationship between individuals' and groups' preferences). Second, we investigate the hypothesis that the coefficients of individual decisions sum to one:

$$\sum_{i=1}^{2} \kappa_i = 1 \qquad , \qquad \sum_{i=1}^{2} \eta_i = 1$$

Together, these two tests imply that the group decision is a convex combination of individual decisions. Hence, the coefficient of the latter can be interpreted as the weights of different members in shaping the group decisions.

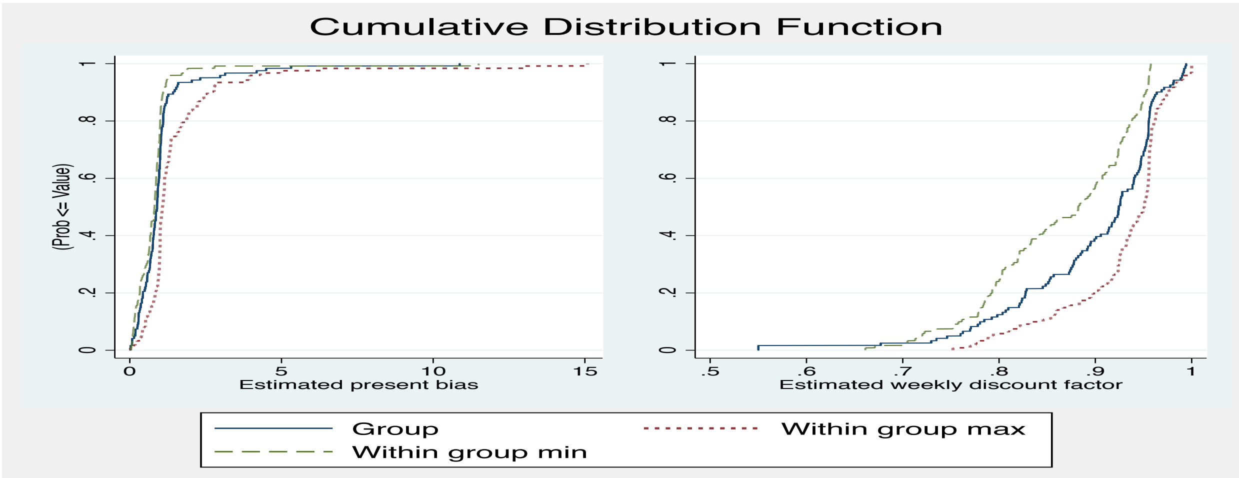

Figure 4: Estimated CDF

Third, we examine the mean hypothesis, according to which group decisions are simply a function of mean individual decisions:

$$\hat{\beta}_g = \alpha_1 + \frac{\kappa}{2}\hat{\beta}_{min} + \frac{\kappa}{2}\hat{\beta}_{max} \quad , \quad \hat{\delta}_g = \alpha_2 + \frac{\eta}{2}\hat{\delta}_{min} + \frac{\eta}{2}\hat{\delta}_{max}.$$

This hypothesis implies that the mean is a sufficient statistic for the group's decision. If $\kappa = 1$, then the mean present-bias parameter exactly predicts the component of the group present-bias parameter that varies with individual preferences (that is, we can reject the hypothesis that $\kappa_1 = \kappa_2$).

Fourth, the strong mean hypothesis further requires the mean to exactly predict the group present-bias parameter, and it requires us to test whether $\kappa_1 = \kappa_2 = \frac{1}{2}$. These arguments also hold true for the long-run discount parameter $\hat{\delta}_g$.

In Table 6, we report results from regressing the group-decision estimated time-preference parameters on the individual-decision parameters. Models (1) and (3) show basic linear specifications, while models (2) and (4) test for robustness of the results by including controls for order effects. In both models of present bias, columns (1) and (2), the coefficient, κ_1, is positive and significant. This is an important result signifying that the individual with higher present bias, essentially the more constrained individual, dictates the group present-bias dynamics. The positive constant term indicates complementarity within the group's

Table 6: OLS regressions of group choices on individual choices

Dep. Var:	$\hat{\beta}_g$			$\hat{\delta}_g$	
	(1)	(2)		(3)	(4)
$\kappa_1 : \hat{\beta}_{min}$	0.79***	0.79***	$\eta_1 : \hat{\delta}_{min}$	0.19	0.15
	(0.08)	(0.08)		(0.14)	(0.21)
$\kappa_2 : \hat{\beta}_{max}$	0.11*	0.11*	$\eta_2 : \hat{\delta}_{max}$	0.74*	0.76
	(0.04)	(0.04)		(0.40)	(0.46)
α_1 : Constant	0.20***	0.22**	α_2 : Constant	0.03	0.04
	(0.05)	(0.08)		(0.32)	(0.30)
Order Effect	N	Y	Order Effect	N	Y
# Observations	122	122	# Observations	122	122
R^2	0.71	0.71	R^2	0.11	0.11
RMSE	0.64	0.64	RMSE	0.13	0.14
Hypothesis (*p-values*)					
Weak Mean	0.00	0.00	Weak Mean	0.31	0.35
Strong Mean	0.00	0.00	Strong Mean	0.05	0.13
Convex Combination	0.00	0.00	Convex Combination	0.04	0.01

Notes: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The table presents OLS regressions of estimated present-bias and discounting for groups on estimated minimum and maximum parameters of individuals. Columns 1-2 present show results for present-bias, and Columns 3-4 for the long-run discount factor. In Columns 2 and 4, we control for decision ordering. We use robust standard errors.

intertemporal behavior. In both models of the long-run discount factor, columns (3) and (4), we show that although the more patient individual is barely significant in explaining a group's long-run discount rate, the coefficient becomes insignificant when we control for order effects. Hence, the patient individual cannot explain the group's long-run discount factor.

