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Contents

List of Tables

List of Figures

Chapter 1

Inequity Aversion and Limited Foresight in the Repeated Prisoner's Dilemma

1.1 Introduction

One of the most dynamic research fields over the last two decades has been behavioral game theory, i.e. the econometric and theoretical analysis of laboratory games to align observed behavior with game-theoretical concepts. How should we think of beliefs, utilities, and subjects' choices, and is it possible to explain choices as responses to incentives? In some classes of games, most notably auctions, behavior shows to be reasonably consistent with theory after simply accounting for risk aversion (Bajari and Hortacsu, 2005) or biased beliefs (Eyster and Rabin, 2005). In generic normal-form games involving dominated strategies, behavior is captured after relaxing rational expectations (Costa-Gomes et al., 2001); in games without dominated strategies, behavior tends to mainly reflect logistic errors in choice (Weizsäcker, 2003; Brunner et al., 2011); and in games involving the distribution of monetary benefits, preference interdependence seems to organize behavior (Fehr and Schmidt, 1999; Charness and Rabin, 2002). Particular behavioral models tend to be disputed, but overall, there has been substantial progress in aligning observed behavior and theoretical predictions across many classes of games.

One class of games that has experienced less progress in aligning behavior and predictions is the large class of repeated games. Repeated games are the main approach toward modeling long-run interactions, in particular to study cooperation and defection, and they have been a core object of game-theoretic analyses at least since the folk theorem for repeated games with discounting (Fudenberg and Maskin, 1986). Regarding behavior in experiments, however, there is no consensus on what subjects actually do—not even whether they play pure, mixed or behavior strategies—and there is not a single analysis relating round-by-round decisions to beliefs and expected utilities despite its common practice in structural analyses of behavior in static games.

The purpose of this paper is to re-analyze a large data set comprising 12 experiments to robustly estimate strategies and structurally analyze them similar to previous work on static games. We seek to answer three questions: Which strategies do subjects actually play? Are the strategies played and the shares of them predictable across conditions? How do the strategies align with expected utilities, and to what extent is individual behavior consistent with existing models of behavior in games? Regarding the first question, much of the existing literature restricts attention to strategies that are pure (with trembles), but recent evidence suggests that behavior strategies might better explain behavior (reviewed below). Regarding the second question, existing evidence suggests that the type shares playing specific cooperative strategies fluctuate fairly erratically between treatments, which is puzzling but may reflect inadequate constraints to pure strategies that we shall relax in our analysis. The third question is novel in the analysis of repeated games and has been left unexplored in previous work, but it is a central question in many behavioral papers and of major relevance in order to link behavior in repeated games to other literature.

Our main results can be summarized as follows. First, on a data set comprising 145,000 decisions from 12 experiments, we use data-mining techniques to obtain an upper bound for the goodness-of-fit that could be obtained assuming all subjects play versions of pure strategies. We relax many assumptions made in the literature, grant many degrees of freedom "for free", and allow for either no switching, random switching, or Markov switching of strategies between supergames to find the best-fitting pure strategies out of 10^{51} combinations of pure-strategy mixtures across treatments. We then take a simple behavior strategy previously hypothesized in Breitmoser (2015) – dubbed semi-grim. Here, subjects cooperate with probability 0.9 when both cooperated in the previous round, with probability 0.1 when both defected in the previous round, and with probability 0.3 when one player cooperated and the other defected in the previous round. The intuitive interpretation is that subjects expect cooperation when both cooperated in the previous round, or defection when both defected, and hence either cooperate or defect with very high probability. Otherwise, they are unsure and randomize. We extend this semi-grim strategy to include round 1. Following a game-theoretic prediction, we allow for two types, one of which captures subjects who expect cooperation (and therefore cooperate with probability 0.9 in round 1), and the other one captures subjects who are doubtful and cooperate with probability 0.3. The subjects expecting defection are assumed to play always defect as usual. Note that all three probabilities $(0.9, 0.3, 0.1)$ above are taken directly from the small-sample analysis of Breitmoser (2015) and they are neither optimized nor optimal. Nonetheless, this simple constant three-type mixture fits significantly better than the best of the 10^{51} pure-strategy mixtures considered plausible in the existing literature.

Second, we estimate the individual strategies without restrictions to pure or otherwise known strategies, and find that both the bottom-up and the top-down approach toward behavioral modeling converge to the three subject types outlined above, across all treatments and experiments. That is, type 1 plays a slightly perturbed version of always defect, and we refer to subjects of type 1 as defectors. Types 2 and 3 also approximate the above description: both play behavior strategies predicting nearly pure behavior after (c,c) and (d,d) (cooperation and defection, respectively), and they both randomize after (c,d) and (d,c). In round 1, type 2 cooperates with intermediate probability and type 3 with high probability. We refer to subjects of types 2 and 3 as cautious and strong cooperators, respectively. The states will be abbreviated as cc, cd, dc, dd in the following. We obtain these results from an unrestricted estimation of memory-1 strategies, i.e. an estimation of strategies without imposing restrictions to say pure strategies that characterize previous work. The initial focus on memory-1 strategies follows a number of results in the literature on behavior in the repeated PD with perfect information (Dal Bó and Fréchette, 2018; Breitmoser, 2015), and is corroborated by a robustness check (to memory-2) reported in the appendix. Both the data mining of pure strategies and the unrestricted estimation of behavior strategies outlined above are conceptual novelties in the behavioral analysis of repeated games and jointly provide a strong result that the three identified subject types robustly capture behavior across experiments.

Across treatments, the three types of strategies used are largely uncorrelated with treatment parameters or other known predictors of cooperation, while the distribution of types is highly correlated with the discount factor δ: As δ approaches the Blonski et al. (2011) (BOS) threshold of cooperation δ^*, the share of defectors decreases relative to cooperators, and as δ is raised further, the strong cooperators start to outnumber the cautious cooperators. That is, the unrestricted estimation implies that the distribution of subject types stops being erratic and becomes predictable—this is our third major result and addresses the second question above. Yet, the types of strategies that subjects play are all the more puzzling. Specifically, we have no prior explanation for the observation that type shares are correlated with δ (in relation to the BOS threshold δ^*, see Figure 1.4), which suggests that subjects are aware of δ and other parameters when choosing their strategy, while the actual strategies seem largely uncorrelated with δ (Figure 1.3). Subjects seem to be choosing one of three strategies depending on the environment, but hardly adapt the strategy as such to the environment.

To shed on light on this puzzle, and the third question above, we introduce a third conceptual novelty into analyses of repeated PDs by using techniques developed for the structural estimation of static games (McKelvey and Palfrey, 1995; Bajari and Hortacsu, 2005) and dynamic games (Aguirregabiria and Mira, 2007). We aim to understand the individual motivation behind the strategies of cooperative types across treatments. In this way, we also seek to resolve another puzzle that the above results highlight: Cooperating subjects in our unrestricted analysis, and indeed in all previous work, cooperate with a probability close to 1 if both subjects had cooperated in the previous round. They do so even if the expected payoff of cooperating (in the next round) is substantially below the expected payoff of defecting, as we demonstrate below, and even in the three treatments where Grim is not a subgame perfect equilibrium. The latter implies that behavior cannot be explained just by relaxing beliefs about the opponent's strategy. By estimating the dynamic games, we try to understand subjects' preferences in repeated games in a manner similar to previous behavioral analyses of cooperative subjects in one-shot games, which is a key step in linking these literatures.

We find that the strategies of cooperators are consistent with false consensus beliefs about the opponent's type, i.e. that each subject believes their opponent to be of the same type as they are (as in symmetric equilibrium), that subjects display severely limited foresight (as if the discount factor was zero, discussed shortly), and that their preferences are well described by Fehr-Schmidt inequity aversion. The limited foresight implies that subjects do not look beyond the outcome of the present round and do not explicitly consider sums of discounted payoffs. Instead, subjects associate utility values with each of the four possible outcomes of the present round (cc, dc, cd, dd) that encode the subject's value of reaching the respective state. We estimate that these state values induce a coordination game played round-by-round, that is, with one round of foresight, and that these state values can be derived from the stage game payoffs using inequity aversion.

As usual, this coordination game has three Nash equilibria: a cooperative one, a defective one, and a mixed one. Our analysis indicates that subjects use focal points as envisaged by Schelling and thus reliably coordinate on either of the three equilibria: after cc subjects expect cooperation (i.e. believe the opponent to cooperate) and play the cooperative equilibrium of the coordination game, after dd they expect defection and play the defective equilibrium, and after mixed histories (cd or dc) they play the mixed equilibrium. Our results indicate a similar line of reasoning in round 1: Given the actual treatment parameters, some subjects focus on the cooperative equilibrium (the "strong cooperators"), some focus on the defective equilibrium (the "defectors"), and some seem "unsure" playing the mixed equilibrium in round 1 (the "cautious cooperators"). The respective subject shares are predictable using the distance of discount factor δ to the BOS-threshold δ^* derived by Blonski et al. (2011).

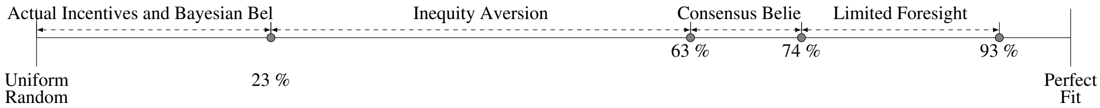
We thus obtain a closed behavioral foundation of the strategies played in the repeated PD. In contrast to previous work, this model *explains* the strategies that we estimated *without restrictions* beyond standard memory-1, rather than merely estimating strategy weights under non-validated restrictions to certain pure strategies. Further, our results bear many relations to previous work in behavioral economics.

Quantitatively, using just four parameters for the 80.000 observations of "experienced subjects" (in their second halves of sessions), the resulting model captures 93% of observed variance across 32 treatments from 12 experiments. Figure 1.1 briefly summarizes the obtained decomposition of behavior using our structural estimates. Our finding that behavior in the repeated PD is characterized by false consensus beliefs relates to a central concept in psychology (Ross et al., 1977) implying symmetric equilibrium[1]; limited foresight relates to a central concept in computer science and behavioral game theory (Jehiel, 2001; Kübler and Weizsäcker, 2004); and inequity aversion is a central concept in behavioral economics (Fehr and Schmidt, 1999).[2] Further,

[1]Recent belief elicitation studies by Aoyagi et al. (2021) and Gill and Rosokha (2020) provide first evidence that subjects "overestimate the popularity of their own strategy" in the repeated PD.

[2]Interestingly, our results shed new light on the findings of Dreber et al. (2014), who found that inequity aversion does not help explain behavior in the repeated PD. The difference in our analysis is that we do not attempt to explain so-called standard strategies, i.e. pure strategies, but behavior strategies estimated without restrictions to purity. Further, inequity aversion in our analysis is closely

Figure 1.1: Decomposition of behavior into model components
(second halves of sessions, based on 79.892 observations)



Note: This plot summarizes the results of our structural analyses (Table 1.5) of the strategies played. Here we focus on the strategies of subjects not classified as playing always defect. The clairvoyance model explaining the strategies of cooperating subjects perfectly across treatments obtains the "perfect fit" (100%), while the model predicting uniform randomization obtains 0%. The remaining percentages are computed proportionally to these two benchmarks. First, the model assuming that subjects play logit responses to Bayesian beliefs over their opponent's strategy obtains 23%, additionally allowing for inequity aversion increases the score to 63%, next adopting consensus beliefs increases the explained variance to 74%, and allowing for a flexible discount factor δ (leading to limited foresight as an estimation result) captures an additional 19% for a total of 93%. Figure A.2 provides information also for behavior in the first halves of sessions and on robustness with respect to modeling assumptions.

the idea that a repeated PD resembles a coordination game in round 1, and iteratively in any subsequent round, has been discussed at least since Rabin (1993). We provide the first empirical confirmation, by demonstrating that this implicit coordination game is endogeneously obtained as an estimation result using econometric techniques known from static games, and by the findings that this coordination game is highly predictable using inequity aversion and that its equilibria are highly predictive of behavior across treatments and experiments. This yields a first explanation for behavior in repeated games and a first set of precise behavioral predictions for future work on repeated games generalizing the repeated PD—a very encouraging step to bridge the gap between behavioral analyses of repeated games and behavioral analyses of static games.

1.2 Background information

Definitions The *prisoner's dilemma* (PD) involves two players choosing whether to cooperate (c) or defect (d). In the normalized PD, each player's payoff is 1 if both cooperate and 0 if both defect. If exactly one player cooperates, the cooperating player's payoff is $-l$ ($l > 0$) and the defecting player's payoff is $1+g$ ($g > 0$). An infinite repetition of this constituent game is strategically equivalent to an indefinitely repeated one that is terminated with probability $1-\delta$ after each round, assuming players are risk neutral and discount future payoffs exponentially (using factor $\delta < 1$). We will refer to these games jointly as repeated PD (or, *supergame*). Given $g, l > 0$, cooperation is dominated in the one-shot game but may be sustained along the path of play in subgame-perfect equilibria of the repeated PD (depending on δ).

A *strategy* σ in the repeated PD maps all finite histories to probabilities of co-

interlinked with limited foresight, which Dreber et al. (2014) did not include in their analysis, and we allow for α and β to be free parameters.

operation in the next round. The strategy has *memory-1* if it prescribes the same cooperation probability for any two histories not differing in the actions chosen in their respective last rounds. It has memory-2 if the same holds for the last two rounds. We denote memory-1 strategies as $\sigma = (\sigma_\emptyset, \sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd})$ corresponding to the five memory-1 histories $\{\emptyset, cc, cd, dc, dd\}$, called *states* in the following. For example, σ_{cd}, denotes the probability of cooperation when a player's most recent action is c and her opponent's most recent action is d. A strategy is a *pure strategy* if it prescribes degenerate cooperation probabilities after all histories ($\sigma \in \{0,1\}^5$), and it is a *behavior strategy* otherwise. It is a *mixed strategy*, when a player randomizes over the set of pure strategies prior to the start of each supergame, but sticks to the drawn pure strategy throughout the supergame. In contrast, when playing a behavior strategy, she randomizes during the supergame.[3]

Table 1.1: Overview of most commonly analyzed strategies (see Table A.7 in the appendix for a more comprehensive list)

Strategy	Abbreviation	Description	$(\sigma_\emptyset, \sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd})$
Always Defect	AD	Always defects	(0,0,0,0,0)
Always Cooperate	AC	Always cooperates	(1,1,1,0,0)
Grim	G	Only cooperate in R1 and after cc	(1,1,0,0,0)
Tit-for-Tat	TFT	Start with c, then copy opponent	(1,1,0,1,0)
Suspicious TFT	STFT, D-TFT	Start with d, then copy opponent	(0,1,0,1,0)
Win-Stay-Lose-Shift	WSLS	Cooperate in R1, cc and dd	(1,1,0,0,1)
Semi-Grim	SG	Behavior strategy satisfying ...	$\sigma_{cd} = \sigma_{dc}$

Note: The conventional definition of AC is $(1,1,1,1,1)$, which is behaviorally equivalent to $(1,1,1,0,0)$. The definition used above implies that any memory-1 behavior strategy that might be observed on average can be rebuilt using some combination of AD, AC, Grim, TFT and WSLS.

Related behavioral literature We will keep the literature review short and focused due to the availability of an excellent recent survey by Dal Bó and Fréchette (2018). The modern experimental research on the repeated PD started with Dal Bó (2005), who criticized earlier experiments for implementing experimental designs that let subjects play against computerized opponents. The first wave of experiments following Dal Bó (2005) includes Dreber et al. (2008), Duffy and Ochs (2009), Blonski et al. (2011) and Kagel and Schley (2013), and focuses on analyzing first-round and total cooperation rates. A second wave comprising Dal Bó and Fréchette (2011, 2015), Bruttel and Kamecke (2012), Camera et al. (2012), Fudenberg et al. (2012), Sherstyuk et al. (2013), Breitmoser (2015), and Fréchette and Yuksel (2017) analyzes the strategies actually chosen by players. The general theme in the reported results is that initial cooperation rates depend on the strategic environment. More specifically, the results indicate that subgame perfection of Grim is necessary but not sufficient for cooperation to emerge (first reported in Dal Bó, 2005), and that subsequent cooperation of subjects depends on their opponent's actions, primarily on those in the previous round. The central importance of initial cooperation is also demonstrated in Fudenberg and

[3] Including the case when she would switch between pure strategies within a supergame.

Karreskog (2020). Many of the second-wave analyses classify individual subjects' strategies into varying sets of pre-selected strategies. Even allowing for noise, these analyses clearly show that subjects do not homogeneously follow a given pure strategy across all supergames. The studies differ in their assumptions of what subjects might be doing instead—whether they are playing pure, mixed, or behavior strategies—and consequently in their conclusions about behavior.

Most analyses assume that decisions are made only prior to the first supergame of a session, with subjects then sticking to a *pure strategy* for the rest of the session. Given this restriction to pure strategies, these analyses typically conclude that the majority of subjects play either AD, TFT, or Grim, with each being attributed weights around 20–30%. For example, Result 6 of Dal Bó and Fréchette (2018, DF18) states that these three strategies account for "most of the data", specifically they "account for 70 percent of strategies in most treatments", but importantly, this result is obtained after a-priori restricting attention to (a subset of) pure strategies without further validating this restriction. We refer to this statement as the *pure-strategy conjecture*.

A second, less common approach is based on the assumption that subjects switch pure strategies between supergames, which we refer to as *mixed strategies* in the game-theoretical sense. For example, DF18 report that 84 percent of choices in supergames lasting more than one round are accounted for by five pure strategies (now also including AC and suspicious TFT) when they allow for strategy switching between supergames (DF18, Footnote 38).[4] The difficulty now is to explain this strategy switching; otherwise, the impression of a perfect fit, not requiring a complicated analysis allowing for noise, is intriguing, but it is only true in a post-hoc sense. Ex-ante, the strategy chosen by a given subject is not perfectly predictable, and the game-theoretical concept closest to such a random choice over varying pure strategies over time is that of a mixed strategy. The probabilities of choosing different pure strategies over time may be path dependent, given the path-dependency they may be degenerate, and they may be heterogeneous between subjects. Below, we shall explicitly allow for these possibilities by considering Markov-switching models to capture strategy switching that contain pure, mixed, and path-dependent mixtures as special cases. This will be one of the major novelties of our analysis and will enable us to determine an upper bound for the goodness-of-fit of pure and mixed strategies.

A third and growing group of studies challenges the pure-strategy conjecture by allowing subjects to randomize in each round of each supergame, as in the game-theoretical concept of *behavior strategies*. Relaxing the restriction to pure strategies, Breitmoser (2015) observed that cooperating subjects play a semi-grim behavior strategy, approximating $(\sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd}) = (0.9, 0.3, 0.3, 0.1)$ without specifying $\sigma_\emptyset$ (*behavior-strategy conjecture*, c.f. Breitmoser, 2015, p. 2889).[5] The intuition attributed to this observation is that subjects expect cooperation after *cc* and then cooperate with high probability, that they expect defection after *dd* and then de-

[4] Specifically, DF18's observation states that subjects' behavior is described "exactly" even if one "does not allow for any mistakes" .

[5] Specifically, a behavior strategy satisfying $(\sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd}) = (0.9, 0.3, 0.3, 0.1)$, with varying $\sigma_\emptyset$, is approximately played in all treatments of a data set comprising four experiments.

fect with high probability, and that they are unsure after the mixed histories cd, dc and then randomize. This intution directly entails a prediction for behavior round 1: Subjects expecting cooperation will cooperate with high probability, subjects that are unsure will randomize, while subjects expecting defection would play always defect as usually assumed. The game-theoretic foundation for this prediction is that, if $(\sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd}) = (0.9, 0.3, 0.3, 0.1)$ is part of an equilibrium strategy, which is approximately the case if symmetric belief-free equilibria exist (Breitmoser, 2015), then the three possible completions of this strategy to a symmetric equilibrium strategy are $\sigma_\emptyset = 0.9$, $\sigma_\emptyset = 0.3$, and $\sigma_\emptyset = 0.1$ (round 1 can be equated with any of the subsequent states). We adopt the first two possibilities and skip the last one ($\sigma_\emptyset = 0.1$), as we are modeling defective players as playing AD by the standard convention.

Additionally, semi-grim behavior strategies are found to better capture behavior than mixtures of pure memory-1 strategies.[6] Recently, Fudenberg and Karreskog (2020) report evidence highlighting the predictive power of semi-grim strategies in repeated PDs with perfect monitoring. The behavioral assumption that decisions are made in each round, instead of say once at the start of a session (as in the pure-strategy conjecture), seems intuitive.[7] However, there are several concerns about Breitmoser's results that might explain why the behavior-strategy conjecture faces skepticism: the data set might be fortunately selected in Breitmoser (2015), behavior might be more complex than memory-1 admits, strategies may be behavior strategies other than semi-grim, subjects might switch strategies as the session progresses, and round-1 behavior was not included in the estimation of strategies. In the next two sections, we address all of these concerns and report arguably conclusive answers to the following questions whose answers then serve as foundation for the structural analysis of preferences and beliefs:

Question 1. *Do subjects play pure, mixed, or behavior strategies?*

Question 2. *Is there heterogeneity in subject types and which strategies are played?*

The case for memory-2 strategies had been made by Fudenberg et al. (2012), who analyze the repeated PD with imperfect monitoring and show that if we assume subjects play pure strategies, then there must be subjects with memory-2, based on evidence for 2TFT and "lenient" Grim2 strategies. Similar ideas are expressed in Aoyagi and Frechette (2009) and Bruttel and Kamecke (2012). Our analysis will allow for memory-2, but in addition, we will relax the restriction to pure strategies, which seems

[6]The only other studies investigating a behavior strategy seem to be Fudenberg et al. (2012), who include the strategy "generous TFT" which randomizes (only) after opponent's defection, and more recently Dvorak and Fehrler (2018). A recent study by Romero and Rosokha (2019) indicates that subjects consider randomizing over single choices even ex-ante.

[7]Here follow the interpretation of behavior in repeated matching pennies games (e.g. Goeree et al., 2003), whereby the description of subjects randomizing say 50-50 each round is simply the best-possible description for the outside observer. Subjects themselves typically do perceive their decisions to be deliberate each round. Similarly, we consider a behavior strategy implying randomization each round to be the best-possible description available to observers of seemingly random but subjectively deliberate (memory-1) decisions that subjects make each round.

critical since behavior strategies also generate decision patterns resembling memory-2 or -3.

The data We re-analyze the exact same set of experiments reviewed in Dal Bó and Fréchette (2018). This set comprises most of the modern experiments on repeated Prisoner's Dilemmas with perfect monitoring, i.e. those published since Dal Bó (2005), and consists in total of data from 12 experiments, 32 treatments, more than 1900 subjects, and almost 145,000 decisions. The set of experiments equates with the experiments listed in Table 1.2. A brief review and an overview table is in Appendix B, but for a detailed discussion, see DF18. Due to its enormous size, the wide range of experiments covered (from different experimenters in various universities and various countries), and its comprehensive character with respect to the recent list of experiments on the repeated PD, this data set appears to be optimal for our purposes. In addition, by sticking exactly to the list of experiments reviewed by Dal Bó and Fréchette (2018), we can rule out the notion that data selection biases the results in favor of any of the hypotheses we intend to test.

Econometric approach Our econometric approach is standard, building on finite-mixture and Markov-switching analyses generalizing the strategy frequency estimation method of Dal Bó and Fréchette (2018) as we simultaneously estimate strategies and their frequencies. All details, including a simulation analysis of validity given the finite data sets considered here, are provided in the Appendix, Section A.1.

1.3 A model-free overview of behavior

In order to provide a foundation for the subsequent analysis and discussion, let us first provide an overview of behavior in the repeated PD without imposing restrictions reflecting any of the above stated three conjectures. To this end, we simply report average cooperation rates in both the first and second halves of sessions of all experiments and discuss how these average strategies align with expected payoffs across states.

Average behavior Table 1.2 reports the average cooperation rates across experiments in each of the four memory-1 states after round 1 and tests for significant differences. For brevity, we aggregate across all treatments per experiment here but provide results by treatment in Table A.10 in the appendix, then also including round-1 behavior. Initially, we skip round-1 behavior as it varies substantially across treatments, as discussed below, but the cooperation rates in the remaining states are fairly similar across treatments and indeed across experiments, as Table 1.2 shows. In state *cc*, cooperation rates are above 0.9, in state *dd* they are mostly at or below 0.1 (with the sole exception of Aoyagi and Frechette, 2009), and after the mixed histories *cd* and dc, cooperation rates fluctuate somewhat in the range $[0.2, 0.5]$. Further, the differences between inexperienced and experienced subjects are very minor overall, the aggregate cooperation probabilities shift by at most five percentage points. This observation notwithstanding, it is customary to distinguish experienced and inexperienced behavior by first and second halves of sessions, which we maintain also for this paper.

Table 1.2: Few subjects play pure strategies and assuming pure strategies yields a striking bias even in large mixture models

	Actual cooperation rates							Number of subjects not randomizing 50-50			
Experiment	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$	(c,c)	(c,d)	(d,c)	(d,d)
First halves per session											
Aoyagi and Frechette (2009)	0.917	$\gg$	0.45	$\approx$	0.408	$\approx$	0.336	32/38	1/23	3/20	7/21
Blonski et al. (2011)	0.89	$\gg$	0.279	$\approx$	0.193	$\gg$	0.034	13/17	1/5	3/3	124/135
Bruttel and Kamecke (2012)	0.91	$\gg$	0.286	$\approx$	0.228	$\gg$	0.08	12/18	6/23	8/21	32/36
Dal Bó (2005)	0.922	$\gg$	0.212	$<$	0.342	$\gg$	0.089	13/13	0/3	2/2	42/54
Dal Bó and Fréchette (2011)	0.951	$\gg$	0.334	$\approx$	0.331	$\gg$	0.063	94/106	28/117	51/128	218/253
Dal Bó and Fréchette (2015)	0.94	$\gg$	0.297	$\approx$	0.335	$\gg$	0.057	216/243	37/137	62/147	404/474
Dreber et al. (2008)	0.904	$\gg$	0.217	$\approx$	0.213	$\gg$	0.036	15/25	3/19	12/18	45/48
Duffy and Ochs (2009)	0.904	$\gg$	0.301	$\approx$	0.33	$\gg$	0.111	43/57	4/25	10/24	61/82
Fréchette and Yuksel (2017)	0.943	$\gg$	0.141	$\approx$	0.266	$\approx$	0.091	21/28	0/0	2/2	5/8
Fudenberg et al. (2012)	0.982	$\gg$	0.4	$\approx$	0.427	$\gg$	0.066	38/43	1/6	5/11	20/25
Kagel and Schley (2013)	0.935	$\gg$	0.263	$\approx$	0.295	$\gg$	0.051	71/81	20/71	32/60	98/111
Sherstyuk et al. (2013)	0.945	$\gg$	0.328	$\approx$	0.371	$\gg$	0.117	37/44	10/36	12/34	41/52
Pooled	0.938	$\gg$	0.304	$\approx$	0.322	$\gg$	0.065	605/713	111/465	202/470	1097/1299
Second halves per session											
Aoyagi and Frechette (2009)	0.958	$\gg$	0.398	$\approx$	0.517	$\approx$	0.375	33/37	0/12	1/12	5/9
Blonski et al. (2011)	0.923	$\gg$	0.287	$\approx$	0.231	$\gg$	0.02	26/32	10/25	11/16	172/178
Bruttel and Kamecke (2012)	0.947	$\gg$	0.221	$\approx$	0.297	$\gg$	0.041	13/15	8/17	9/12	31/35
Dal Bó (2005)	0.92	$\gg$	0.242	$<$	0.388	$\gg$	0.064	18/27	0/3	0/1	50/65
Dal Bó and Fréchette (2011)	0.979	$\gg$	0.376	$\approx$	0.362	$\gg$	0.041	132/137	34/89	62/100	196/215
Dal Bó and Fréchette (2015)	0.976	$\gg$	0.315	$<$	0.402	$\gg$	0.035	340/365	52/162	77/146	448/497
Dreber et al. (2008)	0.917	$\gg$	0.128	$\ll$	0.39	$\gg$	0.009	14/18	6/11	6/12	41/43
Duffy and Ochs (2009)	0.977	$\gg$	0.367	$\approx$	0.391	$\gg$	0.082	80/87	5/35	16/43	60/68
Fréchette and Yuksel (2017)	0.97	$\gg$	0.233	$\approx$	0.398	$\gg$	0.069	33/37	1/6	2/10	20/25
Fudenberg et al. (2012)	0.971	$\gg$	0.487	$\approx$	0.412	$\gg$	0.083	41/44	2/8	4/10	14/17
Kagel and Schley (2013)	0.966	$\gg$	0.262	$\approx$	0.332	$\gg$	0.025	87/90	16/56	30/46	91/97
Sherstyuk et al. (2013)	0.973	$\gg$	0.482	$\approx$	0.437	$\gg$	0.078	44/48	7/24	17/23	23/29
Pooled	0.971	$\gg$	0.327	$<$	0.376	$\gg$	0.039	861/937	141/448	235/431	1151/1278

Note: The "actual cooperation rates" are the relative frequencies estimated directly from the data. The relation signs encode bootstrapped p-values (resampling at the subject level with 10,000 repetitions) where $<, >$ indicate rejection of the Null of equality at $p < .05$ and $\ll, \gg$ indicating $p < .002$. Following Wright (1992), we accommodate for the multiplicity of comparisons within data sets by adjusting p-values using the Holm-Bonferroni method (Holm, 1979). As a result, if a data set is considered in isolation, the .05-level indicated by "$>, <$" is appropriate. If all 24 treatments are considered simultaneously, the corresponding Bonferroni correction requires to further reduce the threshold to $.002 \approx .05/24$, which corresponds with "$\gg, \ll$". Note that all econometric details here exactly replicate Breitmoser (2015), i.e. the statistical tests are not adapted post-hoc. The "number of subjects not randomizing 50-50" indicates the number of subjects with cooperation rates in the various states differing significantly from 50-50 (in subject-level two-sided binomial tests), conditioning on subjects having moved at least five times in the respective state. The required level of significance is set at $p = 0.0625$ such that five observations are sufficient to trigger statistical significance if the subject plays a pure strategy.

Re-analyzing four experiments, Breitmoser (2015) made the observation that average memory-1 strategies have a "semi-grim" pattern. A behavior strategy is called *semi-grim* if $\sigma_{cc} > \sigma_{cd} \approx \sigma_{dc} > \sigma_{dd}$, with the approximation $(\sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd}) = (0.9, 0.3, 0.3, 0.1)$. Based on the vastly extended data set analyzed here, we can scrutinize whether this somewhat surprising observation was the result of a selection effect. The table 1.2 shows that $(0.9, 0.3, 0.3, 0.1)$ is clearly no more than an approximation, but in the initial steps of our analysis in section 1.4, we shall use it nonetheless in order to avoid post-hoc specification adaptations of semi-grim.

We further test for differences in the cooperation rates using bootstrapped p-values, resampling at the subject level, and distinguishing two levels of significance: the conventional level 0.05 and the tighter level $0.002 \approx 0.05/24$. The latter implements the Bonferroni correction for tests across 12 experiments and the two session halves. Naturally, we shall focus on this corrected level of significance, but for clarity we also report the conventional level that does not correct for multiple testing.[8]

Out of all the 24 observations, considering first and second halves separately, only one observation, based on one session half in one experiment (Dreber et al., 2008), indicates a significant violation of the key restriction $\sigma_{cd} \approx \sigma_{dc}$, while the other two restrictions $\sigma_{cc} > \sigma_{cd,dc}$ and $\sigma_{cd,dc} > \sigma_{dd}$ are never violated significantly. In $45/48$ cases they are even confirmed significantly at the tight 0.002 level surviving the Bonferroni correction. Pooling all observations from all experiments, $\sigma_{cd} \approx \sigma_{dc}$ is not rejected in the first halves of sessions but at the 0.05 level it is rejected in the second halves of sessions. The difference of σ_{cd} and σ_{dc} remains small, however, and is not significant at the 0.025 level surviving the Bonferroni correction considering that we run two simultaneous tests for the pooled data (one for the first halves of sessions and one for the second halves). Given this range of observations on a vastly extended data set, we conclude that Breitmoser's observation passed the out-of-sample test on non-selected data, i.e. that average behavior indeed exhibits the semi-grim pattern.

We want to emphasize that, if there is subject heterogeneity, mean cooperation rates provide unbiased estimates of the true cooperation rates but are not necessarily unbiased estimates of the mean strategies (e.g. due to selection effects after round 1). Yet, the behavior-strategy conjecture postulates that this semi-grim pattern does not only characterize the behavior on average but also the strategies of individual subjects. Otherwise, the observation that this pattern recurs across all treatments and experiments would appear to be a striking coincidence—for, if used at all, pure strategies are estimated to be played in strikingly varying weights across treatments (Dal Bó and Fréchette, 2018), which seems incompatible with the observation that mean cooperation rates always exhibit the semi-grim pattern—but our objective is to test this conjecture directly.

The results of a first simple test of this hypothesis are reported in the last four columns of Table 1.2. These columns list the number of subjects (per experiment) that deviate significantly from randomizing 50-50 in the four memory-1 states. We focus on subjects with at least five observations per state, which is sufficient to trigger significance in two-sided Fisher tests if subjects play a pure strategy. The results are fairly clear: In state *cd*, i.e. after unilateral defection of the opponent, all standard pure strategies (except AC , which is rarely observed though) agree on the (pure) prediction that one should defect. This state is unique with respect to the unanimity of the prediction. For this state, however, we find the lowest number of subjects significantly deviating from randomizing 50-50—only around a quarter of the subjects do

[8] In Table 1.2, $<,>$ indicate significance at the conventional level and $\ll,\gg$ indicate significance surviving the Bonferroni correction (see the table notes for details).

so, putting a rather tight bound on the number of subjects potentially playing pure strategies.

To further illustrate this bound, assume that subjects do use pure strategies: On one hand, given that the semi-grim pattern results on average, there have to be subjects that systematically cooperate after unilateral defection of opponents (state *cd*). These subjects are rarely found in analyses, as indicated most clearly by the aforementioned Result 6 of Dal Bó and Fréchette (2018), stating that "always defect" (AD), Grim, and tit-for-tat (TFT) are the "three strategies [that] account for most of the data". This directly contradicts the observation that $\sigma_{cd} \approx \sigma_{dc} > \sigma_{dd}$, unless in addition to the strategies accounting for most of the data a substantial number of subjects systematically cooperate in state *cd*. However, the strategies predicting at least occasional cooperation after *cd*, such as always-cooperate and tit-for-2-tats, were found to fit behavior of only very few subjects in Dal Bó and Fréchette (2018). This contradiction foreshadows what we will find below: even allowing for drastic data mining, pure strategies cannot be pushed to fit behavior as well as a simple behavior strategy does.

Relation to monetary incentives Complementing the model-free description of behavior, let us look at what subjects should be doing under rational expectations. While relating the decisions "cooperate" and "defect" to expected payoffs in each state is a standard behavioral piece of information in analyses of static games, it is novel in analyses of repeated games. The underlying question, whether the actions chosen are at least qualitatively plausible, is of obvious relevance in any attempt to understand behavior.

For this initial model-free exposition, we will estimate the expected payoffs of cooperate and defect, in each state, from the perspective of an agent who assumes continuation play follows the average relative frequencies of cooperation observed above. These relative frequencies are denoted as the behavior strategy $\sigma = (\sigma_{\emptyset}, \sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd})$. Given σ, the expected payoff in state $\omega \in \{\emptyset, cc, cd, dc, dd\}$ is denoted as π_ω, with

$$\pi_\omega = \sigma_\omega \pi_\omega(c) + (1-\sigma_\omega)\pi_\omega(d), \tag{1.1}$$

where $\pi_\omega(c)$ and $\pi_\omega(d)$ denote the expected payoffs of playing c and d in state ω,

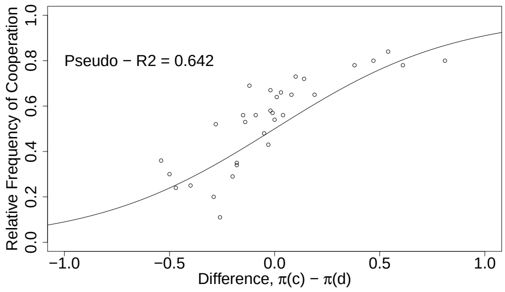
$$\pi_\omega(c) = \sigma_{\omega'}\big(\delta\pi_{cc} + (1-\delta)\times 1\big) + (1-\sigma_{\omega'})\big(\delta\pi_{cd} + (1-\delta)\times(-l)\big), \tag{1.2}$$
$$\pi_\omega(d) = \sigma_{\omega'}\big(\delta\pi_{dc} + (1-\delta)\times(1+g)\big) + (1-\sigma_{\omega'})\big(\delta\pi_{dd} + (1-\delta)\times 0\big), \tag{1.3}$$

with continuation probability δ and ω' the state ω from the opponent's point of view, such that $\sigma_{\omega'}$ is the probability of cooperation by the opponent. By inserting the treatment-specific average behavior strategies σ from above, we can solve the linear equation system, Eqs. 1.1–1.3 for all ω, and obtain the expected payoffs $\pi_\omega(c)$ and $\pi_\omega(d)$.

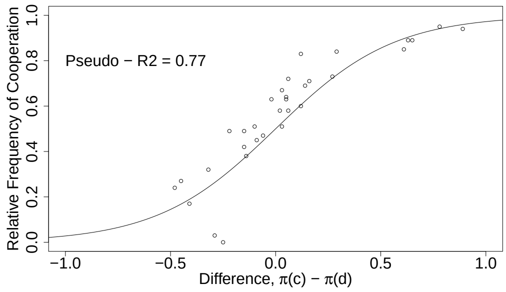
The monetary incentive to cooperate is $\pi_\omega(c) - \pi_\omega(d)$, for each ω. Figure 1.2 provides an overview of the results: We plot the relative frequencies of cooperation across treatments against the respective monetary incentives to cooperate for each state, sep-

Figure 1.2: Relation of monetary incentives and cooperation rates across states (naive beliefs)

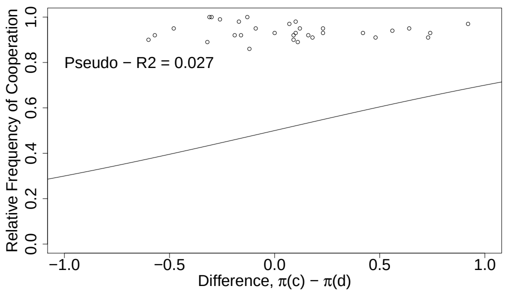
(a) State $\emptyset$, first halves of session



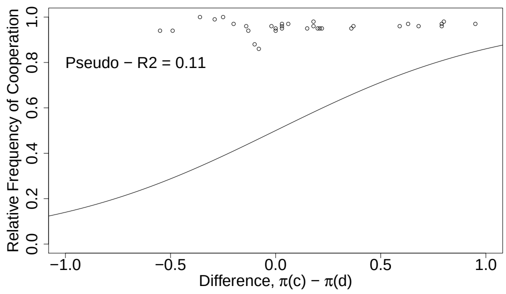
(b) State $\emptyset$, second halves of session



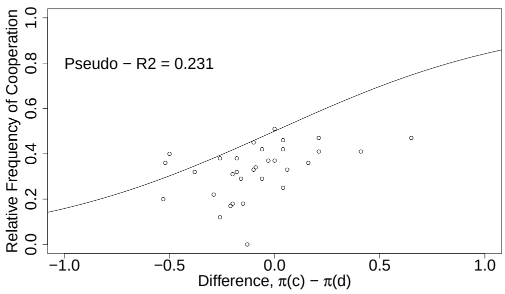
(c) State cc, first halves of session



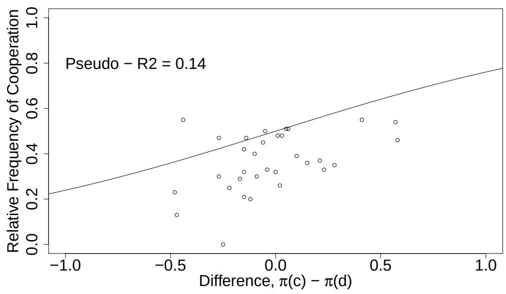
(d) State cc, second halves of session



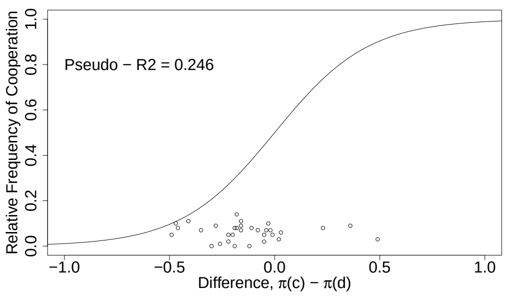
(e) State cd, dc, first halves of session



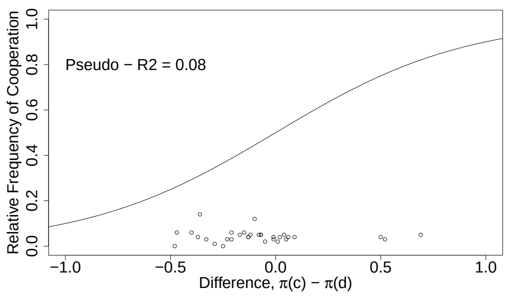
(f) State cd, dc, second halves of session



(g) State dd, first halves of session



(h) State dd, second halves of session



Note: The figures show relative frequencies of cooperation by monetary incentives to cooperate by treatments, for first and second halves of sessions, plus the best-fitting logistic curve. For further information, see Tables A.46–A.53 in the supplement.

arately for first and second halves of sessions. The states *cd* and *dc* are pooled for simplicity. Figure 1.2 additionally shows the best-fitting logistic curve, estimated without intercept such that neutral incentives $\pi_\omega(c) - \pi_\omega(d) = 0$ yield a predicted cooperation probability of 0.50. The pseudo-R^2 of the logistic curves indicate how much of the null deviance is explained by allowing for logistic errors in utility maximization.

The observations can be summarized as follows: For each state, we have observations from treatments with net incentives ranging from around -0.5 to $+1$, i.e. from cases where $\pi_\omega(c) - \pi_\omega(d)$ is highly negative to cases where it is highly positive. Essentially, the former obtains in treatments where Grim is not a subgame-perfect equilibrium strategy and the latter obtains in treatments where the discount factor δ is substantially above the threshold for Grim to be a subgame-perfect equilibrium strategy. Despite this range of induced monetary incentives, relative probabilities of cooperation and monetary incentives are highly correlated only in round 1 (state $\emptyset$). They are statistically close to independent in all states after round 1. For example, in second halves of sessions, when subjects have gained experience, the Pseudo-R^2 of the logit model is above 0.8 in round 1 and below 0.2 in all states afterwards. Obviously, this model-free analysis has the drawback of neglecting subject heterogeneity, which we will address below, but it seems that behavior in states *cc* and *dd* may be difficult to align with monetary incentives. For this reason, we raise the following set of questions, which will be addressed in section 1.5.

Question 3. *Do subjects act rationally and with rational expectations in round 1 but irrationally follow some automaton or heuristic afterwards? How do strategies relate to treatment parameters? Can we rationalize choices after round 1? And are the strategies predictable?*

1.4 Estimating the strategies used by subjects

This section consists of two parts. In the first part, we data mine for the best possible (post-hoc) mixtures of (generalized) pure strategies for *each treatment*. We will not penalize the model for data mining best mixtures but treat the resulting mixtures treatment-by-treatment as if they had been hypothesized ex-ante. As we discuss below, this provides us with an upper bound for the goodness-of-fit of pure and mixed strategies, which we will compare to a simple model that contains only defectors playing AD and cooperators playing semi-grim behavior strategies satifysing $(\sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd}) = (0.9, 0.3, 0.3, 0.1)$ as previously defined in Breitmoser (2015), in all treatments. Due to the one-sided data mining, involving optimizing the post-hoc mixture of pure strategies measured against treatment-invariant behavior strategies, this analysis is heavily lopsided in favor of modeling behavior using pure and mixed strategies. In this sense, we give the pure- and mixed-strategy conjectures the best possible chance.

In the second part, we provide the results of an unrestricted estimation of memory-1 strategies, and then estimate the number of subject types and the strategies played in both a top-down and a bottom-up approach towards model selection. The top-down approach starts with the general model and iteratively eliminates insignificant components, while the bottom-up approach starts with a basic model and iteratively adds model components identified as significant.

Both parts of this section will converge to the same model distinguishing defectors playing AD from cautious and strong cooperators playing semi-grim strategies. Their behavior will be further analyzed in the next section. Section A.2 in the appendix demonstrates robustness to longer memory lengths by demonstrating that model adequacy does not improve by equipping subjects with memory-2, neither for (generalizations of) pure strategies nor for semi-grim. That is, while increasing memory length slightly improves the goodness-of-fit, this increase does not make up for the increased complexity of strategies as evaluated using the Bayesian information criterion.

Pure, mixed or behavior strategies? In order to outline our approach towards estimating an upper bound of the goodness-of-fit of pure strategies, recall that the pure memory-1 strategies AD, TFT, and Grim had been conjectured (Dal Bó and Fréchette, 2018, Result 6) to capture the behavior of most subjects across treatments, but the analysis was restricted to pure strategies. For reasons discussed shortly, we add AC and WSLS to obtain a set of baseline strategies. We then extend this set of strategies in two ways. On one hand, we add generalized versions of these strategies by introducing a free parameter per strategy to relax assumptions on first-round cooperation rates $\sigma_\emptyset$, thus allowing subjects' first-round cooperation rates to be different from 0 in AD, and different from 1 in all other strategies. This is critical, as it allows us to also incorporate STFT. The definition of the continuation behavior remains unchanged, such that $(\sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd}) \in \{0,1\}^4$ for all pure strategies. We refer to these strategies as *generalized pure strategies of type I*. On the other hand, in the set of *generalized pure strategies of type II*, we introduce a free parameter to allow for randomization within supergames to relax assumptions about behavior after histories such as *cd* or *dc*, where the pure strategies tend to fit poorly. Using the notation introduced above, defining strategies as quintuple $(\sigma_\emptyset, \sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd})$, generalized TFT is defined as $(1,1,0,\theta^{TFT},0)$, generalized Grim as $(1,1,\theta^G,\theta^G,\theta^G)$, and generalized WSLS as $(1,1,0,0,\theta^{WSLS})$. Generalized AC and AD are defined as behavior strategies $(1,\theta^{AC},\theta^{AC},0,0)$ and $(0,\theta^{AD},\theta^{AD},\theta^{AD},\theta^{AD})$, respectively, with all $\theta^* \in [0,1]$.[9] The advantage of defining generalized strategies this way is that linear combinations of these generalized strategies, or of the original pure strategies, can reproduce the aggregate semi-grim patterns we observed above. In addition, we will of course consider the pure strategies in their original form, thereby covering the possibility that in at least some treatments neither of the generalizations improves the goodness-of-fit, allowing us to post-hoc save parameters. In addition to all of this, we allow for trembling-hand noise, i.e. that subjects may deviate from the assumed (generalized) pure strategy with probability $\varepsilon \in [0,1]$ in any given round, to then randomize uniformly.