Our results support the hypothesis of a level shift for present bias, while we cannot reject the null hypothesis of no shift in the long-run discount rate—that is, $H_0 : \kappa_2 = 0$. The third part of the table reports the results from our postestimation hypotheses—namely, the weak and strong versions of the mean and convex-combination hypotheses, which we developed for the four OLS models reported in Table 6. For $\hat{\beta}_g$, we reject both versions of both hypotheses; that is, individuals' choices are not equally important to explain groups' present bias. On the other hand, for $\hat{\delta}_g$, we are unable to reject either the weak or strong hypotheses, indicating that individuals' mean is a sufficient statistic for the group's decision.

Next, we investigate how groups' decisions are determined by the present bias of their members. As mentioned earlier, theoretically, in a group context, inconsistencies can arise

Table 7: Summary Statistics

Variables	Mean	Standard Deviation	Minimum	Maximum
$\lvert\Delta(\hat{\delta}_{IND})\rvert$	0.06	0.07	0	0.26
$\lvert\Delta(\hat{\gamma}_{IND})\rvert$	0.36	0.41	0	2.15
$\lvert\Delta(\hat{\omega}_{IND})\rvert$	0.85	0.29	0	1
$\lvert(\Delta\hat{\omega} \approx 1)\rvert_G(=1)$	0.72	0.44	0	1
$(\hat{\beta} \approx 1)_{both}(=1)$	0.05	0.21	0	1
Acquaintance Time Duration (months)	13.84	21.56	0	60

Notes: No. of observations is 244. $|\Delta(\hat{\delta}_{IND})|$ is the absolute difference between the groups' individual members' weekly discount rate. $|\Delta(\hat{\gamma}_{IND})|$ is the absolute difference between the groups' individual members' cost of effort parameters. $|\Delta(\hat{\omega}_{IND})|$ is the absolute difference between the groups' individual members' bargaining/Pareto weights. $(|\Delta\hat{\omega}| \approx 1)_G(=1)$ is the dummy indicator for the group in which one of the members has approximately all the bargaining power. $(\hat{\beta} \approx 1)_{both}(=1)$ is the dummy indicator, which takes the value of 1 for those groups in which both members are time consistent, approximately.

simply from the aggregation of heterogeneous preferences because of variations in individual discount rates and cost-function parameters (Jackson and Yariv 2015). Hence, we now test how variations in individual discount rates and effort-cost parameters as well as differences in within-group bargaining weights could generate group behavior that is more present biased than individual behavior. We also test other important individual factors that shape group behavior, such as coordination externalities within groups.

In Table 7, we show summary statistics for the individual-level variables that may affect group-level behavior: we show the absolute differences in measures of each group's members, such as weekly discount rate, effort-cost parameter, and bargaining power (we use $\hat{\omega}$ to construct a dummy indicator, $(|\Delta\hat{\omega}| \approx 1)_G(=1)$, which indicates a group in which one of the members has virtually all the bargaining power: $|\Delta(\hat{\omega}_{IND})| > 0.98$). We show that the absolute difference between each group's members' weekly discount rate ($|\Delta(\hat{\delta}_{IND})|$) has a mean of 6% with a standard deviation of 0.07. The absolute difference between members' cost-of-effort parameters ($|\Delta(\hat{\gamma}_{IND})|$) has a mean of 0.36 with a standard deviation of 0.41. The absolute difference between members' bargaining weights ($|\Delta(\hat{\omega}_{IND})|$) has a mean of 0.85, indicating that members have different bargaining power and that for most groups the chances of having a nondictatorial setup are quite high. Finally, we show that the high-bargaining-power variable has a mean of 0.72, which shows that in a majority of groups the probability of having a dictatorial member (borrowing the terminology from Jackson and Yariv 2015) is high; that is, the groups typically ignore the preferences of all but one agent.

In our design, the possibility that groups in which each participant is time consistent does not pose any additional challenge for our main experimental findings since we observe both group and individual decisions. Focusing on how aggregation relates to time inconsistency, we explicitly controlled for the underlying individual preferences to isolate the effects of aggregation. In cases in which each participant is time consistent, we construct the variable $(\hat{\beta} \approx 1)_{both}(= 1)$, a dummy indicator taking the value of 1 for groups in which both members are time consistent (which we define as both members having a $\hat{\beta}$ between 0.95 and 1.05). This variable has a mean of 0.05, indicating that in the overall sample, in only 5% of groups are both members nearly time consistent.

Finally, in Table 8, we regress individual-level absolute differences for different variables on the group time-preference parameter. In column (1), we regress the absolute value of the difference between each group's members' discount rates, cost functions, bargaining power, and bargaining-power dummy. We test the robustness of this result in column (4), in which we add control variables: the absolute value of the difference in Big Five; age; and gender. These results show that the weekly-discount-factor heterogeneities among individuals explain group present bias. They also show that the presence of a dictator or individual who is dominant (in terms of bargaining power) reduces group present bias. These results are in line with Jackson and Yariv's (2014) theoretical prediction that for a uniform distribution of discount rates in an otherwise-homogeneous population, group utility maximization generates aggregate behavior that corresponds to hyperbolic discounting and that if there is some fundamental heterogeneity in temporal preferences in the form of differing discount factors, then the only well-behaved collective utility functions that are time consistent and respect unanimity are dictatorial. For these two columns, we see that, given that the individuals are exponential discounters and given that there are no variations in individual discount rates and in effort-cost parameters, the groups' allocation decisions would represent time-consistent patterns.