With this set of strategies in hand, our approach toward data mining the mixtures

[9] Allowing for more than one free parameter per generalized pure strategy would be unreasonable since they would not be similar enough to their name giving pure strategy anymore. In addition, the penalty for free parameters would increase strongly.

across treatments is as follows.

First, we evaluate independently for each treatment which mixture of pure or generalized pure strategies best captures behavior. That is, we determine for each treatment, which combination of *pure* strategies fits best, which combination of *generalized pure strategies of type I* fits best, which of *type II*, and which of the three best combinations fits best. Following the pure-strategy conjecture, we assume the best combination always contains at least TFT, AD, and Grim. We add the remaining strategies when this improves the goodness-of-fit. Thus, we choose the best out of 13 as promising conjectured memory-1 mixtures, for each of the 32 treatments and each of the two half-sessions independently.[10] In total, we therefore evaluate 13^{32} models per level of experience and afterwards pick the best-fitting model in terms of ICL-BIC (see Appendix A.1). Second, we do all of this separately for the three "switching models" designed to capture the three possibilities of strategy switching between supergames: "No Switching" (pure strategy), "Random Switching" (mixed strategy), and "Markov Switching" (strategy switching between supergames follows a Markov process), see Appendix A.1.1 for details.

The results for each of the three switching models are reported in columns 2-5 of Table 1.3. The leftmost column contains the results for the baseline model comprising AC, AD, TFT, Grim, and WSLS without data mining, which can serve as a reference for how much of the goodness-of-fit is due to data mining. For the sake of readability, we report ICL-BICs aggregated by experiment.[11]

The random switching model in column 3 of Table 1.3 capturing mixed strategies generally fits worst, by the enormous amount of more than 2000 points on the log-likelihood scale. This shows that subjects are reasonably consistent in their strategy choice. The no-switching model capturing pure strategies (column 2) fits worse than the Markov-switching model (column 4) in the first halves of sessions, but weakly better in the second halves of sessions. If these models captured behavior well, this could suggest that subjects initially experiment with different pure strategies, though not randomly, as in mixed strategies, but systematically, as in a stochastic Markov process, to then converge to individual choices for strategies as the session progresses. Additionally, Table A.15 (in the appendix) shows that *continuation strategies* of the generalized pure type II (excluding round-1 behavior) perform much better than their counterparts without generalization. The differences in model fit are large, amounting in total to more than 1000 points on the log-likelihood scale. As defined above, these generalized strategies allow for systematic randomization after round 1, which suggests that randomization within supergames is indeed a behavioral facet.

[10] For each of the three classes of strategies (pure, generalized type I, generalized type II), we consider mixtures containing AD, TFT and Grim and in addition either (i) no other strategy, (ii) AD, (iii) WSLS, and (iv) AD + WSLS. This makes 12 combinations in total. In addition, in the case of pure strategies, we allow for a mixture containing noise players (randomizing 50-50 in all states) as type besides AC, TFT and Grim, which are otherwise contained as special case in generalized strategies of type II.

[11] Treatment-wise ICL-BICs are provided in the Appendix A.5, after Table A.16. Each entry in the aggregated table represents the sum of ICL-BICs of the best out of 13 models for each respective treatment. Tables A.15 and A.16 in the appendix contain additional details regarding the intermediate results obtained during data mining for the best model.

Table 1.3: **Best mixtures of pure or generalized strategies in relation to semi-grim.** Strategy mixtures are estimated treatment-by-treatment. The resulting ICL-BICs are pooled for experiments and overall (less is better, relation signs point to better models)

			Best mixture of pure or generalized strategies									Best Mixture
	Baseline Model		No Switching		Random Switching		Markov Switching	Best Switching		Fixed SG 1.5×SG+AD		Best Switching By Treatment
Specification												
# Models evaluated	1		13^{32}		13^{32}		13^{32}	3×13^{32}		1		$39^{32} \approx 10^{51}$
# Pars estimated (by treatment)	5		80		80		278	438		3		438
# Parameters accounted for	5		3–10		3–10		12-35	3–30		3		3–30
First halves per session												
Aoyagi and Frechette (2009)	886.44	$\gg$	756.95	$\approx$	763.11	$\approx$	755.97	755.97	$\approx$	793.63	$>$	755.97
Blonski et al. (2011)	1114.69	$\gg$	1069.58	$\approx$	1104.85	$\ll$	1225.35	1225.35	$\gg$	1043.4	$\approx$	1069.39
Bruttel and Kamecke (2012)	845.41	$\approx$	817.89	$\approx$	835.6	$>$	785.49	785.49	$\approx$	763.66	$\approx$	785.49
Dal Bó (2005)	666.1	$>$	635.04	$<$	674.57	$\approx$	648.75	648.75	$>$	600.66	$<$	631.2
Dal Bó and Fréchette (2011)	7423.23	$\gg$	6904.79	$\ll$	7456.12	$\gg$	6388.49	6388.49	$\approx$	6458	$\approx$	6388.49
Dal Bó and Fréchette (2015)	8880.62	$\gg$	8434.93	$\ll$	9166.72	$\gg$	8158.31	8158.31	$\gg$	7912.58	$<$	8138.61
Dreber et al. (2008)	871.32	$\gg$	787.71	$<$	863.7	$\gg$	752.16	752.16	$\approx$	774.76	$\approx$	752.16
Duffy and Ochs (2009)	1448.71	$\approx$	1395.4	$<$	1461.01	$>$	1372.99	1372.99	$\approx$	1325.28	$\approx$	1372.99
Fréchette and Yuksel (2017)	321.32	$\approx$	300.87	$<$	337.5	$>$	298.53	298.53	$\approx$	284.66	$\approx$	298.53
Fudenberg et al. (2012)	454.09	$\approx$	432.32	$\approx$	432.38	$\approx$	425.54	425.54	$\approx$	421.46	$\approx$	425.54
Kagel and Schley (2013)	2735.02	$\approx$	2685.4	$\ll$	2993.4	$\gg$	2439.06	2439.06	$\approx$	2473.59	$\approx$	2439.06
Sherstyuk et al. (2013)	1389.33	$\approx$	1322.6	$\ll$	1450	$\gg$	1296.85	1296.85	$\approx$	1243.95	$\approx$	1296.85
Pooled	**27218.66**	$\gg$	**25758.38**	$\ll$	**27754.81**	$\gg$	**25166.24**	**25166.24**	$\gg$	**24205.04**	$\ll$	**24863.15**
Second halves per session												
Aoyagi and Frechette (2009)	534.29	$\gg$	416.51	$\approx$	437.8	$\approx$	423.05	416.51	$\approx$	460.38	$\gg$	416.51
Blonski et al. (2011)	1503.41	$\gg$	1398.5	$\ll$	1509.09	$<$	1593.01	1398.5	$\approx$	1350.39	$\approx$	1394.16
Bruttel and Kamecke (2012)	588.33	$>$	538.17	$<$	611.91	$\gg$	516.71	538.17	$\approx$	487.8	$\approx$	516.71
Dal Bó (2005)	751.82	$\approx$	732.27	$<$	786.21	$>$	739.59	732.27	$>$	688.66	$<$	729.48
Dal Bó and Fréchette (2011)	6065.93	$\gg$	5195.88	$\ll$	6378.16	$\gg$	5007.24	5195.88	$\approx$	4966.19	$\approx$	4964.77
Dal Bó and Fréchette (2015)	9085.4	$\gg$	8177.46	$\ll$	9401.19	$\gg$	7910.83	8177.46	$\gg$	7820.35	$\approx$	7893.79
Dreber et al. (2008)	656.38	$\approx$	619.9	$\approx$	662.24	$>$	581.94	619.9	$\gg$	545.25	$\approx$	581.94
Duffy and Ochs (2009)	2010.01	$>$	1883.52	$\approx$	1914.83	$>$	1850.35	1883.52	$>$	1764.77	$\approx$	1850.35
Fréchette and Yuksel (2017)	469.85	$\approx$	433.18	$<$	474.93	$>$	427.79	433.18	$\approx$	436.46	$\approx$	427.79
Fudenberg et al. (2012)	530.3	$\approx$	514.87	$\approx$	516.12	$\approx$	515.97	514.87	$\approx$	493.46	$\approx$	514.87
Kagel and Schley (2013)	1866.19	$\approx$	1751.81	$\ll$	2336.29	$\gg$	1678.7	1751.81	$\approx$	1713.66	$\approx$	1678.7
Sherstyuk et al. (2013)	1027.43	$>$	955.73	$\ll$	1137.49	$\gg$	958.99	955.73	$\approx$	901.89	$\approx$	955.73
Pooled	**25271.72**	$\gg$	**22848.49**	$\ll$	**26409.44**	$\gg$	**22927.9**	**22848.49**	$\gg$	**21738.7**	$\ll$	**22422.07**

Note: Results treatment-by-treatment are in the appendix. Relation signs encode p-values of Schennach-Wilhelm likelihood-ratio tests where $<, >$ indicate rejection of the Null of equality at $p < .05$ and $\ll, \gg$ indicating $p < .002$, which implements the Bonferroni correction of 24 simultaneous tests per hypothesis. "No Switching" assumes that subjects chooses a strategy prior to the first supergame and plays this strategy constantly for the entire half session. "Random Switching" assumes that subjects randomly chooses a strategy prior to each supergame (by i.i.d. draws), and "Markov Switching" allows that these switches follow a Markov process.

However, the arguably most relevant observation at this point concerns the aggregate effect achieved by data mining for the best-fitting combination of pure strategies and switching model. Modeling the behavior of inexperienced subjects (first halves of sessions), our generalizations and data mining combined yield a gain of 2000 points on the log-likelihood scale, comparing the baseline model to the best-fitting Markov switching models, and modeling experienced subjects (second halves), generalization and data mining combined yield a gain of 2500 points compared to the baseline model. Since these scores do not account for the degrees of freedom inherent in the model selection during data mining, they do not imply that the baseline model has to be rejected, but they clearly show that our approach yields an enormous improvement in fit over the standard memory-1 mixtures typically proposed in the literature. Further, since we attempted to include all specifications that may be considered compatible with either the pure- or the mixed-strategy conjecture, and picked the best one for each treatment, we can consider this data-mined specification to be a generous upper bound of the adequacy of these memory-1 models to describe behavior.

Second, this upper bound, reported in column 5 ("Best Switching") of Table 1.3, allows us to test the pure- and mixed-strategy conjectures against the behavior-strategy conjecture. Recall that the behavior-strategy conjecture suggests that the behavior of cooperating subjects is well-described using semi-grim strategies after round 1, approximately $(\sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd}) = (0.9, 0.3, 0.3, 0.1)$, with $\sigma_{\emptyset} \in \{0.9, 0.3\}$ depending on subject type (optimistic or unsure subjects, as discussed above). The third behavioral type capturing actions of non-cooperating subjects is modeled by AD as usual. Thus we obtain three specific subject types, without any free parameters except for the trembles of AD players and the type shares, and merely exploiting the simple insight that cooperating subjects play semi-grim behavior strategies. We evaluate this simple three-type mixture against the data-mined mixture of (generalized) pure strategies, which exploits plenty of free parameters in the strategy definitions, flexible type shares, and post-hoc model selection.

Specifically, we compare the simple three-type model defined in prior work, with just 3 free parameters per treatment, to the "Best Switching" model that was post-hoc picked from 3×13^{32} models, after estimating 438 parameters for each of the 32 treatments, but without accounting for the degrees of freedom used in the model selection process (solely accounting for the 3–10 parameters of the best-fitting model that is finally used — in line with the data mining ideal). The results are reported in column 6 ("Fixed SG, 1.5×SG+AD").[12] Despite this abuse of statistical power, the simple model allowing for semi-grim behavior strategies fits significantly better than the mined mixture of generalized pure or mixed strategies: it improves on the data-mined model by more than 900 points in the first-halves of sessions and even by 1100 points in the second halves of sessions. Since AD players are contained in all models, this demonstrates that the behavior of subjects not playing AD—i.e. behavior of cooperating subjects—is much better described by the semi-grim behavior strategy than using any mixture of received or generalized pure strategies. This is substantial

[12] Slightly abusing notation, 1.5 semi-grim types indicates that the two cooperating types have different cooperation probabilities in round 1 of each supergame but equivalent continuation strategies.

and perhaps surprising, but in the end, it is simply a reflection of the deficiency of deterministic choice rules in capturing behavior discussed above. A robustness check clarifying that this observation also holds true after accounting for memory-2 is reported in the appendix.

Third, we evaluate the arguably extreme model, which identifies the best-fitting combination of (generalized) pure strategies (out of 13 combinations) *and* the best-fitting switching model (out of 3) treatment by treatment without any consistency requirement. Thus, we choose the best-fitting model from 39 models for each treatment, amounting to the enormous selection of the best out of 39^{32} models across all experiments. Note that such analysis without imposing consistency requirements across treatments does not yield economically useful estimates, but if anything, this provides an even more generous upper bound on the economic content of pure and generalized pure strategies of memory-1. The results are reported in the right-most column ("Best Switching By Treatment"). In total, this exhaustively mined model still fits highly significantly worse (by more than 500 points) than the semi-grim model suggested by the behavior-strategy conjecture.[13] We summarize these observations as follows.

Result 1 (Question 1)**.** *Cooperating subjects seem to use memory-1 behavior strategies. The upper bound of behavior that can be captured with received pure or mixed strategies is significantly lower than the adequacy of a model assuming all cooperating subjects play two types of predefined deterministic (semi-grim) behavior strategies.*

Heterogeneity of cooperators and unrestricted estimation Let us now examine to what extent the cooperating subjects are heterogeneous and indeed play semi-grim strategies. In order to test this joint hypothesis of heterogeneity and semi-grim, let us start with a general model allowing for four different subject types (per treatment), one of which plays AD and three that play general memory-1 behavior strategies without imposing restrictions such as semi-grim.[14] In Table 1.4, we refer to this model as "$3 \times P5 + AD$", where $P5$ indicates use of an unrestricted five-parameter behavior strategy. Table 1.4 provides detailed information on a range of models that distinguish either up to three cooperating types playing general behavior strategies or up to three types playing semi-grim strategies. This will allow us to directly test the joint hypothesis.

Before doing so, let us point to an arguably important observation. Table 1.4 reports on a large range of models where cooperating subjects always are assumed to play behavior strategies. All of these models improve on the best of the 10^{51} models assuming subjects play pure or generalized pure strategies ("Best Mixture, Best Switching" in the left-most column of Table 1.4). That is, our earlier result on the inadequacy of pure and generalized pure strategies is confirmed very robustly: whatever specification we use, allowing cooperating subjects to play behavior strategies fits behavior much better. That is, the best of the 10^{51} models assuming pure or generalized pure strategies fits at least weakly worse than the worst of the seven models

[13] Section A.2 in the appendix demonstrates that this result is robust to allowing for memory-2, where we find that memory-2 is overall insignificant.

[14] As a reminder, the general semi-grim restrictions are $\sigma_{cd} = \sigma_{cd}$ and $\sigma_{cc} = 1 - \sigma_{dd}$.

assigning cooperating subjects behavior strategies, and significantly worse than all of the five models allowing for at least two distinct types of cooperating subjects. Notably, this would not be observed if the pure-strategy conjecture was empirically valid: Besides AD, the unrestricted analysis allows cooperating subjects to play any cooperative strategies like TFT, Grim, and say WSLS, STFT or AC depending on treatment (in $3 \times P5 + AD$), and if they actually did so, then the (generalized) pure strategy mixture would fit substantially better without using as many free parameters and by containing exactly as many pure strategies as optimal.

Now, using "$3 \times P5 + AD$" as the baseline, we can analyze which form of heterogeneity is most suitable for describing behavior. Starting with four subject types seems to be sufficient ex-ante, and will turn out to be sufficient ex-post. In Table 1.4, the two right-most columns report on the adequacy of nested models that distinguish only two types or one type of cooperating subjects (besides the AD type). It turns out that distinguishing just two types of cooperating subjects ("$2 \times P5 + AD$") weakly improves on distinguishing three types, while models with just one cooperating type ("$P5 + AD$") fit significantly worse. The latter further corroborates that cooperating subjects are not homogeneous.

To the left of column "$3 \times P5 + AD$", Table 1.4 details information on models assuming the cooperating subjects play semi-grim strategies rather than unrestricted memory-1 strategies. To be exhaustive, we consider models distinguishing three semi-grim types ("$3 \times SG + AD$"), two semi-grim types ("$2 \times SG + AD$") and 1.5 semi-grim types ("$1.5 \times SG + AD$"), besides the model with fixed semi-grim strategies ("Fixed SG, 1.5×SG+AD") defined above. At this point, the discussion can be kept rather short as the results are fairly clear: All models distinguishing at least two types of cooperating subjects and flexible semi-grim behavior strategies fit about equally well. The differences between these models are at best weakly significant, while all of them fit significantly better than the model assuming cooperating subjects are homogeneous ("$P5 + AD$")[15]. Compared to the model specification with the fixed semi-grim strategies used above, the differences are insignificant in first halves of sessions but become significant in second halves of sessions. Initially, that is, cooperating subjects seem to be well-described by $(\sigma_{cc}, \sigma_{cd}, \sigma_{dc}, \sigma_{dd}) = (0.9, 0.3, 0.3, 0.1)$, while their behavior becomes more nuanced and treatment-dependent as they gain experience.

These results provide strong evidence for heterogeneity and the behavior-strategy conjecture, but we need additional guidance for or against modeling the behavior strategy as semi-grim. For additional guidance, we can rely on either the top-down or the bottom-up approach towards model selection. By the top-down approach, we start with the most general model ($3 \times P5 + AD$) and successively reduce its complexity until such reductions dampen its adequacy significantly. The simplest model that we reach this way without a significantly negative impact on adequacy is $1.5 \times SG + AD$—with fixed semi-grim strategies in first halves of sessions and with flexible ones in second halves of sessions. In turn, by the bottom-up approach, we start with the simplest model (Fixed SG, 1.5×SG+AD) and successively increase its complexity as long as

[15] Also compared to '$SG + AD$", see Appendix Table A.18.

Table 1.4: Examining heterogeneity of cooperating subjects and the semi-grim structure of their strategies

	Best Mixture Best Switching		Fixed SG 1.5×SG+ AD		Treatment-specific SG specification 1.5×SG+AD		2×SG+AD		3×SG+AD		3×P5+AD		2×P5+AD		P5+AD
Specification															
# Models evaluated	$39^{32} \approx 10^{51}$		1		1		1		1		1		1		1
# Pars estimated (by treatment)	438		3		7		9		13		19		17		11
# Parameters accounted for	3-30		3		7		9		13		19		17		11
First halves per session															
Aoyagi and Frechette (2009)	755.97	≈	793.63	≈	792.44	≈	777.81	≈	782.63	>	742.33	≈	744.82	≈	744.06
Blonski et al. (2011)	1069.39	≈	1043.4	≪	1104.6	≈	1134.96	≪	1232.97	≪	1332.48	≫	1205.47	≫	1106.01
Bruttel and Kamecke (2012)	785.49	≈	763.66	≈	771.14	≈	762.83	≈	748.06	≈	751.86	≈	759.45	≈	803.58
Dal Bó (2005)	631.2	≈	600.66	<	618.39	≈	600.26	≪	626.56	≈	639.8	>	609.1	≈	620.38
Dal Bó and Fréchette (2011)	6388.49	≈	6458	≈	6352.59	≈	6304.97	≈	6198.12	≈	6216.22	<	6295.32	≪	6553.25
Dal Bó and Fréchette (2015)	8138.61	≫	7912.58	>	7830.12	≈	7810.7	≈	7828.38	≈	7829.74	≈	7775.7	≪	7969.32
Dreber et al. (2008)	752.16	≈	774.76	≈	764.44	≈	763.52	≈	766.77	≈	765.81	≈	767.32	≈	783.45
Duffy and Ochs (2009)	1372.99	≈	1325.28	≈	1361.15	≈	1320.71	≈	1297.84	≈	1291.42	<	1345.16	≈	1361.86
Fréchette and Yuksel (2017)	298.53	≈	284.66	≈	289.54	≈	284.11	≈	289.88	≈	294.05	≈	285.33	≈	291.69
Fudenberg et al. (2012)	425.54	≈	421.46	>	377.96	≈	370.01	≈	380.86	≈	381.34	≈	372.32	≈	377.33
Kagel and Schley (2013)	2439.06	≈	2473.59	≈	2450.24	≈	2421.27	≈	2385.02	≈	2354.05	≈	2398.74	≪	2551.68
Sherstyuk et al. (2013)	1296.85	≈	1243.95	≈	1234.52	≈	1200.28	≈	1184.82	≈	1177.24	≈	1186.92	≪	1286.14
Pooled	**24863.15**	≫	**24205.04**	≈	**24202.44**	≈	**24079.69**	≈	**24196.07**	<	**24469.37**	>	**24219.83**	≪	**24704.09**
Second halves per session															
Aoyagi and Frechette (2009)	416.51	≈	460.38	≫	421.21	≈	422.29	≈	423.63	>	404.95	≈	408.6	≈	409.04
Blonski et al. (2011)	1394.16	≈	1350.39	≈	1370.16	≈	1385.91	<	1442.85	≪	1555.48	≫	1453.1	≫	1379.87
Bruttel and Kamecke (2012)	516.71	≈	487.8	≈	480.47	≈	478.23	≈	470.25	≈	443.83	≈	471.73	<	528.54
Dal Bó (2005)	729.48	>	688.66	≈	677.24	≈	679.04	<	697.21	≈	707.25	≈	687.86	≈	696.41
Dal Bó and Fréchette (2011)	4964.77	≈	4966.19	≫	4565.93	≈	4545.08	≈	4426.48	≈	4461.98	≈	4493.1	≪	5045.34
Dal Bó and Fréchette (2015)	7893.79	≈	7820.35	≫	7306.25	≈	7310.27	>	7170.25	≈	7089.56	≈	7151.84	≪	7683.76
Dreber et al. (2008)	581.94	≈	545.25	≈	544.66	≈	541.83	≈	539.47	≈	519.28	≈	518.82	<	562.99
Duffy and Ochs (2009)	1850.35	≈	1764.77	>	1656.55	≈	1602.93	>	1518.65	≈	1509.7	<	1598.04	≪	1715.88
Fréchette and Yuksel (2017)	427.79	≈	436.46	≈	422.61	≈	381.63	≈	375.03	≈	384.11	≈	382.16	<	409.93
Fudenberg et al. (2012)	514.87	≈	493.46	≫	433.74	≈	414.24	≈	405.22	≈	410.69	≈	421.81	≈	448.37
Kagel and Schley (2013)	1678.7	≈	1713.66	≫	1572.95	≈	1541.38	>	1488.49	≈	1477.87	≈	1527.47	≪	1748.01
Sherstyuk et al. (2013)	955.73	≈	901.89	>	834.74	≈	823.06	≈	799.39	≈	801.53	≈	815.26	≪	935.01
Pooled	**22422.07**	≫	**21738.7**	≫	**20541.83**	≈	**20454.18**	>	**20231.09**	<	**20459.26**	≈	**20403.95**	≪	**21818.46**

Note: This table verifies a number of possible mixtures involving semi-grim types as a robustness check for the sufficiency of focussing on the mixtures examined above. E.g. "3× SG refers to a model containing three different versions of memory-1 semi-grim with allowing for heterogeneity of randomization parameters across subjects.

these increments significantly improve model adequacy. Starting with with this, adequacy improves significantly only in second halves of sessions, then by allowing for flexible semi-grim strategies, but beyond that, further increments again are not significant in a manner surviving the Bonferroni correction (indicated by $\gg$ or $\ll$ in Table 1.4).

That is, both the top-down and the bottom-up approach converge to the same conclusion that we need to distinguish two types of cooperating subjects, whose behavior differs only in round 1 of each supergame. On average, the less cooperative type cooperates with probabilities in $[0.2, 0.5]$ in round 1, similar to the cooperation probabilities after mixed histories cd/dc, and the more cooperative type cooperates with probabilities above 0.9 in most treatments, similar to cooperation probabilities after cc. Table A.4 in the appendix provides detailed results.

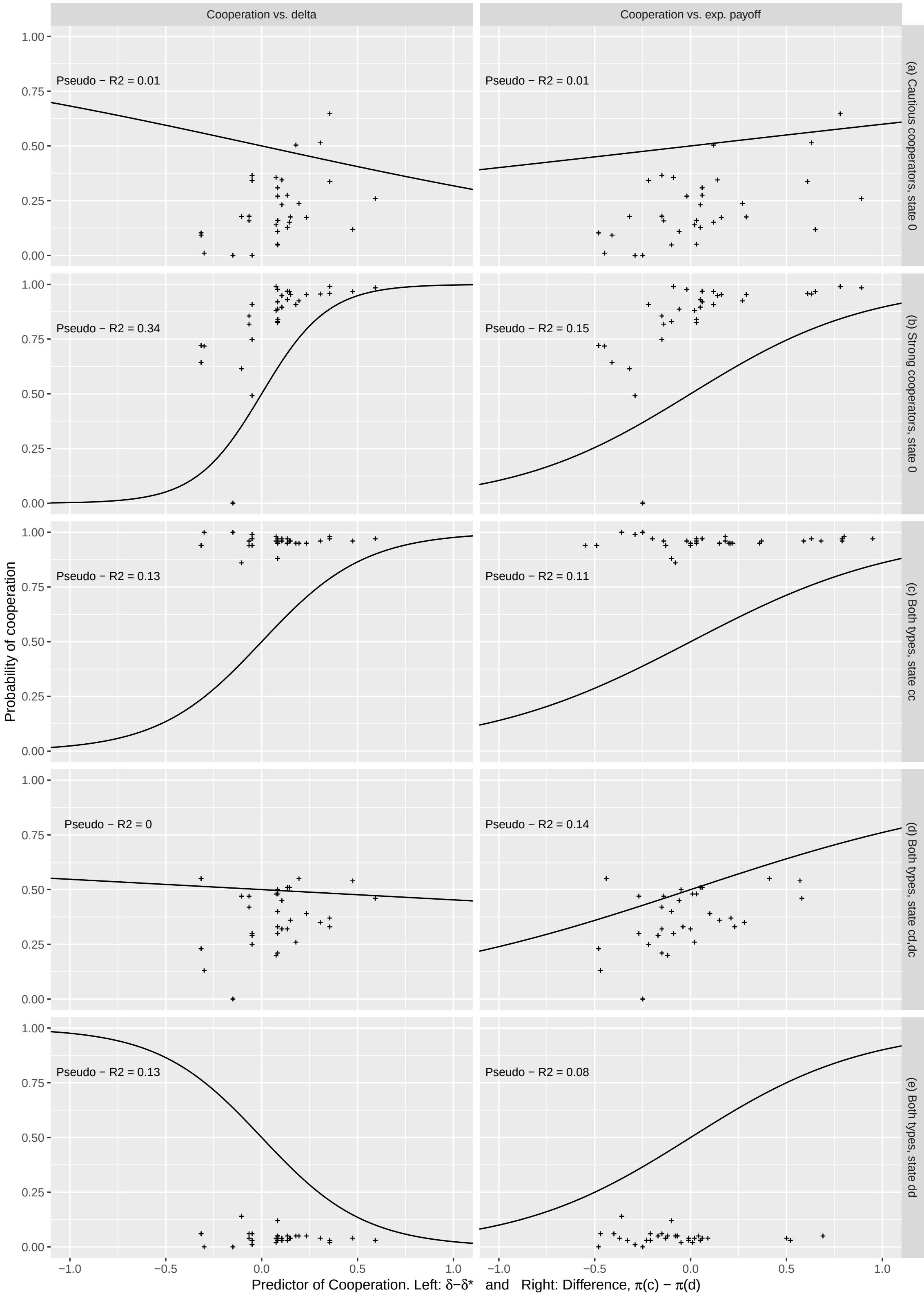
Result 2 (Question 2)**.** *The analysis identifies two types of cooperating subjects playing the same semi-grim continuation strategy but different cooperation probabilities in round 1 (**cautious cooperators** and **bold cooperators**) and a subject type playing a strategy close to always defect (**defectors**). A model with this subject composition, and any other model allowing for two types of cooperating subjects playing behavior strategies, fits significantly better than all* 10^{51} *models assuming pure or generalized pure strategies.*

1.5 How do strategies relate to supergame parameters?

Having estimated the number of subject types and their strategies, we can revisit Question 3 and ask to what extent the subjects' strategies are functions of treatment parameters, to what extent they are rationalizable, and to what extent they may be predictable. In light of the above results, we distinguish defecting and cooperating subjects. The defecting subjects play slightly perturbed strategies close to AD, which are essentially invariant to treatment parameters and rationalizable to the extent that AD is rationalizable (note that AD is a best response to itself in all supergames considered here). For this reason, we shall focus on the strategies played by cooperating subjects. By Result 2, there are two types of cooperating subjects, both identified as playing semi-grim supergame strategies with significant differences found in the probability of cooperation in round 1. The strategies are significantly treatment-dependent when subjects are experienced, i.e. in second halves of sessions, on which we shall focus in the following.

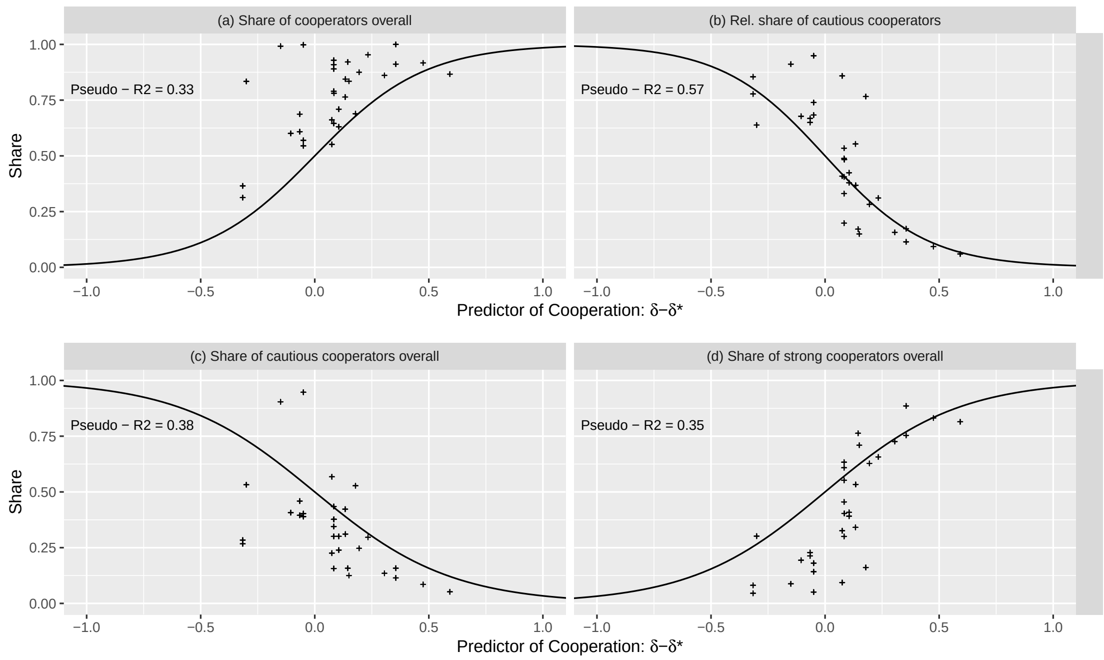
Overview Recall that Figure 1.2 plotted the average cooperation rates across states against the expected payoffs from cooperation, which suggested that subjects act highly rationally in round 1 but ignore expected payoffs afterwards. We suspected confounds due to looking at raw cooperation rates, most notably possible selection effects, and our estimates of the strategies of (cooperating) subject types allow us to resolve these concerns. Figure 1.3 now plots the cooperation probabilities according to the estimated strategies of cooperating subjects against two predictors of cooperation

Figure 1.3: Relation of δ **(left) and monetary incentives (right)** to cooperation rates (second halves of sessions)



Note: For further information, set Tables A.46–A.53 in the Appendix.

Figure 1.4: Relation of $\delta - \delta^*$ to shares of cooperators (second halves of sessions)



Note: This figure shows how the ratios of the three strategies – defectors, cautious cooperators, and strong cooperators change with the distance of δ to the BOS cooperation threshold δ^* across treatments. The solid line represents the best fitting logistic curve estimated without intercept such that the share is 0.5 for $\delta = \delta^*$. Panel (a) displays the total share of both cooperators, panel (b) the relative share of cautious cooperators among cooperators, panel (c) the share of cautious cooperators overall, panel (d) the share of strong cooperators overall.

(expected payoffs and $\delta - \delta^*$). In the left column of plots, we see how the cooperation probabilities across states relate to the difference of discount factor δ and BOS threshold δ^*. In the right column of plots, we see how the probability of cooperation relates to the monetary incentive to cooperate, $\pi_\omega(c) - \pi_\omega(d)$ as defined above, Eqs. 1.1–1.3, for each state ω. For these plots, we assume that subjects hold "false consensus" beliefs that their opponent plays the same strategy that they play. That is, strong cooperators believe they face strong cooperators and weak cooperators believe they face weak cooperators. In comparison to Figure 1.2, the results do not change substantially: Behavior is still close to being independent of the predictors of cooperation in most states (bottom three panels), arguably with the exception of strong cooperators in round 1 (top two panels).

Recall that we know from Dal Bó (2005) and subsequent work that average cooperation rates change as payoff parameters change, and above we have seen that most of these changes can be reduced to changes in round 1. Yet, as just seen, the type strategies are largely independent of the payoff parameters. To illuminate this further, we next test the complementary statistic and examine how the shares of the three subject types change as parameters change. Figure 1.4 plots the shares of cooperators as a function of the discount factor δ in relation to the BOS-threshold δ^*. We see two relatively strong effects: As δ approaches δ^*, the overall share of cooperators increases, i.e. defectors become cooperators, and at the same time, the relative share of cautious cooperators declines, i.e. cautious cooperators turn into strong cooperators.

Result 3 (Question 3 – part 1)**.** *The shares of subjects playing either of the three strategies change highly predictably. As δ increases defectors are replaced by cooperators and as it passes the BOS-threshold δ^* the strong cooperators start to outweigh the cautious cooperators ($\tilde{R}^2 \geq 0.2$ in all cases). The strategies themselves are largely invariant to treatment parameters and monetary incentives. The only exception satisfying $\tilde{R}^2 \geq 0.2$ are strong cooperators in round 1, whose strategies correlate with treatment parameters ($\delta - \delta^*$) but not with monetary incentives, and only in round 1.*

That is, the behavioral changes observed in the literature are mainly transitions from defection to cautious cooperation and from cautious cooperation to strong cooperation. These transitions are neatly predictable, being logistic functions of $\delta - \delta^*$, which is a substantial result in relation to previous work that found no reliable association between strategies used and payoff parameters (Dal Bó and Fréchette, 2018). This result directly follows from the unrestricted estimation of strategies, which thus not only fits better but also renders type shares predictable. In turn, the actual strategies associated with these seemingly archetypical behavioral types are largely invariant of payoff parameters, which also is a novel result that we further investigate next.

Structural analysis of preferences and beliefs The above observations suggest that it seems straightforward to explain the shares of subject types across treatments, as they are simple functions of payoff parameters (i.e. of $\delta - \delta^*$), but it is not immediately obvious how to explain the largely invariant strategies chosen by these subject types. Should we think of cooperating subjects as choosing automata, as first described by Rubinstein (1986), or are these strategies predictable and rationalizable in some way? This question can be answered in a structural analysis of behavior, a standard approach in behavioral analyses of normal-form games, but novel in analyses of the repeated PD. Thanks to the existing work on behavior in normal-form games, we can build on central ideas from three literatures. First, regarding belief formation and relating to the above discussion, much of the pychological literature emphasizes that people overestimate the extent to which others are similar to themselves. In analyses of games, this basic psychological observation has been analyzed as projection of information (Madarász, 2012) and projection of types or strategies (Breitmoser, 2019). In the context of the PD Aoyagi et al. (2021) and Gill and Rosokha (2020) provide first evidence for such behavior. By our results above, the types are defined in terms of strategy, and in this sense, projection of types equates with projection of strategies, and both correspond with the false consensus beliefs discussed above. We will contrast these consensus beliefs about opponents' strategies with naive beliefs and Bayesian beliefs in order to test the above suggestion that consensus beliefs best capture behavior (for formal definitions, see Appendix A.3).

The above results imply, however, that relaxing assumptions on belief formation is insufficient to comprehensively explain behavior. To see this, recall that subjects cooperate after cc and cd/dc even in treatments where Grim is not a SPE, and if Grim is not a SPE, a strategy involving cooperation is not rationalizable in any state (i.e. never a best response to any belief in any state). Thus, the behavior of cooperating subjects is in general not rationalizable in the classical sense—by varying beliefs—but it may be rationalizable after (also) relaxing assumptions on preferences. A standard approach towards explaining cooperative behavior in the absence of strategic incentives, e.g. if Grim is not a SPE, is to allow for interdependence of preferences. This has been observed in several other literatures, most prominently in finitely repeated public goods games, where such behavior seems related to a preference for conditional cooperation, concerns of inequity aversion, or concerns for fairness and altruism (see for example Keser and Van Winden, 2000, and Fischbacher et al., 2001). Building on this existing evidence, and seeking to avoid post-hoc experimentation, we will only consider these four standard models in our analysis (the standard definitions are provided in Appendix A.3).

In addition, we allow for the possibility that subjects misperceive the discount factor δ. Such prescinding from the discount factor might arise if subjects are used to engaging in repeated interactions with discount factors close to 1 or 0, for example because the most prominent real-life interactions (with say family members and colleagues) have low break-up probability and occur with high frequency, implying that discounting is negligible. Specifically, we allow the perceived discount factor $\tilde{\delta}$ to be a function of the true discount factor as in $\tilde{\delta} = \delta^x$. If $x = 1$, subjects correctly perceive the discount factor (or, break-up probability), for $x < 1$ they underestimate it, with the limiting case $x \to 0$ where they simply disregard the break-up probabibility and play the game as if it had an infinite time horizon (without impatience, in the laboratory). In turn, if $x > 1$, subjects overestimate the break-up probability, and in the limiting case $x \to \infty$, subjects seem "myopic" and play a sequence of one-shot games. Such limitations of foresight characterize many approaches towards long-run interactions, most notably perhaps chess. In the extreme case $x \to \infty$, agents simply evaluate the resulting outcome of the present round, i.e. *cc*, *dc*, *cd* or *dd*, which implicitly encodes the continuation payoff expected from the subsequent rounds.

Regarding the econometric implementation of the analysis, we use standard specifications of structural analyses of games, following McKelvey and Palfrey (1995), Costa-Gomes et al. (2001), Bajari and Hortacsu (2005), as extended to analyses of dynamic games by Aguirregabiria and Mira (2007). All details of these overall standard definitions are provided in Appendix A.3. In order to quantify to what extent the different approaches allow us to capture behavior, we also estimate two standard benchmark models. First, we provide results for the lower-bound benchmark of *uniform randomization*, i.e. the goodness-of-fit of predicting 50-50 randomization in all states. Second, we consider the upper-bound benchmark *clairvoyance* predicting the actually estimated probabilities of cooperation for the two cooperating types by treatment in all states. Additionally, as a presumably trivial benchmark model, we examine the possibility that subjects play the actual stage game (without interdependent preferences) but misunderstand δ as captured by $x \neq 1$. By design, all models of interdependent preferences allowing for $x \neq 1$ should improve on this benchmark, as it is always contained as a special case for interdependence weights equal to zero. This benchmark allows us to understand how much can be explained by allowing for misperception of δ on its own. In the estimation x is limited to an upper bound of 100 for viability.

The results are presented in Table 1.5 and summarized in Figure 1.1 above. Table 1.5 distinguishes, for each model, three sets of estimates. This gives us a sense of the robustness of the results. In the right-most columns ("Fit to each treatment"), we allow for treatment-specific parameters. Since the behavior of cooperating subjects in each treatment is described by five parameters (round-1 behavior of each type and three parameters capturing continuation behavior), the four free parameters per model, when allowed to be treatment specific, should capture behavior close to "clairvoyance" (i.e., perfectly). This is indeed the case for models allowing for false-consensus beliefs but not for the other belief models, as discussed shortly.

In the the middle set of columns ("Heterogeneous variance"), we allow for treatment-specific variance of noise but now invoke the standard assumption that the preference parameters are constant across all treatments and experiments, while the clairvoyance benchmark model remains unchanged (aside from a change in the penalty term to reflect the change in the number of free parameters of the models for which it is the upper bound). This informs us to what extent interdependence of preferences actually captures behavior, rather than being able to fit behavior post-hoc treatment by treatment. In the left-most set of columns ("Homogeneous variance"), we additionally assume that the noise variance (as captured by the precision parameter λ in the logistic specification) is constant across treatments. This yields a very parsimonious model of behavior, using four parameters to describe the preferences of both cooperative types across all 32 treatments analyzed here—which may not be expected to fit exactly. Explaining behavior across treatments and experiments with one set of parameters gives us a sense of how robust (and thus predictable) behavior is, however.

As indicated, for each belief model, we evaluate the aforementioned four models of social preferences with potentially misperceived δ, and a benchmark of inequity aversion assuming the correct δ. Two observations stand out: First, for each of the models with interdependent preferences, and each of the three measures for the goodness-of-fit, false consensus beliefs best fit behavior—that is, cautious cooperators seem to believe they play against cautious cooperators and strong ones seem to believe they play against strong ones. In all cases, the distance to other belief models is on the order of 5000 likelihood points, which is highly significant and corresponds to about 20% of the total score, implying that it is behaviorally also highly relevant.

To understand this first observation, let us assume that subjects update beliefs following Bayes' Rule after each round, most notably perhaps after round 1—which could explain the poor fit of actions in relations to expected payoffs after round 1. Since all *cooperating* subjects are estimated to play the same continuation strategy, their differences in round 1 cannot be in preferences but must be in the beliefs they hold, and specifically in the beliefs about behavior in round 1, as the behavioral differences are observed in round 1. False consensus about strategies directly predicts this intuition— that cautious cooperators expect to play with cautious cooperators and that strong ones expect to play with strong ones—and it also reflects the standard theoretical assumption that agents play symmetric equilibrium strategies.

Table 1.5: Testing interdependence of preferences (second halves; see also Tables A.5 and A.6 for analyses of first and both halves)

	Fit to pooled data					
	Homogeneous variance		Heterogeneous variance		Fit to each treatment	
Model (free parameters)	*BIC*	Estimates	*BIC*	Estimates	*BIC*	Average Estimates
Upper bound BIC (Clairvoyance)	20460.6		20692.6		21388.8	
Lower bound BIC (Uniform Random)	51487.3		51719.4		52415.6	
False Consensus Beliefs						
True supergame (g,l,δ), no free par $(-)$	45115.4	$(-,-,-)$	42523.4	$(-,-,-)$	43219.6	$(-,-,-)$
True stage game g,l, free $(\delta^X,-,-)$	45096.6	$(1.08,-,-)$	42134	$(1.32,-,-)$	39948.6	$(8.79,-,-)$
True δ, inequity aversion $(-,\alpha,\beta)$	28542.4	$(-,0.96,0.6)$	29407.7	$(-,1.6,0.66)$	27950.4	$(-,-100,0.52)$
Inequity Aversion (δ^X,α,β)	22607.6	$(100,0.82,0.14)$	22330.2	$(18.44,0.77,0.11)$	21452.4	$(17.05,0.37,-0.01)$
Cond Cooperation (δ^X,α,β)	27159.5	$(100,1.61,-0.27)$	25680.3	$(5.91,1.7,-0.01)$	21767.4	$(16.79,1.79,-0.06)$
Altruism (δ^X,α,β)	24309.4	$(68.15,1.45,-0.32)$	23419.6	$(19.92,1.38,-0.24)$	21451.1	$(4.17,0.98,0.12)$
Gen Fairness Equilibrium (δ^X,α,β)	28525.3	$(6.53,6.66,0.22)$	26864.2	$(6.75,26.51,0.21)$	22067.6	$(11.03,24.23,0.07)$
Naive Beliefs						
True supergame (g,l,δ), no free par $(-)$	44692.6	$(-,-,-)$	43458.3	$(-,-,-)$	44154.5	$(-,-,-)$
True stage game g,l, free $(\delta^X,-,-)$	44638.9	$(1.08,-,-)$	43310.6	$(1.14,-,-)$	41986.3	$(2.53,-,-)$
True δ, inequity aversion $(-,\alpha,\beta)$	31003	$(-,-100,-3.27)$	31175.5	$(-,-100,-2.18)$	30032.2	$(-,-100,-2.34)$
Inequity Aversion (δ^X,α,β)	27869.8	$(100,6.99,0.98)$	27782.3	$(100,4.57,0.98)$	28007.6	$(100,8.48,0.81)$
Cond Cooperation (δ^X,α,β)	34743.7	$(100,5.88,0.03)$	31846.3	$(4.73,3.3,0.28)$	28008.3	$(99.06,4.76,-0.12)$
Altruism (δ^X,α,β)	29473.8	$(100,33.58,-0.8)$	28683.2	$(20.19,4.48,-0.7)$	28008.3	$(100,12.53,-0.54)$
Gen Fairness Equilibrium (δ^X,α,β)	29630.5	$(4.64,-8.1,0.53)$	28729.9	$(4.11,-5.92,0.53)$	28008.3	$(34.26,-10.75,0.54)$
Bayesian Beliefs						
True supergame (g,l,δ), no free par $(-)$	44424.9	$(-,-,-)$	42421.6	$(-,-,-)$	43117.8	$(-,-,-)$
True stage game g,l, free $(\delta^X,-,-)$	44022	$(0.78,-,-)$	42342	$(0.89,-,-)$	41036.3	$(10.09,-,-)$
True δ, inequity aversion $(-,\alpha,\beta)$	31871.5	$(-,2.15,0.93)$	33302.6	$(-,2,0.65)$	33004.8	$(-,100,100)$
Inequity Aversion (δ^X,α,β)	28095.3	$(100,5.71,0.81)$	28091.1	$(74.82,16.36,0.79)$	28508.4	$(30.89,15.78,0.87)$
Cond Cooperation (δ^X,α,β)	35378.4	$(100,3.53,-0.11)$	32160.8	$(3.85,2.04,0.12)$	28501.6	$(1,5.66,-0.3)$
Altruism (δ^X,α,β)	29162	$(100,-50.45,5.08)$	28915.4	$(14.07,-17.8,4.89)$	28505.3	$(34.72,54.88,-0.3)$
Gen Fairness Equilibrium (δ^X,α,β)	34577.4	$(5.58,11.59,0.17)$	32527	$(5.69,11.59,0.15)$	28505.3	$(23.52,100,-0.11)$

Note: This table shows the estimates and BICs for the estimated models including benchmarks. In the rightmost column ("Fit to each treatment") parameters are estimated by treatment – the BICs are aggregated, the reported parameter estimates are averages. In the columns ("Fit to pooled data") parameter sets are estimated to be constant across all experiments with homogeneous variance and heterogeneous variance by treatment, respectively. The upper bound and lower bound BIC are based on the same "Clairvoyance" and "Uniform Random" model in all three columns, with treatment specific strategies for the clairvoyance model, but the BICs take into account the differences in parameter numbers of the interdependent-preferences models across the three columns to make them comparable.