In columns (2) and (5), we include acquaintance duration as a control in the previous two specifications. The results show the effect of the coordination externality on the groups' present-bias estimates. It is natural to think that as *Acquaintance Duration* increases, individuals' coordination problems lessen. This in turn would decrease group present bias. In both columns, the control's estimate is significant at 10%. Under H_0 : $Constant$ $=$

Table 8: Individual vs. Group Regression Analysis

Dependent variable:	$\hat{\beta}_G$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\lvert\Delta(\hat{\delta}_{IND})\rvert$	-3.84**	-3.07**	-3.16**	-3.86**	-3.00**	-3.09**
	(1.25)	(1.19)	(1.28)	(1.26)	(1.23)	(1.32)
$\lvert\Delta(\hat{\gamma}_{IND})\rvert$	0.14	0.21	0.18	0.13	0.24	0.19
	(0.26)	(0.24)	(0.25)	(0.28)	(0.24)	(0.25)
$\lvert\Delta(\hat{\omega}_{IND})\rvert$	-0.25	-0.17	0.07	-0.21	-0.21	0.06
	(0.23)	(0.27)	(0.31)	(0.27)	(0.26)	(0.28)
$(\lvert\Delta\hat{\omega}\rvert \approx 1)_G(=1)$	0.58**	0.43**	0.30	0.57**	0.43**	0.30
	(0.20)	(0.19)	(0.20)	(0.21)	(0.18)	(0.18)
$(\hat{\beta} \approx 1)_{both}(=1)$	-0.27	-0.36	-0.38	-0.30	-0.30	-0.35
	(0.23)	(0.30)	(0.32)	(0.30)	(0.30)	(0.32)
Acquaintance Duration		0.01*	0.01*		0.01*	0.01*
		(0.01)	(0.01)		(0.01)	(0.01)
$\lvert\Delta(\mathit{Big\ 5})\rvert$			-0.08			-0.05
			(0.14)			(0.15)
$\lvert\Delta(\mathit{Age\ (in\ years)})\rvert$				-0.04	0.02	0.06
				(0.06)	(0.05)	(0.07)
$\lvert\Delta(\mathit{Gender})\rvert$				-0.09	0.17	0.11
				(0.22)	(0.18)	(0.20)
Constant	1.02***	0.76***	0.72**	1.11***	0.65**	0.56
	(0.14)	(0.19)	(0.25)	(0.24)	(0.24)	(0.34)
# of Groups	122	122	109	122	122	109
Adj R^2	0.06	0.30	0.30	0.07	0.31	0.31
RMSE	1.13	0.98	1.02	1.13	0.97	1.02
$H_0 : Constant = 1$						
p-value	0.87	0.19	0.27	0.65	0.15	0.19

Notes: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are clustered at the group level. Column (1) presents the estimates of variations in group members' weekly discount factors, cost of effort parameters, bargaining power estimates, presence of dictator, and both time-consistent members dummies . Column (2) presents the estimates of effect of acquaintance duration on group present-bias, controlling for the variables in column (1). Column (3) captures the estimates of effect of within-group differences in Big 5 personality traits, controlling for the variables in column (2). Columns (4), (5), and (6) represent the estimates of theory and non-theory-based factors, controlling for within-group differences in age and gender.

1, $F(1, 121)$ have p-values that show that, given that there are no variations in individual discount rates and in effort-cost parameters, groups' allocation decisions would represent time-consistent patterns even if the individuals were exponential discounters with *Acquaintance Duration* of 0. Last, in columns (3) and (6), we add the absolute value of the difference in Big Five personality traits to our main specifications. These results show that Big Five personality traits cannot explain groups' present bias. The effect of the presence of a within-group dictator is not significant in these columns, which may be attributable to fluctuation of overall sample size.

To summarize, the main message of Table 8 is that groups whose members have misaligned discount rates are present biased and that the presence of a dictator within a group improves the group's present-bias estimate. Emphasizing that divergent preferences within a group are sufficient to render time inconsistency, we find that the variation in discount factors significantly affects group present bias even after controlling for time-consistent individuals and the presence of a dictator. Similarly, the effect of coordination externalities, which is captured by *Acquaintance Duration*, is also important for understanding group present bias.

7 Conclusion

This paper analyzes individual and collective decisions through the preference elicitation method over unpleasant task consumption. The study uses experimental data to analyze task consumption decisions by groups of individuals who have to reach a consensus regarding allocation of tasks over time. For this purpose, a joint experimental elicitation of time preferences was performed for the groups as well as for their individual members.

The main results of the paper are as follows: First, on aggregate, a present-bias exists in participants' behavior, i.e., the participants' intertemporal allocation decisions exhibited time inconsistency. Second, the degree of present-bias was more pronounced in a group's task allocation decisions as compared to an individual's task allocation setting. Third, the order in which decisions were made, whether making the individual task allocation first and then the group task allocation or vice versa had no effect on the degree of present-bias.

Lastly, using within-groups estimates of present-bias and discount factor, the variations in group's individual members discount rates do explain group present-bias, as postulated by Jackson and Yariv (2015).

We acknowledge that the results could be partly explained, by a selection bias. In our experiment, as in any experiment involving longitudinal measures, subjects were supposed to commit to three sessions over a time span of three weeks. Here, a specificity of our subjects is probably their ability to commit and schedule (Frederick et al. 2002; Perez-Arce 2011; Dohmen et al. 2010). The estimates of present-bias and discount rates for individual choices we found are no higher than those found in the literature, although the empirical literature on task consumption is very limited. Moreover, we were mainly interested in comparisons. It is plausible that the selection bias impacted all decisions to a similar extent, thus we have no big effect on our comparisons. Finally, our coordinating device allowed groups to quickly converge towards a given decision. In this respect, our results have implications for the way households, boards and committees can achieve consistent decisions.

References

Andersen, S., Harrison, G. W., Lau, M. I., and Rutström, E. E. (2008). Eliciting risk and time preferences. *Econometrica*, 76(3):583–618.

Andreoni, J., Kuhn, M. A., List, J. A., Samek, A., Sokal, K., and Sprenger, C. (2019). Toward an understanding of the development of time preferences: Evidence from field experiments. *Journal of public economics*, 177:104039.

Andreoni, J. and Sprenger, C. (2012a). Estimating time preferences from convex budgets. *American Economic Review*, 102(7):3333–56.

Andreoni, J. and Sprenger, C. (2012b). Risk preferences are not time preferences. *American Economic Review*, 102(7):3357–76.

Augenblick, N., Niederle, M., and Sprenger, C. (2015). Working over time: Dynamic inconsistency in real effort tasks. *The Quarterly Journal of Economics*, 130(3):1067–1115.

Barrick, M. R. and Mount, M. K. (1991). The big five personality dimensions and job performance: a meta-analysis. *Personnel psychology*, 44(1):1–26.

Beshears, J., Choi, J. J., Laibson, D., and Madrian, B. C. (2008). How are preferences revealed? *Journal of public economics*, 92(8-9):1787–1794.

Bortolotti, S., Dohmen, T., Lehmann, H., Meyer, F., Pignatti, N., and Torosyan, K. (2021). Patience, cognitive abilities, and cognitive effort: Survey and experimental evidence from a developing country. *American Behavioral Scientist*, 65(11):1512–1530.

Bradford, D., Courtemanche, C., Heutel, G., McAlvanah, P., and Ruhm, C. (2017). Time preferences and consumer behavior. *Journal of Risk and Uncertainty*, 55(2):119–145.

Brocas, I. and Carrillo, J. D. (2008a). The brain as a hierarchical organization. *American Economic Review*, 98(4):1312–46.

Brocas, I. and Carrillo, J. D. (2008b). Theories of the mind. *American Economic Review*, 98(2):175–80.

Browning, M. and Chiappori, P.-A. (1998). Efficient intra-household allocations: A general characterization and empirical tests. *Econometrica*, pages 1241–1278.

Cadena, B. C. and Keys, B. J. (2015). Human capital and the lifetime costs of impatience. *American Economic Journal: Economic Policy*, 7(3):126–53.

Callen, M., Gulzar, S., Hasanain, A., Khan, M. Y., and Rezaee, A. (2015). Personalities and public sector performance: Evidence from a health experiment in pakistan.

Carbone, E. and Infante, G. (2015). Are groups better planners than individuals? an experimental analysis. *Journal of Behavioral and Experimental Economics*, 57:112–119.

Castillo, M., Ferraro, P. J., Jordan, J. L., and Petrie, R. (2011). The today and tomorrow of kids: Time preferences and educational outcomes of children. *Journal of Public Economics*, 95(11-12):1377–1385.

Chabris, C. F., Laibson, D., Morris, C. L., Schuldt, J. P., and Taubinsky, D. (2008). Individual laboratory-measured discount rates predict field behavior. *Journal of risk and uncertainty*, 37(2):237–269.

Chiappori, P.-A. (1992). Collective labor supply and welfare. *Journal of political Economy*, 100(3):437–467.

Cohen, J., Ericson, K. M., Laibson, D., and White, J. M. (2020). Measuring time preferences. *Journal of Economic Literature*, 58(2):299–347.

Cubitt, R. P. and Read, D. (2007). Can intertemporal choice experiments elicit time preferences for consumption? *Experimental Economics*, 10(4):369–389.

DellaVigna, S. and Malmendier, U. (2006). Paying not to go to the gym. *american economic Review*, 96(3):694–719.

Denant-Boemont, L. and Loheac, Y. (2011). Time and teams: An experimental study about group inter-temporal choice. Technical report, Working Paper.

Dohmen, T., Falk, A., Huffman, D., and Sunde, U. (2010). Are risk aversion and impatience related to cognitive ability? *American Economic Review*, 100(3):1238–60.

Ericson, K. M. and Laibson, D. (2019). Intertemporal choice. In *Handbook of Behavioral Economics: Applications and Foundations 1*, volume 2, pages 1–67. Elsevier.

Feldstein, M. S. (1964). The social time preference discount rate in cost benefit analysis. *The economic journal*, 74(294):360–379.

Finke, M. S. and Huston, S. J. (2013). Time preference and the importance of saving for retirement. *Journal of Economic Behavior & Organization*, 89:23–34.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic perspectives*, 19(4):25–42.

Frederick, S., Loewenstein, G., and O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of economic literature*, 40(2):351–401.