Second, between the four well-known models of interdependent preferences (detailed in the Appendix A.3), there is a clear ranking when applied to the range of experiments we re-analyze here. Whatever assumption we impose on the belief model, capturing interdependence by inequity aversion fits substantially and significantly better than capturing interdependence by any other model. That is, we observe very robust rankings of models with respect to both dimensions, beliefs and preferences. We attribute this to the comprehensive data set re-analyzed here, which reduces the impact of single observations and allows the law of large numbers to take effect.

Result 4 (Question 3 – part 2)**.** *Subjects' behavior is best described by false consensus beliefs (i.e. symmetric equilibrium) and inequity aversion. Indeed, false consensus fits substantially better than other belief models for all models of interdependent preferences, and inequity aversion equally fits substantially better than other interdependence models for all belief models.*

Next, let us look at the extent of misperception of δ. In total, we consider four models of interdependent preferences, three models of belief formation, and three specifications of treatment dependence of parameters. Between these $36 = 4 \times 3 \times 3$ sets of estimates, we obtain 35 times an estimate indicating $x > 1$, i.e. $\delta^x < \delta$, and in particular, this is true for the identified specifications where subjects either hold false consensus beliefs or exhibit inequity aversion. Indeed, when we allow subjects to both hold false consensus beliefs and exhibit inequity aversion, and in many other cases, we estimate the upper bound $x = 100$, implying $\delta^x \approx 0$. Thus, subjects are clearly best described by limited foresight, similar to (but much more extreme than) the chess players referenced above: Given $\delta^x \approx 0$, subjects in the repeated PD do not seem to look beyond the current round. They capture the expected payoffs from continuation play by the values they associate with each of the four possible outcomes (cc, dc, cd, dd) of play in the current round, and these values relate to the stage game payoffs via inequity aversion.

Result 5 (Question 3 – part 3)**.** *Subjects are estimated to not look ahead beyond the present round, and the state values they associate with the four possible outcomes of play in the present round relate to the stage game payoffs via inequity aversion.*

So, which types of games are induced by the state values that the subjects perceive? The answer depends on the stage game payoffs in the respective treatments, but to give some sense, let us look at two well-known examples.

	c	d
c	$2,2$	$0,3$
d	$3,0$	$1,1$

$\underset{\alpha=0.82,\beta=0.14}{\rightsquigarrow}$

	c	d
c	$2,2$	$-0.42, 0.54$
d	$0.54, -0.42$	$1,1$

	c	d
c	$3,3$	$0,4$
d	$4,0$	$1,1$

$\underset{\alpha=0.82,\beta=0.14}{\rightsquigarrow}$

	c	d
c	$3,3$	$-0.56, 0.72$
d	$0.72, -0.56$	$1,1$

It is easy to verify that for a wide range of stage game payoffs, inequity aversion with the estimated parameters $(0.82, 0.14)$ induces a coordination game. Formally, a coordination game is obtained if $g < \alpha * (1+g+l)$, and using $\alpha = 0.82$, this holds true whenever $g \leq 4$, which includes all of the experimental games we analyze. That is, in terms of the continuation payoffs, subjects generally seem to perceive the repeated PD as a coordination game. Being a coordination game, there exist three Nash equilibria – the defective equilibrium (d,d), the cooperative equilibrium (c,c), and a mixed equilibrium corresponding to $\Pr(c) = 0.49$ in the upper game and to $\Pr(c) = 0.41$ in the lower game. So, how does the econometric model align subjects' behavior with play this coordination game? After round 1, subjects play the "Schelling points" of the coordination game (Schelling, 1960), i.e. the focal point given by the previous round's choices, and they correspondingly play the cooperative, defective or mixed equilibrium after cc, dd, and cd/dc, respectively. In round 1, there is no such focal point, and subjects focus on either the cooperative, or the mixed, or the defective equilibrium, depending on subjective beliefs and yielding the three subject types observed above (strong cooperators, cautious cooperators, and defectors, respectively). As demonstrated, the type shares (i.e. the subjective beliefs) depend in a clear-cut way on the game parameters, and as we also saw by the significance of the type distinction, at the subject level the focus is robust. To clarify, if it were not robust at the subject level, then the distinction of say cautiously and strongly cooperative subjects would not have been found to be significant.

1.6 Conclusion

We summarize our main results as follows.

Re-analyzing 12 experiments, we robustly identify three different types of subjects: defectors, playing a strategy close to AD, and cautious and strong cooperators who play semi-grim strategies that differ in their first-round cooperation probability. The strategies are largely independent of treatment parameters but the shares of subjects picking either of the three strategies depend strikingly on the continuation probability δ in relation to the BOS-threshold δ^* (Blonski et al., 2011). Following rounds where at least one player cooperated, subjects cooperate systematically even in supergames where Grim is not a subgame-perfect equilibrium, which is rationalizable after allowing for interdependent preferences. Testing different belief and interdependent preference models in a structural analysis, we find that the observed behavior can be explained by subjects holding false-consensus beliefs, and having limited foresight as well as inequity-averse preferences.

Specifically, subjects are estimated to play each round of the repeated PD based on subjective valuations of the states that will result from the current round's choices. These state values relate to the original stage game payoffs in a manner compatible with inequity aversion and induce coordination games for the experimental games we consider. The defectors play according to the defective equilibrium in round 1 and thereafter. Some of the cooperating subjects systematically play according to the cooperative equilibrium in round 1 and are identified as strong cooperators, while the others systematically playing according to the mixed equilibrium and are identified as cautious cooperators. This focus in round 1 is persistent at the subject level. In the subsequent rounds, both types of cooperative subjects play the Schelling points, i.e. according to the cooperative equilibrium after (c,c), according to the defective equilibrium after (d,d), and according to the mixed equilibrium after $(c,d)/(d,c)$.

This description of behavior in the repeated PD is the result of a flexible structural analysis of 12 experiments, it closely relates to a wide range of previous results in behavioral economics, and it fits behavior very well also quantitatively (see Figure 1.1). Using merely four parameters to explain 65.910 and 79.892 observations of inexperienced and experienced subjects (respectively), it captures 89% of the variance in behavior of inexperienced subjects and 93% of behavior of experienced subjects from 32 treatments. The results also connect with key results in several large strands of the literature. False consensus is a central concept in psychology (Ross et al., 1977), the idea that the actions in the previous round serve as focal point for the actions in the present round is (informally) predicted by the focal point theory (Schelling, 1960), limited foresight and state recognition/evaluation are central ideas in games with indefinite time-horizon in computer science (Levy and Newborn, 1982), in economics (Jehiel, 2001; Kübler and Weizsäcker, 2004), and even for grand-master chess players (Gobet and Simon, 1996), and inequity aversion (Fehr and Schmidt, 1999) is a central concept of interdependent preferences. Further, we can rule out many potential confounds related to overfitting when a model with four parameters explains 93% of variance from close to 80.000 observations that were taken in a wide range of conditions.

The observations that subjects assign values to future states and that these state values closely relate to stage game payoffs in a manner compatible with inequity aversion are very encouraging for future work, and perhaps most importantly, they represent a first behavioral foundation of play in repeated games—i.e. a formally closed explanation of behavior that enables predictions for all repeated games. Experimental work on repeated games other than the repeated PD is needed to evaluate these predictions, but the observation that closed behavioral models, and structural analyses such as those known from static games, are possible also for repeated games demonstrate that it is feasible and important to move beyond strategy estimation in attempts towards understanding behavior. In addition, our results raise a number of novel and interesting questions with respect to analyses of the repeated PD. We considered inequity aversion mainly because it is a well-established model of interdependent preferences used to explain cooperative behavior in prior work. Thinking of state values, should we not also include the true discount factor δ as a relevant factor? Is it a coincidence that the recurring semi-grim strategies are specific instances of belief-free equilibria (Ely et al., 2005)? Is their apparent invariance after round 1 not reminiscent also of analogical reasoning (Samuelson, 2001)? Over time, behavior in round 1 seems to somewhat change as subjects gain experience (Fudenberg and Karreskog, 2020)—though the changes cancel out across treatments (see Table 1.2)—does the "precision" λ change, do beliefs change, or do preferences change? Following the approach towards structurally analyzing behavior in repeated games developed above, it will be possible to ask and answer these and many more such questions in exciting future work.

Chapter 2

Training in Late Careers – a Structural Approach

2.1 Introduction

In view of aging populations, pay-as-you-go public pension systems face severe challenges: Decreasing numbers in younger generations and increasing life expectancy are threatening the system. In response many OECD countries have reformed their retirement policies, for example, they have raised the normal retirement age to encourage longer working lives (e.g. Blundell et al., 2016b; Staubli and Zweimüller, 2013).

Yet, older employees' labor market chances are worse than those of younger employees (Daniel and Heywood, 2007; Göbel and Zwick, 2012), which is one of the main reasons why increases in the statutory retirement age do not translate into a one-to-one extension of the working life, even if financial incentives for staying employed are high. Lack of employment is especially prevalent and problematic among the less-educated (see, for example, Blundell et al., 2016b; Börsch-Supan and Ferrari, 2017).

Therefore, it is crucial to understand the labor market outcomes of less-educated employees in their late careers and to investigate which instruments can foster employment. One instrument often discussed in this context is training (see, for example, Sanders et al., 2011). It is meant to keep employees' skills up to date so they meet the demands of today's tasks on the labor market, such that their productivity improves. Consequently, it increases the firms' incentives to keep them employed and preserve or even raise their wages (e.g. Picchio and Van Ours, 2013; Zwick, 2011; Bellmann et al., 2013). Many countries use training in their active labor market policy portfolio (see, for example, Kluve, 2010). A study by Gohl et al. (2020) supports the relevance of this instrument in the context of aging populations as it finds positive effects of an increase in statutory retirement age on the prevalence of training.

However, to date, it has not yet been resolved whether policy-makers should increase training supply or incentivize individual training take-up to foster overall training participation. Moreover, it is not clear how this increase in training participation would affect the employment outcomes of less-educated employees in their late careers.

In this paper, I use a structural dynamic discrete-choice model to answer this question: I investigate the role of on-the-job training for the employment outcomes of less-educated employees in their late careers and evaluate potential channels for policy interventions. First, I explicitly model the cost-benefit trade-offs that these individuals face when deciding on whether to invest in their human capital, by participating in training, or not. Second, in contrast to other studies, I use a data set that enables me to identify different channels of frictions related to training participation: The data of the German National Education Panel Study (NEPS) provides information about the availability of firm-sponsored training. Thus, I can separate non-participation due to the lack of availability of training from non-participation due to the individual cost-benefit trade-offs. This allows me to quantify first, the benefits of training for the employee, and, second, to show in counterfactual simulations how different types of policy interventions affect the employee's employment prospects. Should policy interventions target the training supply at the firm side or the training take-up incentives of individuals?

My model focuses on less-educated male employees aged above 50. Each period they decide whether they want to continue working and whether they want to participate in training, conditional on their available choice options: That is, the employer may not offer training, such that the employee cannot choose training, or the employee may lose his job in which case he automatically becomes unemployed. Employees decide on whether to invest in training by trading off the benefits of training with respect to future employment prospects, wages, and retirement benefits against instantaneous utility costs of training. I estimate the model parameters reflecting the utility costs and the benefits of training and employment with the maximum-likelihood method.

The estimated parameters determining the training choices and labor market outcomes of the men in my sample are in line with the literature: I find very small and insignificant effects of training on wages, and a positive effect of training on employment prospects. Training further decreases the estimated disutility of working. On the other hand, training participation creates significant utility costs.

In my counterfactual simulations I show that a policy intervention that fosters the availability of training in firms would not be effective to increase the employment rates of less-educated employees near retirement: If training was available for everyone, the training participation would increase by 30% but the employment rate near retirement would only increase by 0.5%.

In contrast, a policy intervention that seeks to reduce the individual utility costs of training has the potential to positively impact employment near retirement. Under a full compensation of the individual utility costs of training, the training participation would quintuple to 50% and the employment rate in the year before retirement could be increased by almost 5%. However, training in its current form is not able to fully counterbalance the decreasing employment rates of less-educated employees near retirement.

This paper is related to the literature in various ways: There is a number of reduced-form studies discussing the effects of training on productivity, wages, and employment, indicating the importance of this topic. See Leuven (2005) for a review of the theoretical literature. The overall evidence of empirical studies on further training is mixed.[1] Papers investigating effects of training on *wages* mostly find insignificant or very small effects: Pischke (2001) investigates the link between training and subsequent wage growth using German SOEP data and only finds insignificant positive estimates. Conti (2005) does not find positive wage effects using Italian panel data. Jürges and Schneider (2004) use GSOEP data to investigate effects of on-the-job training on wages with different approaches and find insignificant effects. Bassanini (2006) only finds positive effects on wages for high-educated and young employees using European Community Householdpanel (ECHP) data. Fouarge et al. (2013) argue that wage returns to on-the-job training are positive and do not significantly differ by education level using Dutch data but admit selection problems. Finally, Görlitz (2011) finds insignificant short-term impact of on-the-job training on wages in Germany, and Ehlert (2017) only finds significantly positive short-run effects on wages for employer financed mandatory training using NEPS data. Other papers have looked at firm level productivity (Göbel and Zwick, 2013; Zwick, 2002) and found mixed results.[2]

Papers investigating the impact on *employment* find mostly positive effects: E.g. Cairo and Cajner (2018) conclude that on-the-job training is the reason for different volatility levels in employment (via job separations) between high- and low-educated employees in the US. Picchio and Van Ours (2013) find that firm provided training significantly increases future employment prospects, even for older workers. Likewise, Bassanini (2006) finds positive results on employment security. Further, a study by Dauth (2020) finds positive effects of subsidized training on employment duration of low-skilled workers in Germany.

In contrast to these reduced-form studies a structural set-up allows to explicitly model endogeneities and trade-offs of individual decisions. Further, it allows for counterfactual simulations to find out which policy interventions are effective in increasing employment rates of less-educated employees near retirement: Interventions that target the provision of firm sponsored training or interventions that target the individual participation incentives?

Existing structural papers on this matter either do not use training data to identify their effects (Kuruscu, 2006; Fan et al., 2017), or focus on middle-aged women (Blundell et al., 2019), who arguably face different trade-offs than male employees in their late careers. None of these studies uses data that allows for adapting individual choice options in the model to the availability training. Thus, this paper closes a gap in the literature by providing a structural model that is explicitly designed to understand the training decisions of less-educated male employees in their late careers and by using

[1] The largest part of the empirical training literature looks at vocational training, training in early careers, or (public) training programs for unemployed.

[2] Göbel and Zwick (2013) find no effects, Zwick (2002) finds positive association of training intensity with productivity.

a data-set that provides information to distinguish whether non-participation in training is due to a lack of the provision of firm-sponsored training or due to individual cost-benefit trade offs.

The remainder of this paper is structured as follows: Section 2.2 introduces the data set and provides first descriptive evidence. Section 2.3 contains all details of the structural model. Section 3.6 presents estimation results and the model fit. Section 2.5 shows the results of the counterfactual simulations, and section 3.7 concludes.

2.2 Data and descriptive evidence

2.2.1 Data

For the analysis, I use adult-cohort data from the National Education Panel Study (NEPS) – see Blossfeld et al. (2011). This is a comprehensive survey data set focusing on adult education and lifelong learning. The earliest observations in the data set were collected in 2007[3], while the NEPS itself started in 2009 and has been repeated every year since. The main advantage of this data set is that it is specifically designed for collecting information about further education and training among adults and therefore contains very detailed information about it. It contains information about training participation, type of training, attitudes with respect to work and training, and, importantly, the availability of training support by the company. The latter is the key feature that allows me to separate individual training costs from the availability of training in the firm in my model. For my analysis, I transformed the data into an annual panel format.[4]

In my analysis I will focus on male employees in their late careers with up-to-intermediate education, i.e. those who are aged above 50 and who do not have completed high-school but may have completed vocational training. I call them "low" or "less" educated as abbreviation.[5] In line with the findings of the previous literature (see, for example, Cairo and Cajner, 2018) the less-educated employees in my sample have lower employment rates than high-educated employees.[6] Figure 2.1 shows the employment rate of college educated and less-educated (no high-school diploma) male employees. It shows significantly lower employment rates after age 60 for less educated men.

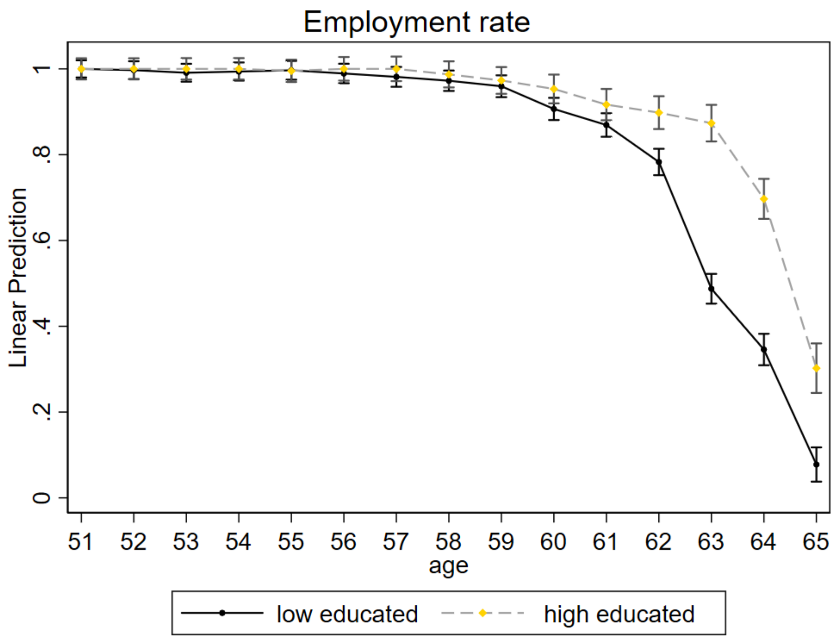
[3]The initial survey was called ALWA (Arbeiten und Lernen im Wandel (Working and Learning in a Changing World) run by the Institute for Employment Research (IAB))

[4]The NEPS consists of several data sets with different formats: Some as spell data, some as panel data, which can be merged in several ways depending on data requirements. Details on the data processing are available upon request.

[5]This classification is based on the education classification by Blundell et al. (2019) who use the three groups – up-to-intermediate education, high-school degree, and college degree.

[6]Considering only men aged 50-64 who are in dependent employment when entering the sample, the group with up-to-intermediate education is largest with 51% of the observations, college educated are 34%, and the group of men with high-school degree but no college education is smallest with only 15%.

Figure 2.1: Employment rate by age and education



Source: NEPS; own calculations based on estimation sample. For male employees only. Low educated denotes people with no high-school diploma, high-educated denotes people with college degree.

Furthermore, Figure 2.1 shows that, while most college-educated men in my sample leave the labor market at age 65, a large proportion of the less educated group already leaves the labor market at age 63. From this age, the German public pension system allows very long-term insured (those who have contributed for more than 45 years) to retire early without deductions.[7] People whose health status does not allow them to continue working may retire before age 63. To avoid confounding from this type of retirement and differing attitudes with respect to work of these people, I drop all those employees who state bad health status before age 63.[8] I further drop all remaining observations indicating retirement before age 63.[9]

Training data The most prevalent form of training among older employees in Germany is non-formal on-the-job training (Ehlert, 2017; Kruppe and Trepesch, 2017), i.e. training conducted while the individual is being employed and receives a regular

[7]For long-term insured (at least 35 years) it is allowed to retire *with deductions* from that age. From the year of birth 1953 onwards, the age limit for this deduction-free pension will gradually increase. For all those born in 1964 or later, the age limit is 65 years (Deutsche Rentenversicherung, 2020). Also for people born before 1953 it was possible to retire early after unemployment (with deductions).

[8]Possible answers are "very good", "good", "intermediate", "bad", "very bad". I drop all individuals who stated at least once "bad" or "very bad".

[9]After removing people with bad health status, there is only few (20) observations left who still retire before age 63. For those people early retirement could be due to partial retirement plans or retirement after unemployment.

salary without the awarding of any official certificate. The NEPS provides records of participation in such non-formal training for all employed individuals in every survey wave (for details see Kruppe and Trepesch, 2017). It also contains information about the availability of financing for such training.

In summary, my **sample** includes only men aged 50-63 without a high-school diploma; who are in dependent full-time employment when they enter the sample; who have at least two observations, no missing data for wages and training participation; and who state at least intermediate health status before age 63.

Note that this study investigates the role of on-the-job training, i.e. training of employed people, in future employment prospects. Less-educated men who are still in employment at age 50 are not representative of all less-educated people, who often suffer from unemployment at multiple points of their career. The reintegration of less-educated unemployed into the labor force, e.g. with public sector sponsored training programs, is not the subject of this study.

2.2.2 Descriptives

Training offers and training participation

One of the requirements for an employee to participate in on-the-job training is the employer's support for such activities. A key feature of the NEPS is that it provides information about the availability of training support in the employee's firm as stated by the survey participant: Does the firm provide company agreements, further education planning, financing for training, or a responsible person? Throughout my analysis I use the availability of firm-sided funding for training to proxy whether the employee has the possibility to participate in on-the-job training or not – denoted as "**training offers**" (TO) in the following.

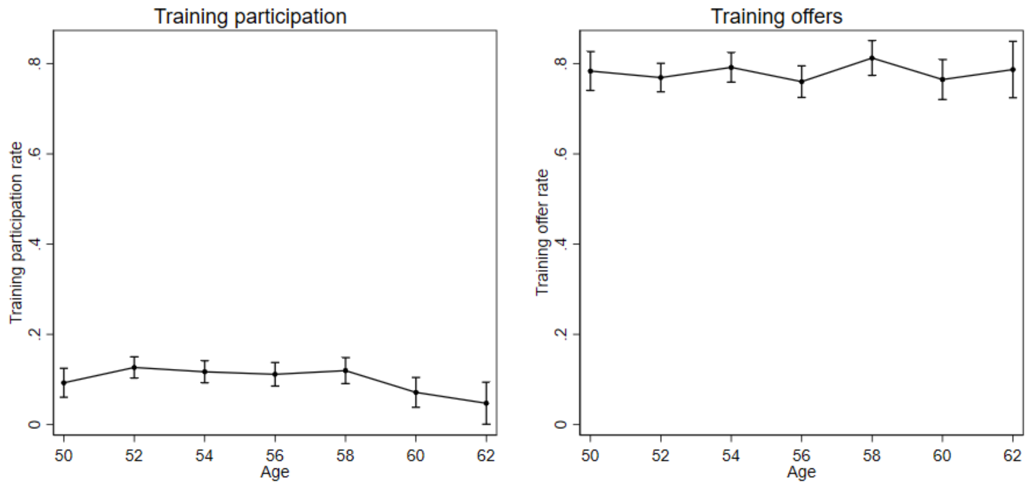
I use this indicator for three reasons: First, it shows to be a necessary condition for training participation.[10] Second, stated training offers based on this indicator are unlikely to be determined by the employees' demand for training: Many who state that funding is available still do not train. Third, there is no difference between employees with and employees without training offers in terms of beliefs about the usefulness of training and in terms of self stated laziness.[11] Further, there is no indication that people with better employment prospects select into firms which offer training: The employment rate is not higher for individuals who have (or used to have) training offers, see Figure B.2. If anything it is lower for people with training offers near retirement.