Fudenberg, D. and Levine, D. K. (2006). A dual-self model of impulse control. *American economic review*, 96(5):1449–1476.

Fudenberg, D. and Levine, D. K. (2011). Risk, delay, and convex self-control costs. *American Economic Journal: Microeconomics*, 3(3):34–68.

Giné, X., Goldberg, J., Silverman, D., and Yang, D. (2018). Revising commitments: Field evidence on the adjustment of prior choices. *The Economic Journal*, 128(608):159–188.

Gollier, C. and Zeckhauser, R. (2005). Aggregation of heterogeneous time preferences. *Journal of political Economy*, 113(4):878–896.

Golsteyn, B. H., Grönqvist, H., and Lindahl, L. (2014). Adolescent time preferences predict lifetime outcomes. *The Economic Journal*, 124(580):F739–F761.

Gul, F. and Pesendorfer, W. (2001). Temptation and self-control. *Econometrica*, 69(6):1403–1435.

Harrison, G. W., Lau, M. I., and Williams, M. B. (2002). Estimating individual discount rates in denmark: A field experiment. *American economic review*, 92(5):1606–1617.

Hausman, J. A. (1979). Individual discount rates and the purchase and utilization of energy-using durables. *The Bell Journal of Economics*, pages 33–54.

Holcomb, J. H. and Nelson, P. S. (1992). Another experimental look at individual time preference. *Rationality and Society*, 4(2):199–220.

Jackson, M. O. and Yariv, L. (2014). Present bias and collective dynamic choice in the lab. *American Economic Review*, 104(12):4184–4204.

Jackson, M. O. and Yariv, L. (2015). Collective dynamic choice: the necessity of time inconsistency. *American Economic Journal: Microeconomics*, 7(4):150–78.

John, O. P., Naumann, L. P., and Soto, C. J. (2008). *Paradigm shift to the integrative Big Five trait taxonomy: History, measurement, and conceptual issues.* The Guilford Press.

Khwaja, A., Sloan, F., and Salm, M. (2006). Evidence on preferences and subjective beliefs of risk takers: The case of smokers. *International Journal of Industrial Organization*, 24(4):667–682.

Koopmans, T. C. (1960). Stationary ordinal utility and impatience. *Econometrica: Journal of the Econometric Society*, pages 287–309.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, 112(2):443–478.

Laibson, D., Repetto, A., and Tobacman, J. (2007). Estimating discount functions with consumption choices over the lifecycle.

Lawrance, E. C. (1991). Poverty and the rate of time preference: evidence from panel data. *Journal of Political economy*, 99(1):54–77.

Mankiw, N. G., Romer, D., and Weil, D. N. (1992). A contribution to the empirics of economic growth. *The quarterly journal of economics*, 107(2):407–437.

Manser, M. and Brown, M. (1980). Marriage and household decision-making: A bargaining analysis. *International economic review*, pages 31–44.

Marglin, S. A. (1963). The social rate of discount and the optimal rate of investment. *The Quarterly Journal of Economics*, pages 95–111.

Mazzocco, M. (2007). Household intertemporal behaviour: A collective characterization and a test of commitment. *The Review of Economic Studies*, 74(3):857–895.

McElroy, M. B. and Horney, M. J. (1981). Nash-bargained household decisions: Toward a generalization of the theory of demand. *International economic review*, pages 333–349.

Meier, S. and Sprenger, C. D. (2013). Discounting financial literacy: Time preferences and participation in financial education programs. *Journal of Economic Behavior & Organization*, 95:159–174.

Metcalfe, J. and Mischel, W. (1999). A hot/cool-system analysis of delay of gratification: dynamics of willpower. *Psychological review*, 106(1):3.

Milch, K. F., Weber, E. U., Appelt, K. C., Handgraaf, M. J., and Krantz, D. H. (2009). From individual preference construction to group decisions: Framing effects and group processes. *Organizational Behavior and Human Decision Processes*, 108(2):242–255.

Noor, J. (2011). Temptation and revealed preference. *Econometrica*, 79(2):601–644.

Noor, J. and Takeoka, N. (2022). Optimal discounting. *Econometrica*, 90(2):585–623.

O'Donoghue, T. and Rabin, M. (1999). Doing it now or later. *American economic review*, 89(1):103–124.

O'Donoghue, T. and Rabin, M. (2001). Choice and procrastination. *The Quarterly Journal of Economics*, 116(1):121–160.

Perez-Arce, F. (2011). The effect of education on time preferences.

Picone, G., Sloan, F., and Taylor, D. (2004). Effects of risk and time preference and expected longevity on demand for medical tests. *Journal of Risk and Uncertainty*, 28(1):39–53.

Rae, J. (1905). *The sociological theory of capital: being a complete reprint of the new principles of political economy, 1834*. Macmillan.

Samuelson, P. A. (1937). A note on measurement of utility. *The review of economic studies*, 4(2):155–161.

Schaner, S. (2015). Do opposites detract? intrahousehold preference heterogeneity and inefficient strategic savings. *American Economic Journal: Applied Economics*, 7(2):135–74.

Sprenger, C. (2015). Judging experimental evidence on dynamic inconsistency. *American Economic Review*, 105(5):280–85.

Sunde, U., Dohmen, T., Enke, B., Falk, A., Huffman, D., and Meyerheim, G. (2022). Patience and comparative development. *The Review of Economic Studies*, 89(5):2806–2840.

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics letters*, 8(3):201–207.

Thaler, R. H. and Shefrin, H. M. (1981). An economic theory of self-control. *Journal of political Economy*, 89(2):392–406.

Van der Linden, D., te Nijenhuis, J., and Bakker, A. B. (2010). The general factor of personality: A meta-analysis of big five intercorrelations and a criterion-related validity study. *Journal of research in personality*, 44(3):315–327.

Warner, J. T. and Pleeter, S. (2001). The personal discount rate: Evidence from military downsizing programs. *American Economic Review*, 91(1):33–53.

Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data mit press. *Cambridge, MA*, 108(2):245–254.

8 Appendix

A1: Nonlinear Least Squares Method

Let there be N experimental subjects and P Convex Time Budget, (CTBs). Assume that each subject j makes her $v_{1tij}, i = 1, 2, ..., P$, decisions (both individual and group) according to the non-linear Euler equation mentioned above, but that these decisions are made with some mean-zero, potentially correlated error. That is, let

$$f(V, R, \mathbf{1}_{d=1}, k, \gamma, \delta, \beta) = \left(\frac{\beta^{\mathbf{1}_{d=1}} \delta^k V}{\gamma R^2 + \beta^{\mathbf{1}_{d=1}} \delta^k} \right),$$

then

$$v_{1t}{}^*_{ij} = f(V, R, \mathbf{1}_{d=1}, k, \gamma, \delta, \beta) + e_{tij}.$$

Stacking the P observations for individual j making her individual and group decisions, we have

$$\boldsymbol{v_{1t}}{}^*_j = \boldsymbol{f}(V, R, \mathbf{1}_{d=1}, k, \gamma, \delta, \beta) + \boldsymbol{e}_j.$$

The vector $\boldsymbol{e}_j$ is zero in expectation with covariance matrix $\boldsymbol{V_j}$, a $(P \times P)$ matrix, allowing for arbitrary correlation in the errors e_{ij} . We stack over the N experimental subjects to obtain

$$\boldsymbol{v}^*_{\mathbf{1t}} = \boldsymbol{f}(V, R, \mathbf{1}_{d=1}, k, \gamma, \delta, \beta) + \boldsymbol{e}.$$

We assume that the terms e_{ij} may be correlated within groups (or individuals within the same group) but that the errors are uncorrelated across groups (or individuals within the same group), $E(\boldsymbol{e}_j^{'} \boldsymbol{e}_g) = 0$ for $j \neq g$. Therefore, $\boldsymbol{e}$ is zero in expectation with covariance matrix $\boldsymbol{\Omega}$, a block diagonal $(NP \times NP)$ matrix of clusters, with groups, covariance matrices, $\boldsymbol{V_j}$. We define the usual criterion function $S(V, R, \mathbf{1}_{d=1}, k, \gamma, \delta, \beta)$ as the sum of squared residuals,

$$S(V, R, \mathbf{1}_{d=1}, k, \gamma, \delta, \beta) = \sum_{j=1}^{N} \sum_{i=1}^{P} (v_{1t}{}^*_{ij} - f(V, R, \mathbf{1}_{d=1}, k, \gamma, \delta, \beta))^2,$$

and minimize $S(.)$ using non-linear least squares with standard errors clustered on the group level to obtain $\hat{\beta}$, $\hat{\delta}$, and γ. NLS procedures permitting the estimation of preference parameters at the aggregate or individual level are implemented in many standard econometrics packages (in our case, *Stata*).

Table 9: Two-Limit Tobit Regression Analysis

Dependent variable:	Log of Tasks Allocated to the 1st Day			
	(1)	(2)	(3)	(4)
β_1 : Log Task Rate	-0.49***	-0.50***	-0.49***	-0.50***
	(0.08)	(0.08)	(0.08)	(0.08)
β_2 : Immediate Decision (=1)	-0.12**	-0.12**	-0.10	-0.10
	(0.04)	(0.04)	(0.07)	(0.07)
β_3 : Individual Decision First (=1)			-0.02	-0.04
			(0.06)	(0.06)
β_4 : Immediate Individual Decision First (=1)			-0.03	-0.02
			(0.08)	(0.08)
β_5 : *Age (in years)*		0.02		0.02*
		(0.01)		(0.01)
β_6 : *Gender (Female = 0)*		0.03		0.02
		(0.05)		(0.05)
β_7 : *Has a On campus Job (Yes = 0)*		-0.03		-0.02
		(0.11)		(0.11)
β_8 : *Had a Savings Account (Yes = 0)*		0.06		0.06
		(0.07)		(0.07)
β_9 : *Has a Savings Account (Yes = 0)*		-0.02		-0.02
		(0.06)		(0.06)
β_0 : Constant	4.96***	4.42***	4.97***	4.35***
	(0.08)	(0.44)	(0.09)	(0.42)
# of Obs	1464	1464	1464	1464
# of Groups	122	122	122	122
F-stats	21.07	7.26	11.06	5.79
Adj R^2	0.02	0.02	0.02	0.02
Hypothesis (*p-values*)				
$H_0 : \beta_2 = 1$	0.00			
$H_0 : \beta_2 = 1$		0.00		
$H_0 : \beta_2 + \beta_4 = 1$			0.00	
$H_0 : \beta_2 + \beta_4 = 1$				0.00

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Standard errors are clustered at the group level. The table presents the estimates of Immediate Decision (=1) and its interactions with other experimentally induced variations using the Two-Limit Tobit Regression technique. Column (1) presents aggregated decisions, estimates. Column (2) captures the estimates of Immediate Decision (=1) along with demographic variables. Column (3) represents the results of effect of decision ordering and its interaction with Immediate Decision (=1). Column (4) represents the results of effect of the decision ordering and its interaction with Immediate Decision (=1), controlling for demographic variables.