To indicate **training participation** I will use a binary variable following Blundell et al. (2019). In my case an employee is denoted as having participated in training if he did at least 20 hours of training in the past 12 months. Figure 2.2 shows the training participation and training-offer rate by age.

[10] If funding is not available 96% don't do any training.

[11] See appendix Figure B.1.

Figure 2.2: Training participation and training offer rate



Notes: Whiskers depict 95% confidence intervals. *Source:* NEPS; own calculations based on estimation sample.

The training-offer rate is, at close to 80%, much higher than the training-participation rate, at around 10%. While the training-offer rate remains constant with age, the training-participation rate decreases. The decreasing training-participation rate reflects the lower returns compared to the costs of training for higher ages. Yet, it does not decrease to zero.

Training and individual characteristics

In this subsection I examine differences in characteristics between training participants and non-participants as well as employees with and without training offers to check whether people with specific employment-related characteristics select into either group.

The NEPS includes questions about people's career ambitions and attitudes in some waves. Hence, I can check whether the responses differ between training participants and non-participants in my sample.[12] Table 2.1 shows the average response by training participation. The career ambitions of training participants are very similar to those of non-participants. The ambitions for status maintenance, for career advancement, to perform tasks better, and the general importance of the career are slightly higher for training participants. However, the importance of job security, for keeping up with colleagues, and self stated laziness are the same between the two groups. Note that both, training participation and ambitions may evolve with age. Therefore, I provide figures with ambitions and attitudes broken down by age in the appendix (Figure B.3 and B.5). They do not show distinct patterns in training participants' ambitions.[13]

[12] Possible answers for ambitions range from 1 "very important" to 5 "very unimportant" and for self stated laziness from 1 "not lazy at all" to 5 "very lazy".

[13] When looking at the ambitions at a single age 55 there are no significant differences for most

Table 2.1: Individual characteristics by training participation

	No training	Training
Ambitions		
Importance of status maintenance	1.784	1.709
	(1.123)	(1.077)
Importance career advancement	3.420	3.247
	(1.054)	(1.109)
Importance perform tasks better	1.944	1.814
	(0.917)	(0.733)
Importance job security	2.054	2.258
	(1.301)	(1.422)
Importance of keeping up	2.097	2.064
with colleges	(1.089)	(1.040)
Attitudes		
Lazy	2.212	2.212
	(1.102)	(1.147)
Importance of career	2.765	2.680
	(1.046)	(1.049)
Wages		
Monthly gross-wage	3568.4	4040.5
	(1473.7)	(1522.0)
Monthly net-wage	2391.1	2657.9
	(991.1)	(950.5)

Mean values, standard deviations in parentheses. Ambitions: 1 = very important, 5= very unimportant. Laziness: 1= not lazy at all, 5= very lazy. For a brake down by age see Figures B.3 and B.5 . Differences in wages are not significant when controlling for wage-level endowments, as I will do in my model. *Source*: NEPS data, low educated male employees in full time employment only.

It behaves similarly with training *offers*: the groups of people with and without training offers are very similar in terms of their ambitions (Table B.1 and Figures B.4 and B.5). Hence, selection into training participation or firms with training offers based on ambitions and attitudes is not a problem in my sample of less-educated male employees in their late careers.

Stated gross- and net-wages of training participants are significantly higher compared to non-participants.[14] Thus, it will be important to control for wage-levels later

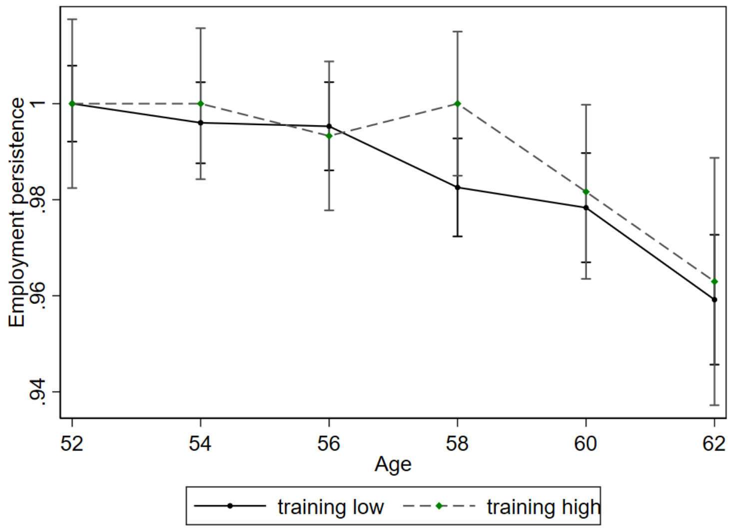
ambitions.

[14]In the NEPS all participants are asked about their gross- and net-wages last month. If they do not know the exact number they are asked to classify themselves into an income category. First with a rough grid with 3 categories and then with a finer grid with 9 categories, i.e. 3 finer categories depending on

in the analysis.

Training and employment

Figure 2.3: Persistence in employment by human capital gained from training



Source: NEPS; own calculations bases on estimation sample. Whiskers represent 95% confidence intervals. High training is defined as having at least 0.9 units of discounted human capital of training, i.e having participated at least once in 20 hours of training within the last two years or having participated more than once more than two years ago would suffice. For a formal definition of human capital of training see section 2.3.3.

In order to get first evidence on whether on-the-job training participation correlates with employment in my data, I look at the difference in employment persistence between training participants and non-participants. For this I define each person's *human capital of training*, that is, the human capital gained from training, as the discounted sum of past training participation.[15] Figure 2.3 shows the employment rate conditional on being employed in the previous year for the group of employees who have a human capital of training of at least 0.9, that is, for example, who participated in at least 20 hours of training per year within the last 2 years since age 50, and those who did not. For most ages, the persistence in employment is slightly higher for people with training, indicating that training might affect employment security. But the mean differences are not significant.

the previous response. The income variable I use takes the most precise available value. In case of categories the midpoint of the range is used.

[15] See section 2.3.3 for a formal definition of the human capital of training.

Table 2.2 shows simple linear-probability model regressions of employment status (columns 1 and 2) and wage growth (columns 3 and 4) on the human capital of training, conditional on previous period employment, while controlling for wage levels (and training offers). I find significantly positive coefficients for the human capital of training on employment persistence. This remains true when controlling for training offers (columns 1 and 2). Regressing wage-growth on the human capital of training yields insignificant coefficients in both specifications with and without training offer controls (columns 3 and 4). These outcomes are in line with the findings of the literature.

Table 2.2: Simple regression

	(1) Employment	(2) Employment	(3) Wage growth	(4) Wage growth
Human capital of training	0.00568*	0.00585*	0.000941	0.000494
	(0.00241)	(0.00245)	(0.00328)	(0.00334)
Age	-0.00366***	-0.00366***	-0.00147	-0.00146
	(0.000557)	(0.000557)	(0.000767)	(0.000767)
Wage level	-0.00280	-0.00268	-0.00489	-0.00521
	(0.00194)	(0.00196)	(0.00266)	(0.00270)
Training offer		-0.00166		0.00438
		(0.00437)		(0.00599)
Constant	1.197***	1.199***	0.119**	0.116**
	(0.0315)	(0.0317)	(0.0433)	(0.0435)
R^2	0.0145	0.0145	0.00219	0.00237
N	3050	3050	2975	2975

Notes: Linear probability model regression. Wage level is defined as initial wage divided by 1000. Age relative to age 50. Standard errors in parentheses. Significance codes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

This is first evidence to indicate that the human capital of training may indeed play a role in less-educated men's employment prospects in their late careers. However, this descriptive evidence is unable to reproduce the dynamic trade-offs that individuals face when considering training participation. The employee's decision to work or participate in training is based on a dynamic cost-benefit trade-off. Therefore, a reduced form model can not identify the impacts of training on the share of job-separations and employment prospects of employees. Further, it could not identify the individual costs of training, which are necessary for counterfactual analyses to evaluate potential policy interventions. Only then I can investigate whether policy interventions should target the supply of training or the individual participation incentives.

In the next section I will turn to the design of the structural model, which allows me to evaluate these interventions later on.

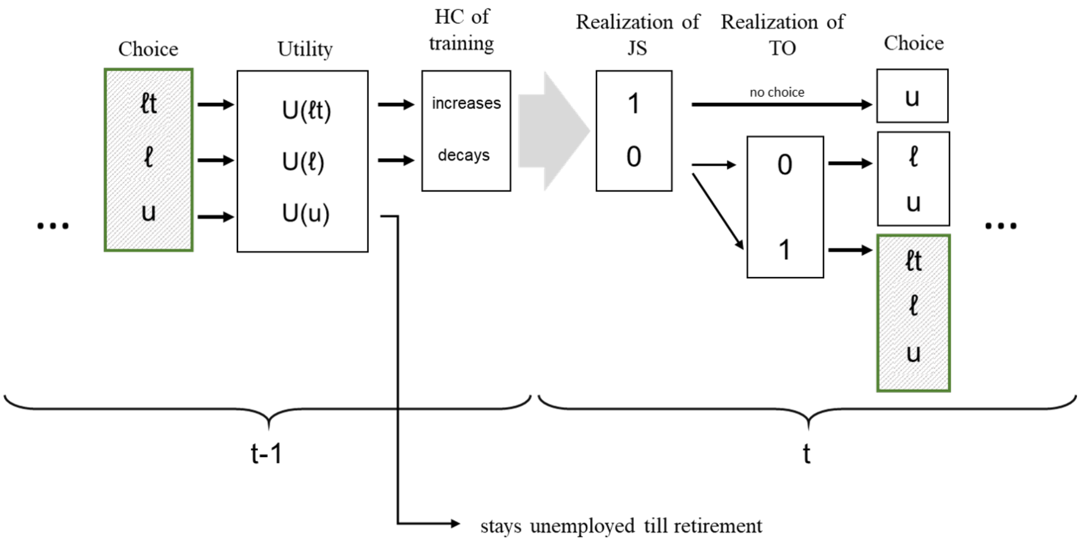
2.3 Model

The previous section has shown that less-educated men in my sample indeed have lower employment rates close to retirement and that on-the-job training exhibits to be positively correlated with employment. I will now turn to the structural model, which explicitly models the trade-offs that individuals face when making choices about labor market participation and human capital investments.

2.3.1 Outline of the model

Employed men enter the model at age 50. In each period, they make a decision about whether to continue working and whether to invest in training, depending on their choice set. The choice set is determined by their employer's training offers (TO) and by the job separation rate (JS). Both, training and working are associated with a disutility. On the other hand, training and working can have positive effects on wages and future employment prospects. Therefore, they represent investments in monetary returns from the labor market.

Figure 2.4: Timeline from choice to choice



Notes: This is a stylized sketch of the model to illustrate the timing of events during working life of the individuals. It does not represent all interdependences between variables. For details on functional forms and dependent variables see section 2.3.2 ff. Choice sets depend on realizations of job separations (JS) and training offers (TO). Abbreviations: Choices: work and training (ℓt); work (ℓ); unemployment (u).

During working life the individual has up to three different choice options available (unemployment u, working ℓ, working and training ℓt). Figure 2.4 shows a stylized sketch of the timing of the events in my model for the case where an individual has all three choices available in $t-1$: After the individual has made his decision

($d_t \in \{\ell t, \ell, u\}$), he receives his reward and the human capital (HC) of training is adjusted according to the decision. If the person chooses unemployment, he will be unemployed for the rest of his working life until retirement. If the person has chosen to work, realizations of the job separations (JS) and training offers (TO) occur in the next period. Depending on these realizations the individual faces one of the three possible choice sets, represented by the boxes, and again makes a decision. This choice process continues until a person becomes unemployed or retires at age 63. The utility and the job-separation rate in the model also depend on human capital investment decisions that the individual has made previously (details follow below).

2.3.2 The individual's optimization problem

At every age t the individual maximizes the following optimization problem. I drop individual subscripts for convenience.

$$max_{d \in D} \quad E_t \sum_{s=t}^{\bar{T}} \delta^{s-t} U(R_s, d_s), \tag{2.1}$$

with choice set $D_t \subseteq \{u, \ell, \ell t\}$ (u unemployment, ℓ work, ℓt work and training) during working life and $D_t = \{r\}$ (retirement) from age $t \geq 63$[16], and last period $\bar{T} = 85$.[17] Following Low et al. (2010) and Haan and Prowse (2014) I use a **utility function** that allows me to relate costs of work and training directly to the utility of consumption, which is set equal to rewards R_s in my model[18] (the rewards are defined in section 2.3.4).

$$U(R_s, d_s) = \begin{cases} \frac{\alpha}{1-\eta} \left[R_s(\ell t)\,(1 - \zeta - \zeta_{age} * age - \tau * train - \nu)\right]^{1-\eta} + \varepsilon_t & \text{if } d_s = \ell t \\ \frac{\alpha}{1-\eta} \left[R_s(\ell)\,(1 - \zeta - \zeta_{age} * age - \tau * train)\right]^{1-\eta} + \varepsilon_t & \text{if } d_s = \ell \\ \frac{\alpha}{1-\eta} \left[R_s(d_s)\right]^{1-\eta} + \varepsilon_t & \text{if } d_s \in \{r, u\} \end{cases} \tag{2.2}$$

The parameter ν is the disutility of training. The disutility of labor ζ is allowed to

[16]Most people claim benefits as soon as they become available despite actuarial incentives (Gustman and Steinmeier, 2005). Also see Figure 2.1. I choose a common retirement age at age 63 for all employees to avoid inconsistencies with eligibility criteria that may arise in survey data (employment histories are based on retrospective surveys in NEPS).

[17]Age 85 roughly corresponds to the life-expectancy of someone who is today 62 years old. The life-expectancy varies by age but the difference between age 50 and 60 is small. It increases only by 0.7 year. Thus I generously use a horizon of 85 for everyone. As individuals only make choices up to age 62 life-expectancies for years beyond that age are irrelevant.

[18]Similar to the paper by Keane and Wolpin (1997) where individuals optimize over rewards instead of consumption. In contrast to Keane and Wolpin (1997) where individuals maximize their expected present value of their lifetime rewards, I assume that individuals maximize over the utilities of these rewards, allowing for decreasing marginal valuation of additional money.

differ by age ζ_{age} and can depend on the human capital of training τ.[19] The disutility of labor can vary by age as leisure might become more attractive with deteriorating physical capacities (see for example Gustman and Steinmeier, 2005). Training could increase the enjoyableness of work as employees are/feel more proficient. The curvature of the CRRA utility function is determined by η, the risk aversion parameter. Individuals face random utility perturbations, represented by ε_t, which are extreme value type-1 distributed. The parameter α determines the importance of the preferences regarding earnings and effort relative to the random utility perturbations. Given that it is difficult to identify the risk aversion parameter,[20] I set the parameter η at a fixed level of 0.7, which is within the range Chetty (2006) finds.[21] The discount rate is set at 0.98 following Blundell et al. (2019) and Haan et al. (2018); all other parameters will be estimated.[22]

Utility costs of work and training The disutility parameters, which are defined as relative withdrawal from the reward,[23] have a rather broad interpretation. For example, disutility of work can also include (negatively) the joy of work or a benefit of not being unemployed. Likewise, the parameter ν reflects the sum of all sorts of immediate utility changes that are associated with training – this can be e.g. effort costs, monetary costs, or other frictions.

The **choice set** D_t is determined by the individual's age, exogenous training offers (TO) provided in the data (see section 2.2.1), and involuntary job separations that occur with probability JS (see section 2.3.5 for details). During working life the choice set can consist of up to three choice options $D_t = \{u, \ell, \ell t\}$ if the individual receives a training offer and does not face a job separation (TO=1, JS=0). If he does not receive a training offer he can only choose between unemployment and work $D_t = \{u, \ell\}$ (TO=0, JS=0), and if he loses his job (JS=1) he has no choice $D_t = \{u\}$ and becomes unemployed. Once employees become unemployed (due to choice or separations), they remain unemployed until retirement. This assumption is reasonable, as very few low-educated individuals return to employment once they become unemployed after

[19]See Section 2.3.3 for a definition of human capital of training.

[20]As it is the case in many structural models even in papers, which attempt to estimate this parameter.

[21]Also Wakker (2008) implies that this is a reasonable assumption. Note that individuals' instantaneous utility is created by the income not consumption – individuals may have higher risk aversion with respect to the latter. For higher values of η, employees would care too little about disutilities of work and training.

[22]As the household context is arguably less important for employment decisions of this subsample which entered the labor market in the 1970s/1980s I will model the decisions independent of the presence of a partner or children. This further allows me to circumvent the problem that the NEPS does not provide income information of other household members. As I use only men aged above 50, who are relevant for my research question, I do not need to make strong assumptions about the equivalence of training and working conditions across decades, that are necessary in life-cycle models (e.g. Blundell et al., 2019).

[23]This implies larger withdrawals from the reward for higher wages. Yet, this effect is diminished in the respective utility due to the curvature of the utility function. For $\eta = 1$ (i.e. log-utility) the utility loss would be equivalent for different income (reward) levels. For $\eta < 1$ the utility loss would be higher for higher reward levels, for $\eta > 1$ it would be lower.

age 50.[24] It further faciliates identification. At age 63, all individuals are assumed to retire and remain in retirement until the end of their life $D_t = \{r\}$ for $t \geq 63$. That is, individuals will not have any more choices to make once they become unemployed or retired.

2.3.3 Human capital

Training When individuals enter the model their human capital of training ($train$) is normalized to 0. Any human capital of experience and training that was acquired before is assumed to be reflected in the endowments of the wage-level w_{t0} and in the fact that they are in employment when entering the model. In the subsequent periods each time when the employee chooses to train ($tr_t = 1$) this adds to his human capital account but the human capital of training decays over time at the rate $\delta_{hc} := 0.93$.[25]

$$train_t = \sum_{s=t0}^{t} \delta_{hc}^{t-s} I(tr_t = 1) \tag{2.3}$$

The average level of human capital of training acquired since age 50 lies well below 1. It increases up to age 58 to an average level of 0.63 and then decreases again up until retirement.[26]

Training offers The availability of training, that is financing for on-the-job training by the employer (as observed in the data), is assumed to be exogenous.[27] For future time periods individuals expect their training offer to be equivalent to their current training offer: $E_t TO_{t+1} = E_t TO_{t+2} = TO_t$. Training offers are observed before the choice is made.

2.3.4 Rewards

When individuals are employed, their rewards equal their annual net wage $R_t(\ell) = R_t(\ell t) = w_t$, that is they receive the same salary when engaging in training.[28] The NEPS provides both stated gross and net wages. I use net wages, because these are

[24] Less than 8% of the low educated between 50 and 62 return to work once getting unemployed in my data, Etgeton (see also 2018).

[25] This corresponds the average of the human capital depreciation rates in Blundell et al. (2019).

[26] See Figure B.6 for average level of $train$ by age.

[27] Selection of older workers into firms with training offers at this age is unlikely. Section 2.2.2 confirmes that attitudes and ambitions of employees with and without training offers are similar.

[28] This model assumption is purposely different from typical human capital investment models, e.g. as applied in Fan et al. (2017), as in the context of on-the-job training of German employees in their late careers, where the company mostly finances and often even provides the training (Pischke, 2001; Görlitz, 2011), it would be an unreasonable assumption to model training costs as forgone earnings. Instead, potential training costs, monetary or non-monetary, are captured by the flexible parameter ν in the utility function. This way of modeling training costs is similar to Blundell et al. (2019).

closer to consumption and hence more useful for representing the individual's utility returns from work. I do not include savings in the model as savings are arguably of minor relevance for less-educated employees' late career choices due to the fact that savings would typically be close to zero for this group (see, for example, Börsch-Supan et al., 2015). When unemployed, the reward equals some unemployment benefit $R_t(u) = UB_t$ and, when retired, the reward equals the retirement benefit $R_t(r) = RB$. Details on the values of these rewards are provided below.

Wages w_t

As I include only individuals who are employed when entering the sample, I observe an initial wage w_{t0} for everyone. This wage reflects the market valuation of the employee's work when entering the model, including the human capital levels at this time and the general ambitions of the respective employee. In the subsequent periods, the development of this wage is assumed to depend on a general wage trend, human capital of training, and age.[29] Wages are assumed to emerge in the following way:

$$w_t = w_{t0} * (1 + \alpha_0 + \alpha_1(train_t) + \alpha_2 age_t)^{t-t0} \tag{2.4}$$

with the *age* relative to age 50, human capital of training $train$.[30] This definition allows wage level to decrease if the human capital of training decays. This assumption is in line with much of the literature (see eg. Blundell et al. (2016a)) and is reasonable, as the data reveals that a relevant share of the employees face negative wage growth at times. I assume that wages are deterministic from the worker's perspective. However, from the researcher's perspective they are not as I only observe wages that potentially include measurement error.

Unemployment benefit UB_t

I set the unemployment benefits to 60% of the previous wage, which is in line with the German rules.[31] They are paid for up to two years for employees aged 50 or older. After this period they receive means tested transfers and housing benefits. This is also reflected in the reward function for unemployed people. The level of means tested transfers plus housing benefits is set at EUR 959 for everyone.[32]

[29] The data does not indicate differences in relative wage growth across different wage levels for the group of less-educated, hence I removed this as control to save parameters.

[30] Log wages are assumed to follow a normal distribution. Measurement error follows a normal distribution with mean zero. Hence observed sample wages are assumed to be given by: $Log(w_t) + \varepsilon_t$ with $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.

[31] For individuals with dependent children 67%. I will use 60% for everyone.

[32] EUR 409 "ALGII"+550 housing benefit. As I don't have precise information about individuals' household context, savings, or housing costs an exact computation of means tested transfers is not possible.

Retirement benefit *RB*

In Germany, the retirement benefits depend on the time that an individual has contributed to the system, i.e. employment years, and on the contribution level in these years. More specifically, if the individual contributes less or more than the average person in a year, then the contribution year is scaled down or up, corresponding to the contribution level. The pension level is computed by adding up the scaled contribution years and multiplying it with the current "Rentenwert" (retirement benefit value) and penalties are deducted for early retirement (Deutsche Rentenversicherung, 2020). It turns out that for 45 contribution years, the gross retirement benefit amounts to roughly 45% of the average gross wage and that a missing contribution year leads to a deduction of roughly 1%. I reflect this in my model by considering the observed wage level and using penalties for years of unemployment prior to retirement during my observation period.[33] Each retiree receives this annuity (*RB*) for the rest of his life.