A2: Additional Two-Limit Tobit Regression Analysis

Table A2.1 provides robustness results for the non-structural estimation specifications discussed in the paper. Using the intertemporal individual decisions, the results provide the comparison of the estimates, controlling for the demographic variables.

Table 10: Additional Individual vs. Group Regression Analysis

Dependent variable:	$\hat{\beta}_G$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\lvert\Delta(Age\ (in\ years))\rvert$	-0.06							-0.06
	(0.14)							(0.14)
$\lvert\Delta(Gender)\rvert$		-0.10						-0.20
		(0.41)						(0.45)
$\lvert\Delta(Outside\ Class\ Study\ Hrs)\rvert$			-0.12					-0.12
			(0.08)					(0.07)
$\lvert\Delta(On\ Campus\ Job)\rvert$				-0.61				-0.82
				(0.37)				(0.51)
$\lvert\Delta(Family\ Income\ in\ Log)\rvert$					-0.17			-0.18
					(0.21)			(0.24)
$\lvert\Delta(Past\ Savings\ Acc.)\rvert$						0.22		0.19
						(0.49)		(0.92)
$\lvert\Delta(Curr.Savings\ Acc.)\rvert$							-0.59	1.05
							(0.37)	(0.76)
Constant	1.08***	1.04***	1.212***	1.06***	1.11***	0.97***	1.14***	1.42***
	(0.19)	(0.18)	(0.23)	(0.12)	(0.18)	(0.10)	(0.17)	(0.38)
# of Groups	122	120	120	120	110	122	122	110
R^2	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.06

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. Standard errors are clustered at the group level. The table presents the estimates of other important demographic variables' differences on groups' present-biased estimated variable.

A3: Additional Individual vs. Group Analysis

Table A2 shows the association of additional individual characteristics (mentioned in the demographic section) with the group estimated present-bias parameter. The results signify the fact that beyond discount factor heterogeneity there is no association between group present-bias and differences in groups' individual members' characteristics per se. Table A3 presents the robustness test of the point estimates obtained in Table 8. Controlling for the other important demographic variables mentioned in the empirical literature, the point estimates of variation in individual member discount factors and *Acquaintance Duration* between them remain the same. F stats also indicate that, given there are no variations in individual members' discount rates and in effort cost parameters, the group's allocation decisions would represent the time-consistent pattern even if the individuals are exponential discounters with no *Acquaintance Duration*.

Table 11: Individual vs. Group Regression Analysis

Dependent variable:	$\hat{\beta}_G$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\lvert\Delta(\hat{\delta}_{IND})\rvert$	-3.84**	-3.47***	-3.76***	-3.86***	-3.26***	-3.53***
	(1.28)	(1.18)	(1.12)	(1.20)	(1.16)	(1.27)
$\lvert\Delta(\hat{\gamma}_{IND})\rvert$	0.20	0.24	0.23	0.32	0.23	0.37
	(0.22)	(0.30)	(0.22)	(0.25)	(0.22)	(0.25)
$(\hat{\beta}_{min} \approx 1)_{IND}(=1)$	0.16	0.11			0.16	0.11
	(0.30)	(0.45)			(0.36)	(0.54)
$(\hat{\beta}_{max} \approx 1)_{IND}(=1)$	-0.23	-0.34			-0.06	-0.04
	(0.13)	(0.23)			(0.12)	(0.16)
Acquaintance Duration			0.63**	0.63***	0.64**	0.66**
			(0.27)	(0.23)	(0.27)	(0.27)
$\lvert\Delta(\hat{\delta}_{IND})\rvert \times$ *Acq Duration*			-6.29**	-6.64**	-6.37*	-6.60**
			(2.70)	(2.89)	(2.75)	(2.94)
Constant	1.23***	1.54***	1.13***	1.29***	1.05***	1.11
	(0.21)	(0.49)	(0.14)	(0.30)	(0.14)	(0.30)
Control for Demographic Variables	No	Yes	No	Yes	No	Yes
# of Groups	122	110	122	110	122	110
R^2	0.04	0.10	0.23	0.28	0.34	0.39
$H_0 : Constant = 1$						
p-value=	0.26	0.27	0.35	0.32	0.71	0.69

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. Standard errors are clustered at the group level. Column (1) again represents the formal test of Jackson and Yariv's (2015) main hypothesis. Column (5) represents the robustness of the results obtained in column(1), controlling for differences in demographic variables mentioned in Table above. Columns (3) and (5) are the same as in Table 7, and columns (4) and (6) represent the corresponding robustness check of the results obtained.

A4: Experiment Protocol

Instructions

Thank you for participating in our experiment. We will begin shortly.

Eligibility:

To be in this study, you need to meet the following criteria:

- You must be willing to participate for three consecutive Fridays. Participation will require your presence on specific days as outlined.
- You will need at least one hour and at max three hours on Friday 13th March, Friday 20th March and Friday 27th March.

Informed Consent:

Placed in front of you is an informed consent form to protect your rights as a subject. Please read it. If you choose not to participate in the study you are free to leave at this point, deciding to leave later would seriously harm our resources allocated to this study. If you have any questions, we can address those now. We will collect the forms after the main points of the study are discussed.