2.3.5 Job separation rate

The probability of becoming unemployed (job separation rate *JS*) depends on the employee's age, the human capital of training, and the initial wage level $wage_{t0}$[34] when the individual entered the sample. The JS is assumed to follow a binomial-logit functional form:[35]

$$JS(train, age, wage) = \Lambda(\beta_0 + \beta_1 train + \beta_2 age + \beta_3 wage_{t0}) \tag{2.5}$$

The parameter vector β captures the impact of the state variables on the job separations and hence the choice set. That means, the realization of *JS* and the resulting choice options that the individual has depend on his previous investments in human capital of training. The individual observes the realization of *JS* before making his decision.[36]

As I do not observe involuntary job-separations in the data, the relative magnitude of job-separations compared to voluntary transitions into unemployment, due to the

[33] For the first two years of unemployment (ALG I) the contribution is reduced by 20%. As I do not observe all wage levels in the employment history and only very rough information about actual contribution years, I generously use the last wage level to calculate the retirement benefit and assume that the individual was fully employed in all years prior to my observation period. Therefor I do not account for the fact that the lower relative tax burden in retirement years improves the ratio with respect net-wages and benefits compared to the gross values.

[34] $wage_{t0}$ is divided by 1000 in this equation to avoid very small parameters in estimation.

[35] $\Lambda(.) = exp(.)/(1 + exp(.))$

[36] The special set up in my model allows me to omit an experience variable. All employees who enter my model are employed and once they become unemployed they will remain unemployed until they are eligible for retirement. Any market valuation of experience that was gained prior to entering the model will be reflected in w_{t0} and the fact that the person is still employed. Any return to experience after entering the model is captured by the constant α_0 for wages and β_0 and β_2 (negatively) for the job separation rate.

individual's utility considerations, are determined by the functional form of my model. Similarly, the functional form determines the way the effect of human capital of training on employment is split between the job-separation rate and the utility function. However, the policy-relevant measure for my research question is the combination of the job-separations *and* the voluntary transitions: the employment persistence and the employment rate. The latter are identified with the data.[37]

2.3.6 Value functions

The resulting value functions of this dynamic-programming problem are defined as follows:

The value function when choosing working and participating in on-the-job training:

$$\begin{aligned}
V_t^{\ell t}(s_{it},\theta) &= U(R_s(\ell t),\ell t) \\
&\quad + \delta\Big[(1-Pr(JS=1|s_{i,t+1},\theta)) \\
&\quad \big[Pr(TO=1|s_{i,t+1})Emax\{V_{t+1}^{u}(s_{i,t+1},\theta),V_{t+1}^{\ell}(s_{i,t+1},\theta),V_{t+1}^{\ell t}(s_{i,t+1},\theta)\} \\
&\quad + (1-Pr(TO=1|s_{i,t+1}))Emax\{V_{t+1}^{u}(s_{i,t+1},\theta),V_{t+1}^{\ell}(s_{i,t+1},\theta)\}\big] \\
&\quad + Pr(JS=1|s_{it+1},\theta)E\{V_{t+1}^{u}(s_{i,t+1},\theta)\}\Big]
\end{aligned}$$

The value function when choosing working

$$\begin{aligned}
V_t^{\ell}(s_{it},\theta) &= U(R_s(\ell),\ell) \\
&\quad + \delta\Big[(1-Pr(JS=1|s_{i,t+1},\theta))\big[Pr(TO=1|s_{it})Emax\{V_{t+1}^{u},V_{t+1}^{\ell},V_{t+1}^{\ell t}\} \\
&\quad + (1-Pr(TO=1|s_{i,t+1}))Emax\{V_{t+1}^{u},V_{t+1}^{\ell}\}\big] \\
&\quad + Pr(JS=1|s_{i,t+1},\theta)E\{V_{t+1}^{u}\}\Big]
\end{aligned}$$

and for unemployment

$$V_t^{u}(s_{it},\theta) = U(R_s(u),u) + \delta E\{V_{t+1}^{u}(s_{i,t+1},\theta)\}.$$

with parameters θ and the current state variables s_{it} reflecting wage, the human capital of training, age, and employment status. ($V_{t+1}^{\cdot}$ abbreviates $V_{t+1}^{\cdot}(s_{i,t+1},\theta)$.) $V_t^{\ell}(s_{it},\theta)$ and $V_t^{\ell t}(s_{it},\theta)$ differ in the instantaneous utility and in the value of the state variable "human capital of training" in $t+1$. The value function $V_t^{u}(s_{it},\theta)$ reflects that the individual will not make any further decisions. The value function is solved via

[37]It would be interesting for further research to look more into the distinction between the effects of training on the job-separation rate and the utility function beyond the functional form, especially to validate the robustness of the reduction in the disutility of work due to training. This requires a data-set containing both detailed information about training participation and involuntary job separations. For a large enough data set also an exogenous shock to either channel would do.

backward induction, starting at the terminal period $\bar{T}$, which corresponds to age 85. See Appendix B.2 for details on the estimation.

Potential effect of training on employment

If training reduces the job separation rate, it has a first and a second order effect on employment: First, job separations are reduced and hence the involuntary unemployment decreases. Second, voluntary unemployment becomes more costly relative to employment when the probability of future involuntary job loss is reduced. Similarly, if the effect of training on wages is positive, then voluntary unemployment becomes more costly, as the individual would miss out on increased future wage growth.

2.4 Results and model fit

In this section I present the model-parameters estimated with the maximum-likelihood estimation and provide information about the in-sample fit.

2.4.1 Estimation results

Table 2.3 shows the parameter estimates for the wage function, the job separation rate, and the utility function, with standard errors in parentheses.

The results show a positive constant for the nominal wage growth rate of 2.1%. Parameters of wage-growth function indicate that wage growth increases with human capital of training and decreases with age on average but both coefficients are very small and not significant. This is in line with the results from most of the previous literature, which does not find significant effects of training on wages (see Section 2.1). The rate of job separations (JS) increases with age (significant at 10% level) and also significantly with the initial wage level, but it decreases significantly with training. Figure 2.5 shows the job-separation rate by age for an initial wage-level of EUR 2500 by different levels of human capital of training. One can see that the job-separation rate increases with age and consequently the largest percentage-point decrease due to human capital of training can be achieved near the retirement age. For example, at the age of 58, for an initial wage level of 2500 having one unit of human capital of training compared to having 0 units of human capital of training decreases the probability of job loss from 1.90% to 1.71%, i.e. by 0.19 percentage points. For age 62 one unit of human capital of training reduces the job-separation rate by 0.72 percentage points. The relative reduction is 10% for one unit of human capital of training and about 19% for two units compared to 0 units. Yet, even for two units of human capital of training, which lies far above the average of 0.42, training cannot fully counteract the age related increase in employment loss. Small effects of training on employment of older workers were also found by previous literature (see e.g. Picchio and Van Ours, 2013). The average job separation rate lies within the range

Table 2.3: Parameter estimates

Parameter		Estimate	Std. Err.
Wage function			
α_0	(Intercept)	0.02091	(0.00203)***
α_1	(HC of training)	0.00015	(0.00011)
α_2	((Age-49)/10)	-0.00031	(0.00226)
Employment risk (JS)			
β_0	(Intercept)	-7.7561	(0.7361)***
β_1	(HC of training)	-0.1076	(0.0489)*
β_2	(Age-49)	0.3067	(0.0801)***
β_3	($wage_{t0}$/1000)	0.2990	(0.09767)**
Utility function			
ζ	(Disutility of employment)	0.40533	(0.16780)*
ζ^{age}	(Change in ζ by age)	0.00993	(0.01198)
τ	(Change in ζ by HC of training)	-0.00695	(0.00265)**
ν	(Disutility of training)	0.06370	(0.00828)***

Notes: Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1. SD measurement error of wages $\sigma_\varepsilon = 0.1379496$ (SE 0.0003549). Utility scaling parameter $\alpha = 1.2034$. N=3050.
Source: NEPS data, less-educated male employees only.

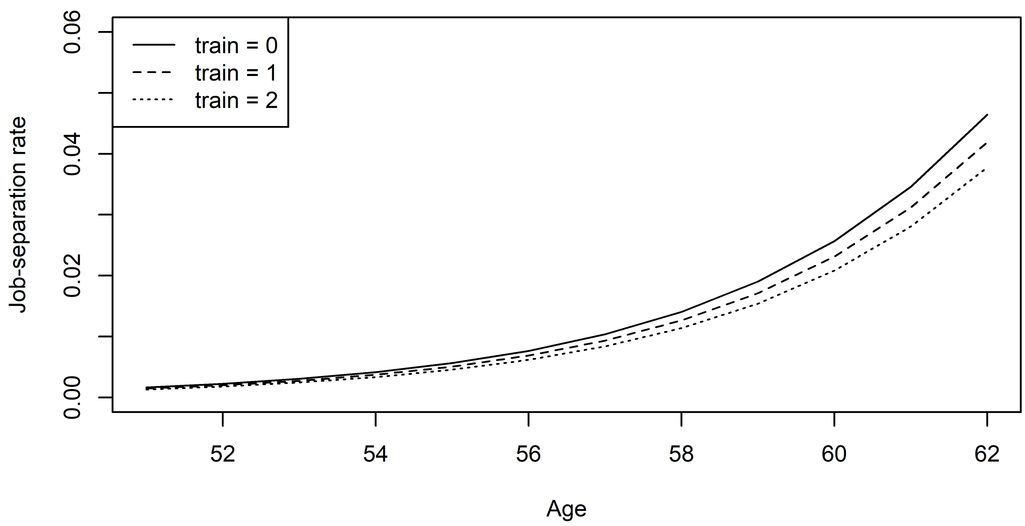
of the findings of previous literature (see Haan et al., 2017).[38]

The parameters of the utility function indicate that working is associated with a dis-utility of 40% of the net-wages, which decreases slightly with human capital of training. The age trend of the disutility is positive but not significant. The disutility of training is 6.4% and significant.[39] That is, individuals face positive costs when participating in training despite the fact that their firm provides the financing and they continue to receive their regular salary. These costs could include effort costs, general taste, small time or monetary costs, or other frictions related to training participation. Despite these positive costs it can still be worthwhile for individuals to participate in training as it reduces the probability of becoming unemployed and it reduces the disutility of work for future periods. Due to the fact that the training costs are relatively low, some people still participate in training when they are near retirement and the remaining working periods where training could pay off are limited.

[38]This indicates that the distinction between job separations and chosen unemployment via the functional form of my model works sufficiently.

[39]This level of training costs is comparable to the paper by (Blundell et al., 2019) who fix the training costs at 2 hours forgone wage, which would be 5% in a 40 hrs week.

Figure 2.5: Job-separation rate by age and human capital of training



Notes: The black lines show the predicted job separation rate by age for individuals with no human capital of training (solid line), with human capital of 1 (dashed line), and 2 (dotted line) for an initial wage level of 2500 EUR. *Source:* NEPS; own calculations.

2.4.2 Goodness of fit

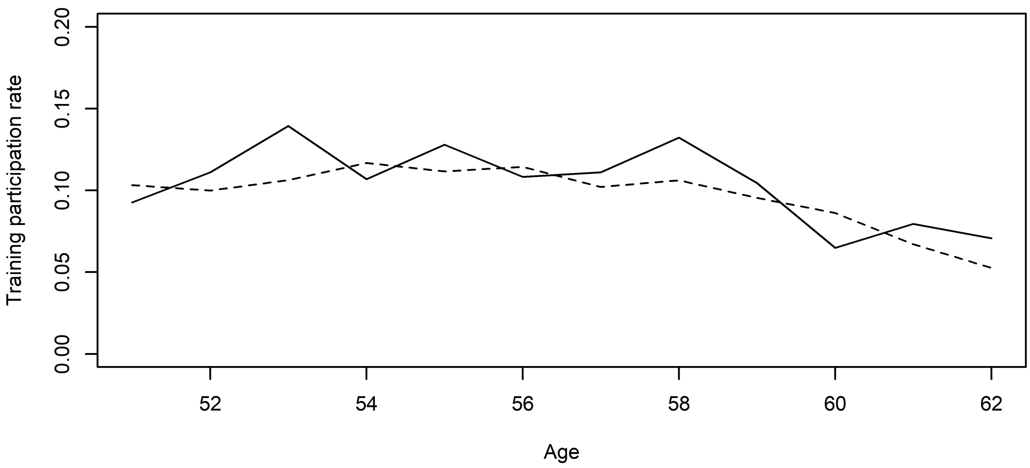
To evaluate the goodness of fit I compare the actual choices and wages in the data with the choices and wages that the model would predict by age.[40]

Overall the model fits well. Average training participation (Figure 2.6) fits well and deceases slightly with age, as it does in the original data. Also the average employment persistence, i.e. the probability to remain employed, by age fits well (Figure 2.7). It is very close to 1 in the early 50s and then first decreases slowly and then more sharply when approaching retirement age.

Figure 2.8 displays the original density of wages in solid black and the simulated in dashed green. The simulated wage density has a less pronounced spike around 2000 but nicely overlaps the original date. Figure 2.9 shows the mean and median wages by age. The simulated mean and median are slightly higher but roughly fit the data. The simulated median wage also reflects the decay close to retirement age as it can be observed in the original data.

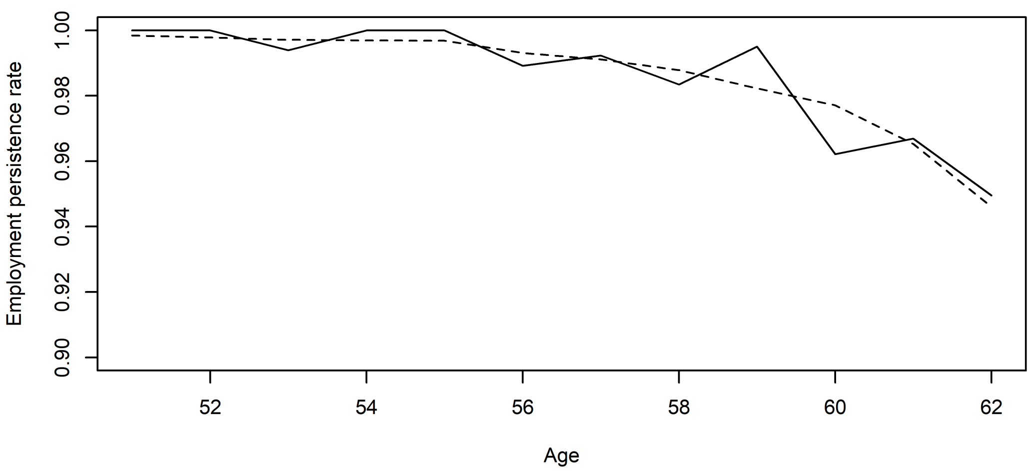
[40]For the simulated choices I replicate my sample 50 times to allow for different draws of random utility perturbations and measurement error.

Figure 2.6: Training rate by age original vs simulated



Notes: Training participation by age. Original values in solid line. Simulated values in dashed line. *Source:* NEPS data, subsample. Own calculations.

Figure 2.7: Employment persistence by age original vs simulated

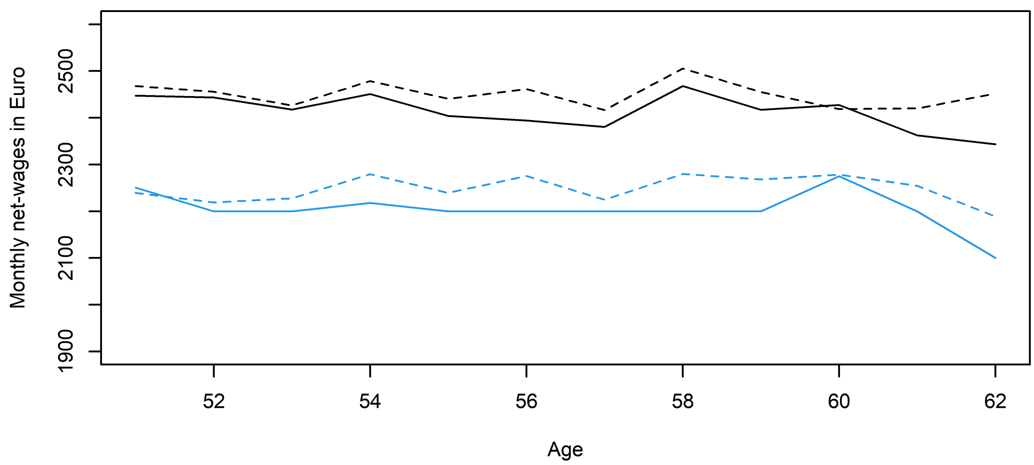


Notes: Share staying employed (employment persistence rate) by age. Original values in solid line. Simulated values in dashed line. *Source:* NEPS data, subsample. Own calculations.

Figure 2.8: Density of original wages and simulated wages

Notes: Density of monthly net-wages. Original values solid line, simulated wages in dashed line. *Source:* NEPS data, subsample. Own calculations.

Figure 2.9: Wages by age simulated vs. original



Notes: Mean and median monthly net-wages. Original values in solid line (black: mean wage; grey: median wage). Simulated values in dashed line. *Source:* NEPS data, subsample. Own calculations.

2.5 Counterfactual simulations

In the previous sections I have quantified parameters that determine the training decision of the less-educated men in my sample. I showed that on the one hand individuals have significant participation costs but on the other hand human capital of training has a positive impact on the employment prospects. My data set has allowed me to separate individual costs of training from the availability of training offers, that is the general availability of training funding in the firm. In this section I can now turn to the question whether a policy intervention should target training supply or individual participation incentives conditional on training supply, in order to increase employment near retirement. I investigate these two channels separately: First, the training offers (section 2.5.1) and second, the individual costs of training (section 2.5.2).

For the counterfactual simulations I randomly redraw 10,000 times from the sample of 51 year old in my data (less-educated male employees) and simulate their choices and corresponding human capital and wage measures till retirement age.[41] Afterwards, I calculate aggregate employment outcomes and compare the counterfactual to the baseline model.

2.5.1 Increasing training offers

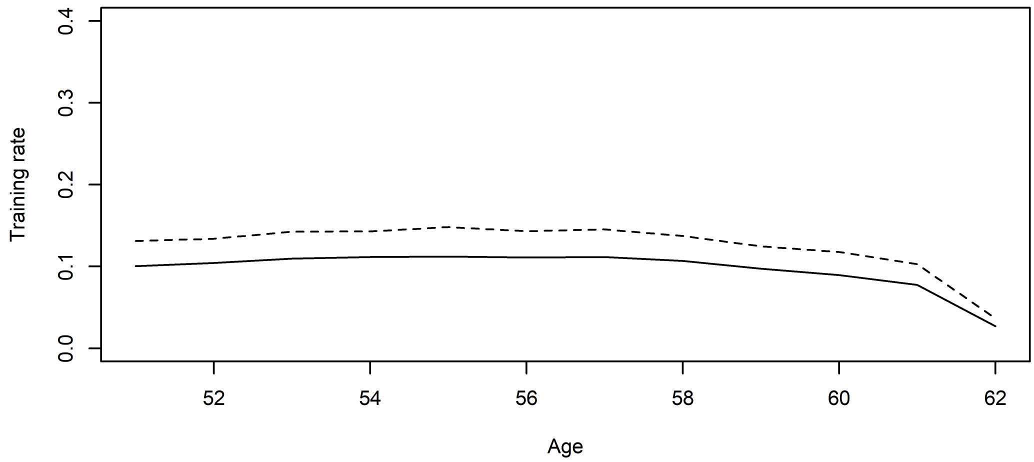
Scenario 1 An increase in training offers would enable more employees to choose training. Hence it could increase the incidence of training, and its beneficial effects on employment outcomes. Therefore, a policy intervention, like a subsidy of training costs for firms, might improve employment prospects of less-educated men in their late careers. I investigate the impact of an extreme policy intervention that would increase training offers to 100%: $TO = 1$ for everyone at any age. Note that the general willingness of the employers to invest in training (as reflected by the training offer rate) is with 80% quite high in my sample already, while the training participation rate is close to 10%. Consequently, I expect a relatively small impact of such an increase in the training-offer rate on employment outcomes.

This is exactly what I observe in my simulation. The change in the simulated training participation rate is very small (Figure 2.10). The average training participation in my sample increases from 9.7% to 12.6%. This small change in the training rate has hardly any impact on the employment persistence (Figure 2.11) and employment rate (Figure 2.12). At age 62, where the effect is largest, the employment rate rises from 83.5% to 84.0%, i.e. by 0.55 percent.

In summary, the simulation shows that a policy intervention that targets only the willingness of firms to invest in training would not be effective in increasing the employment of less-educated men in their late careers, even if it achieves to increase the training offer rate to 100%. In practice an implementation would additionally be challenged by potential crowding out effects of firm provided further-education invest-

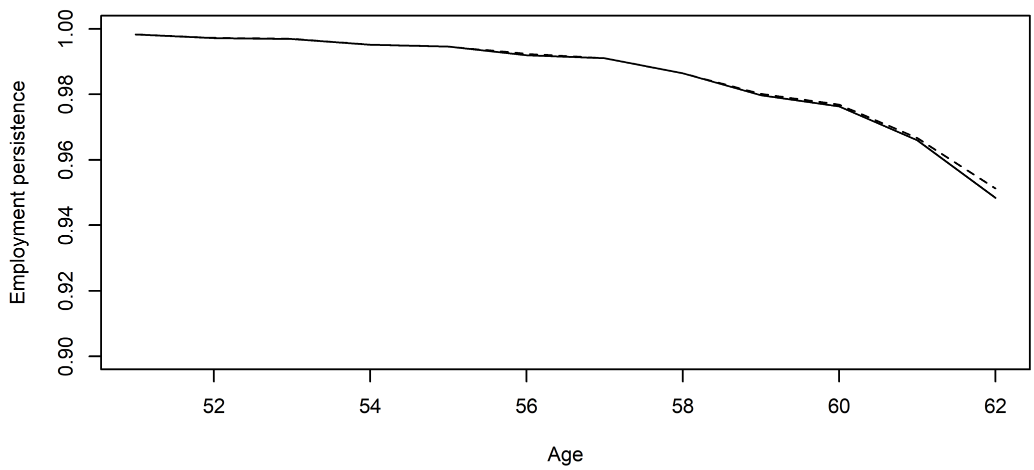
[41] I do this separately, for the baseline model (without intervention) and for the counterfactual scenarios.

Figure 2.10: Scenario 1: Training rate – baseline model versus counterfactual



Notes: Baseline solid line, counterfactual scenario 1 dashed line. Simulation based on 10,000 randomly re-sampled individuals drawn from the original sample of 51 year old. *Source:* NEPS data. Own calculations.