Anonymity:

Your anonymity in this study is assured. All the information we acquire, will be used only for the purpose of communication with you. After the study, your email information will be destroyed and will not be connected to your responses in the experiment.

Venue:

- Venue for Friday 20th March will be the same.
- For Friday 27th March, you do not have to be present physically. You can work from anywhere remotely, given that you have an internet connection.

Rules:

- Please turn off your own cell phones.
- If you have a question at any point, just raise your hand.
- There will be a short survey once we are finished with the instructions.
- During the process of reviewing your answers in your survey, if we find your responses in violation of any of the instructions, you might get removed from the experiment.
- You will receive Rs.500 a participation fee. Participation means showing up on the first two Fridays.
- If you complete the assigned tasks on all required days of participation as instructed, a completion payment of Rs.1500 will be provided.
- You may receive additional earnings during the experiment if you participate in potential survey games.
- If you choose to end your participation before the completion of the experiment, please report this to study administrators at the mentioned email address.
- All payments will be made on 1st April in IGC office room 161. You will return the phones given to you for experiment purposes to IGC to receive this payment.

Task:

In this study there is only one task. This task will be completed over time. Some portion of the task may be completed sooner, and some portion of the task can be completed later depending on your choices and chance.

This task will consist of taking a specific number of pictures of books via cell phones. Remember, your phone has a unique IMEI number. Once you take a picture, you need to upload the picture using the application on the phone. Make sure your pictures are clear and the numbers are legible. If the numbers are not legible, they will not be counted. Some portion of the task may be completed on the second Friday, and some portion of the task can be completed on the third Friday. You will practice using the phone application before the actual task starts.

Task Rates:

The allocation decisions across two weeks depend on the task rate. The task rate will vary across your decisions. On the target-setting page of the application (installed the cell phones given to you), every slider bar corresponds to a specific task rate. For example, the first slider bar the task rate is 1:0.8, such that every task you allocate to the second Friday reduces the number of tasks allocated to the third Friday by 0.8. For simplicity, the task rates will always be represented as 1:X, and you will be fully informed of the value of X when making your decisions.

The Experiment Timeline:

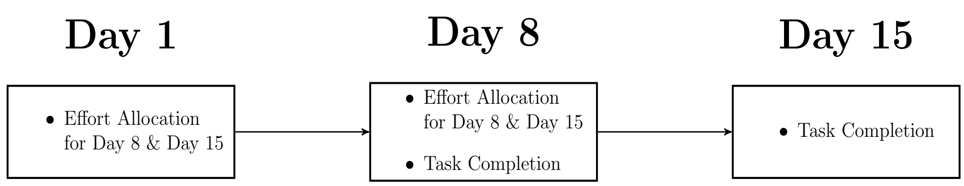

Figure 5: Timeline

Notes: Three weeks experimental timeline figure provided to all participants

Before explaining the activities to be done on each Friday you need to have an overall picture of the timeline.

First Friday (13th March 2015):

- First, all of the Subjects will be required to fill out different survey forms.
- After the Survey forms have been completed and collected, you will be asked to make a series of three decisions for task distribution as an individual.
- Once you have made decisions for individual task distribution, again you will be required to make three decisions and distribute the task as a group.
- Keep in mind that your decision today is for the task you will be doing on 20th and 27th March. This applies to both Individual and Group decisions.

- In each decision you are free to allocate your tasks as you choose.

Second Friday (20th March 2015):

- During our second session here in the very same venue, again you will be asked to make three Decisions (both individually and as a group) as you did during the first session.
- By this time we will have 12 decisions from every subject (3 Individual + 3 Group on the 13th and 3 Individual + 3 Group on the 20th).
- Exactly one of your 12 total decisions will be implemented randomly.
- We will discuss how this allocation decision is chosen during our training session.
- We refer to this allocation decision as the "decision-that-counts." The tasks you allocated yourself for the 20th and 27th in the decision-that-counts must be completed.
- If you do not complete the tasks according to the decision-that-counts, you will not receive the completion amount of Rs. 1500 and will receive on the participation fee of Rs. 500.
- In order for your tasks on the second or third Friday to be counted, they must be completed between 9:30 pm and 10:30 pm of that Friday.
- Surveys will be conducted, which will give you a chance to earn more money.

  Third Friday (27th March 2015):

  - You will have to complete your tasks for this day according to your decision-that-counts.
  - You can do this remotely from anywhere.

  How we will choose the decision-that-counts:

  The process of selecting the decision-that-counts is simple probability. *Three stages to determine the decision-that-counts:*

1. First, you will be allocated either 13th March Decisions or 20th March Decisions according to a 20% and 80% chance, respectively.
2. Once you have been allocated to a specific date (13th or 20th March) either you will be given an Individual Task or a Group Task with a 33% and 66% chance, respectively.
3. After both of the steps given above are complete, you will receive one of the three decisions you made for that specific date and specific task type with equal chance.

EACH DECISION COULD BE THE DECISION-THAT-COUNTS, SO TREAT EACH DECISION AS IF IT WAS THE ONE DETERMINING YOUR TASKS.

Short Survey: Please answer the following questions:

1. How many weeks do we require you to participate?
2. In which of the three weeks are you asked to participate remotely and not come to this venue?
3. What is the percent chance that one of your 20th March allocations will be implemented?
4. If you face a 1:2 task rate for allocations between weeks 2 and 3, every task you allocate to week 2 decreases by how many number of the tasks you allocate to week 3?