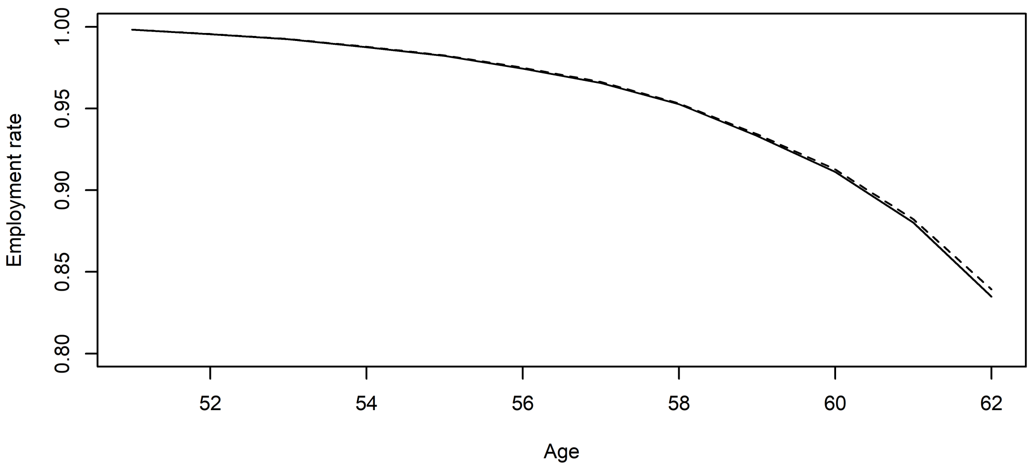
Figure 2.11: Scenario 1: Employment persistence – baseline model versus counterfactual



Notes: Baseline solid line, counterfactual scenario 1 dashed line. Employment rate of individuals who have been employed in previous period. Simulation based on 10,000 randomly re-sampled individuals drawn from the original sample of 51 year old. *Source:* NEPS data. Own calculations.

ments (see Görlitz, 2010). This risk is larger in a setting where general willingness to invest in training is already high - as in my data. Thus, any potential implementation of such a policy would need to be carefully deliberated. Given the negligible returns

Figure 2.12: Scenario 1: Employment rate – baseline model versus counterfactual



Notes: Baseline solid line, counterfactual scenario 1 dashed line. Simulation based on 10,000 randomly re-sampled individuals drawn from the original sample of 51 year old. *Source:* NEPS data. Own calculations.

of a successful implementation, this intervention does not appear too promising.

2.5.2 Reducing individual training cost

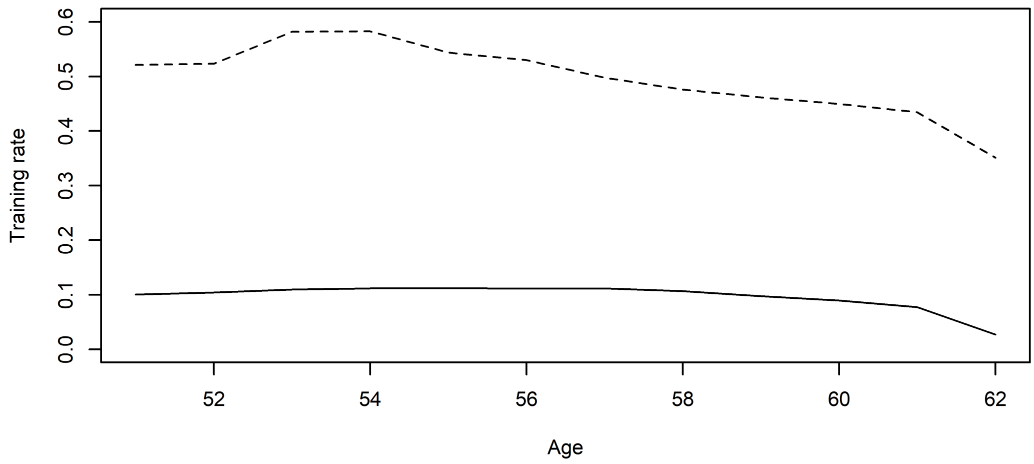
Scenario 2 Since the rate of training participation is much lower than the training-offer rate it might be more promising to think about a policy intervention that targets individual incentives, i.e. the utility costs of training (ν). Thus, I exogenously reduce the training costs in this second counterfactual analysis. To see the full potential of a policy that targets individual incentives for training participation I analyze the extreme case of $\nu = 0$. That is the employee's full disutility of training is compensated. Corresponding potential policies could pay fringe benefits or other compensation payments, which are payed in the year of training participation, or they could try to reduce the non-monetary costs of training participation. For instance, frictions like the effort to gather information about courses or to enroll in courses could create non-monetary costs. Easy access to information about training or default sign-up rules could reduce these costs.[42]

Reducing the utility costs of training to 0 would have a large impact on the training participation: It would increase to 50% on average, with the highest participation rate of 58.3% at age 54.[43] As a consequence the employment persistence and em-

[42]For the design of a precises policy intervention an additional analysis on the composition of the individual training costs would help.

[43]Note that less than 80% of the employees have a training offer, that is about two thirds participate in training on average.

Figure 2.13: Scenario 2: Training rate – model vs counterfactual



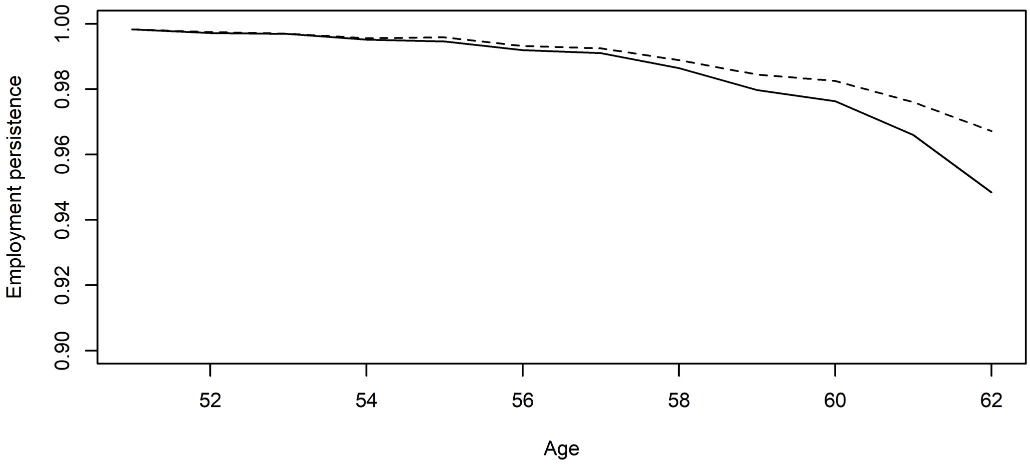
Notes: Baseline solid line, counterfactual scenario 2 dashed line. Simulation based on 10,000 randomly re-sampled individuals drawn from the original sample of 51 year old. *Source:* NEPS data. Own calculations.

ployment rate of older employees (Figures 2.14 and 2.15) would increase. The largest percentage point increase in employment would be achieved for the oldest employees: Assuming the same effect of training on involuntary separations under such a dramatic increase in training participation, this would increase the employment rate of 62 year old less-educated males from 83.5% to 87.6%. This corresponds to a 4.9% increase in the employment rate of 62 year old. For age 60 the employment rate would increase from 91.1% to 92.8%, i.e. by 1.9%.

This second counterfactual simulation shows that a policy intervention which directly addresses the utility costs of employees could be more effective than an intervention that addresses the general provision of training from the firm side. Such a reduction could be achieved by different policy instruments: Besides compensation payments, which would amount to EUR 1911 for an employee with a monthly net-wage of EUR 2500 in this scenario, the reduction of non-monetary costs could be effective. For example, a study by Van den Berg et al. (2019) provides evidence that providing information about training programs can increase the training participation.

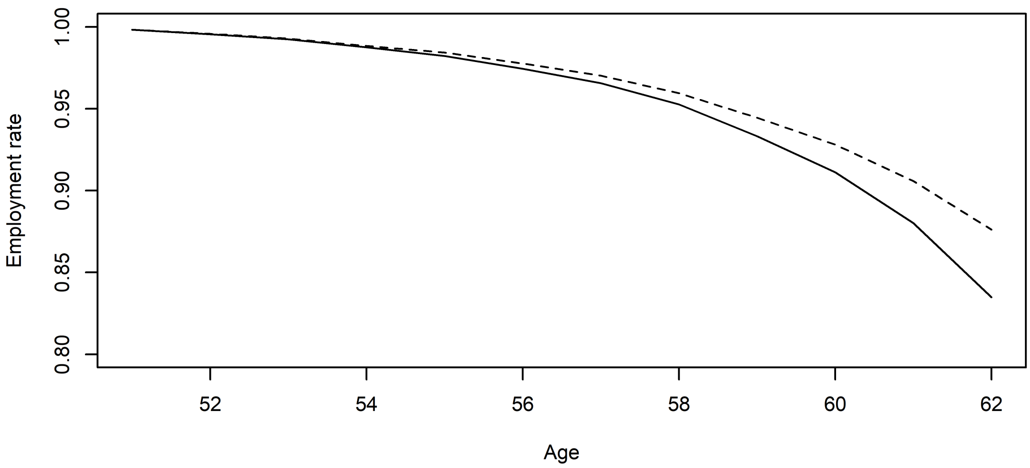
Yet, even a compensation of the entire training costs could not fully counteract decreasing employment rates of less-educated employees approaching retirement age. This is driven by two forces: First, the relative size of the absolute value of the training coefficient in the employment risk function is smaller than the age coefficient reflecting that training cannot fully compensate for advancing age. Second, some part of this unemployment is a result of the employee's trade-off between the utility of an additional full salary plus no penalties for the retirement benefit compared to the unemployment benefit without any disutility of work, despite the fact that the increased training activity would have decreased the disutility of work slightly.

Figure 2.14: Scenario 2: Employment persistence – baseline model vs counterfactual



Notes: Baseline solid line, counterfactual scenario 2 dashed line. Simulation based on 10,000 randomly re-sampled individuals drawn from the original sample of 51 year old. *Source:* NEPS data. Own calculations.

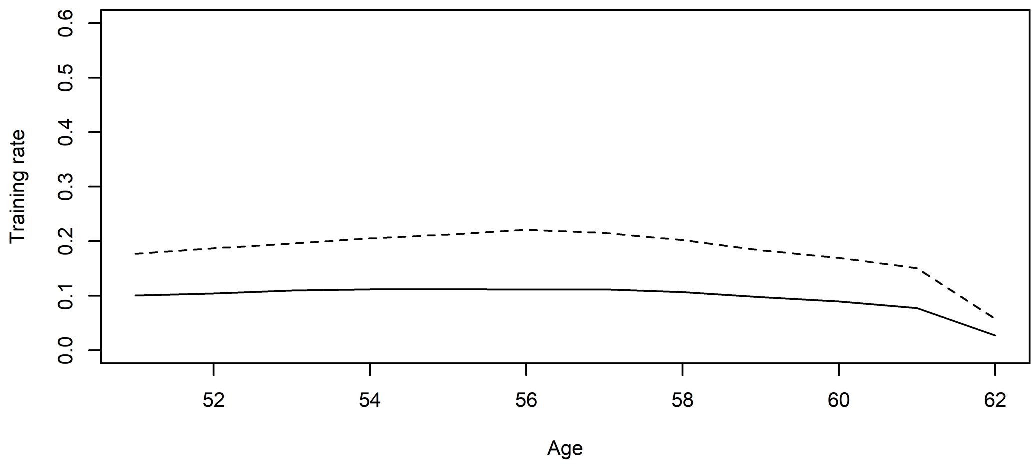
Figure 2.15: Scenario 2: Employment rate – baseline model versus counterfactual



Notes: Baseline solid line, counterfactual scenario 2 dashed line. Simulation based on 10,000 randomly re-sampled individuals drawn from the original sample of 51 year old. *Source:* NEPS data. Own calculations.

Scenario 2b The intervention in scenario 2 may appear extreme as we look at a 100% reduction in training costs, while we looked at a 25% increase in training offers in scenario 1. That is why I add a counterfactual simulation where I consider a 25% reduction in training costs (scenario 2b). That is, if the chosen policy instrument is compensation payments to reduce the individual training costs, an employee with a monthly net-wage of EUR 2500 would receive a tax free compensation of EUR 478 for his training participation.[44]

Figure 2.16: Scenario 2b: Training rate – model vs counterfactual



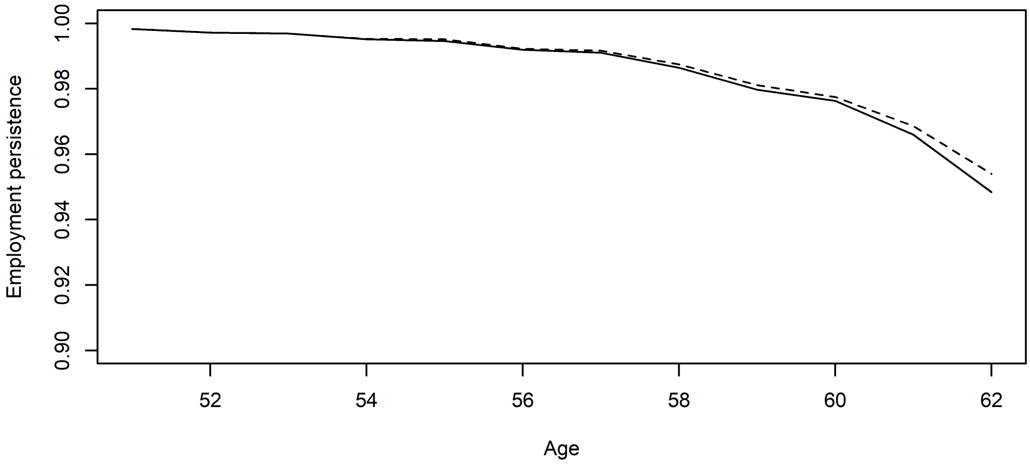
Notes: Baseline solid line, counterfactual scenario 2b dashed line. Simulation based on 10,000 randomly re-sampled individuals drawn from the original sample of 51 year old. *Source:* NEPS data. Own calculations.

As we see in Figure 2.16 the reduction of the individual training costs by 25% would lead to a less pronounced increase in the training rate compared to a 100% reduction: The average training participation would increase to 18.1% on average, with an increase by 98% at age 57 from 11.2% to 21.5% (compared to a maximum increase of 33% in scenario 1). As a consequence the effects on the employment persistence and employment rate (Figures 2.17 and 2.18) would also be more pronounced compared to scenario 1: At age 62 the employment rate would increase by 1.4% from 83.5% to 84.6%.

In conclusion, even a 25% reduction in the individual training costs would have a larger effect on employment than a 25% increase in training offers. Importantly in the simulation in scenario 1 I already reached the maximum possible intervention intensity for this channel, while the individual training cost could in principle even be overcompensated and could consequently achieve an even further increase in training participation in scenario 2. Hence, it reveals to be more promising to target individual incentives of training participation than the provision of training from the firms' side.

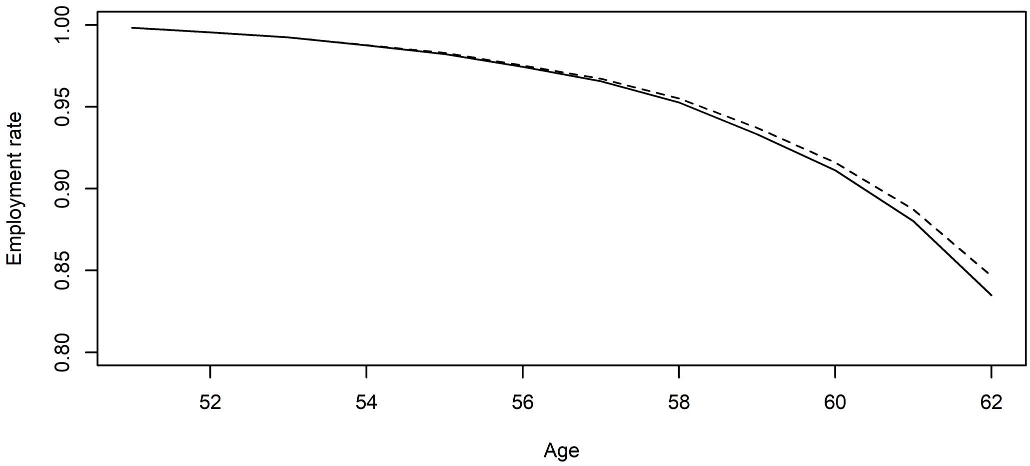
[44]This magnitude of the costs is still difficult to compare to scenario 1, as it is unclear what the firms would pay for the training provision and to what extend crowding-out would play a role.

Figure 2.17: Scenario 2b: Employment persistence – baseline model vs counterfactual



Notes: Baseline solid line, counterfactual scenario 2b dashed line. Simulation based on 10,000 randomly re-sampled individuals drawn from the original sample of 51 year old. *Source:* NEPS data. Own calculations.

Figure 2.18: Scenario 2b: Employment rate – baseline model versus counterfactual



Notes: Baseline solid line, counterfactual scenario 2b dashed line. Simulation based on 10,000 randomly re-sampled individuals drawn from the original sample of 51 year old. *Source:* NEPS data. Own calculations.

2.6 Discussion and conclusion

In this paper, I investigate the role of on-the-job training for employment outcomes of less-educated men aged above 50 using a structural dynamic discrete-choice model. This model provides novel insights into the trade-offs that these employees face when they decide whether to participate in on-the-job training. An important feature of my data set, the NEPS, is that it provides the necessary information to distinguish between the general availability of training funding in the firm and the individual utility costs of training. Using this feature in my structural model I was able to quantify the benefits and costs of training for the employee and to simulate the effect of different policy interventions on employment outcomes. As a consequence I could answer the question whether policy makers should increase training supply or incentivize individual training take-up to foster overall training participation.

The estimated parameters support findings from the existing literature, which indicate that the human capital of training has little effect on wages but has an impact on the employment outcomes. Further, I find that training causes a small reduction in the disutility of work, which could be an interesting starting point for further research addressing work motivation of less-educated employees in their late careers.

The counterfactual simulations in the last section illustrated, that it is less the lack of training funding in firms that determines whether or not employees participate in training and more the individual training costs. Further, training participation is shown to have a positive impact on the employment rate. In an extreme case, where the individual training costs were reduced to zero, a small increase in elderly employees' employment persistence would be achieved and hence result in an increase in employment rates near retirement from 84% to 88%. Therefore, fostering on-the-job training could play a part in future policy interventions that seek to address unemployment of less-educated employees in their late careers. However, in its current form on-the-job training would not be able to fully counteract the fact that employees' employment persistence decreases with age. It would be interesting to see more research on the question of how on-the-job training could become more effective in improving employment outcomes among elderly less-educated employees; for example, on the quality of training or the fit to the needs of older less-educated employees.[45] Furthermore, research on the composition of the utility costs of training could help to design an effective policy intervention targeting individual costs of training.

In conclusion, incentivizing on-the-job training participation for less-educated employees past their 50s could help to improve their employment outcomes near retirement.

[45] A study by Bellmann et al. (2013) provides first descriptive evidence on this topic.

Chapter 3

Can a federal minimum wage alleviate poverty and income inequality?

Ex-post and simulation evidence from Germany

3.1 Introduction

The argument that a minimum wage should guarantee disposable incomes above the poverty level has always been part of the minimum wage debate (Gramlich, 1976; Dube, 2019). It is used increasingly in political discussions about harmonizing and increasing minimum wage levels in the European Union (EU). The EU commission started a political initiative for EU-wide "fair minimum wages" (European Commission, 2020b,a; Council of the European Union, 2021). A central argument for raising minimum-wage levels is to ensure a decent living standard for workers and reduce (in-work) poverty. Germany is a case in point where rising income inequality and poverty were among the central arguments for the introduction of a statutory minimum wage in 2015.[1] Especially employees working full-time should not depend on welfare transfers. The fact that people with regular jobs cannot afford a basic standard of living and may require top-up benefits to cover their daily expenses was perceived as a particular injustice (Bruckmeier and Bruttel, 2020; Mindestlohnkommission, 2018). Outside the regular adjustment mechanisms of the minimum-wage commission, the coalition agreement of the newly elected government proposes a substantial increase of the minimum wage level to finally reach these goals (Coalition, 2021).

Existing empirical literature on the distributional impact of the minimum wages in Europe and, in particular in Germany, has either focused on earnings and hourly wages (Caliendo et al., 2017; Bossler and Schank, 2020), or has been based on ex-ante simulation studies (Müller and Steiner, 2013; Brenke and Müller, 2013). This paper provides ex-post evidence on the distributional effects of a federal minimum

[1] This line of argument was used in the reasons stated in the draft of the minimum-wage law (Deutscher Bundestag, 2014). The Left party (Deutscher Bundestag, 2011b) and the Social Democrats (Deutscher Bundestag, 2011a) used the term "poverty wages" in earlier minimum wage bills.

wage on disposable household incomes in Germany. Given that significant wage effects are a prerequisite for a pass-through to incomes, we first investigate the impact of the minimum wage on hourly wages of eligible employees addressing non-compliance and measurement error. Second, we analyze the minimum wage's effect on the distribution of disposable household incomes. Third, we examine various mechanisms that could explain the limited impact of an hourly wage increase on disposable incomes: We investigate welfare dependence and benefit withdrawal to assess whether specific redistributive goals – the reduction of top-up benefits (*Aufstocker*) and overall welfare dependence – have been reached. Further, we determine where in the disposable household income distribution the minimum-wage earners are found, and look at changes in employment outcomes across the household income distribution at the intensive and extensive margin.

Since the statutory minimum wage in Germany was introduced uniformly across all regions at the same level, 'natural' control groups for a causal analysis of inequality and poverty are not available.[2] Therefore, we do not apply a difference-in-difference type design based on a variation in treatment (see, e.g., Bonin et al., 2019; Burauel et al., 2019b; Garloff, 2019 for Germany), but accumulate descriptive evidence on the actual situation of individuals and households, with a special focus on those affected by the reform. We systematically compare different moments of the hourly-wage and household income distributions, as well as inequality and poverty measures, before and after the introduction of the minimum wage to changes over time between pre-reform periods. Dustmann et al. (2019) apply similar comparisons on individual outcomes in a difference-in-difference framework. For the analysis of the underlying mechanisms, we define "affected" individuals by their relative position in the annual wage distributions, to account for wage and employment fluctuations that are particularly prevalent among low-wage earners.[3]

To evaluate the magnitude of the observed changes and to establish an upper bound for the redistributive potential of the minimum wage in a "best-case" outlook without negative secondary effects on employment or compliance issues, we also simulate two counterfactual full-compliance scenarios. In the first scenario, all eligible employees earn at least the statutory minimum wage of 8.50€ per hour. In the second scenario, employees receive a substantially higher level of 12€ per hour as proposed in the coalition agreement by the newly eleceted federal government, other left-wing parties, and the Germany labor unions (Coalition, 2021). Both simulations serve as ceteris paribus upper-bound benchmarks for the full redistributive potential of the minimum wage.[4] To compare disposable incomes based on observed wages with those

[2]See Allegretto et al. (2017) and Neumark (2019) for a general discussion of alternative treatment/control group designs and Caliendo et al. (2018) for a discussion of available control groups for the German case.

[3]Results in this paper are not sensitive on the specific definition of this threshold which corresponds to the bottom 11% of the hourly wage distribution. Robustness checks with thresholds of 9% and 13% are available upon request. Inequality and poverty measures referring to the overall wage or income distributions do not depend on the definition of "affected" individuals and households.

[4]Additional scenarios, e.g. a minimum wage level of 12€ per hour with markedly lower compliance rates and a counterfactual situation without minimum wage are available upon request.

derived from wages in counterfactual scenarios, we employ a microsimulation model that allows us to compute disposable household incomes reflecting the details of the German tax and welfare system (Steiner et al., 2012). Assuming full take-up allows us to sidestep the issue of benefit non-take-up when assessing minimum-wage effects. We discuss this problem separately and provide robustness checks with reported disposable household incomes and transfers.[5]

We find that neither (in-work) poverty nor overall inequality in disposable incomes declined after the minimum-wage introduction. We show that this cannot be explained by non-compliance (Burauel et al., 2017) or measurement error in hourly wages. Instead, we identify the minimum wage in Germany as a poor redistributive tool with respect to disposable household incomes. It does not target low-income households because minimum-wage earners are spread across the entire income distribution. This is the main reason why the minimum wage is not effective in reducing poverty and income inequality. Consequently, neither top-up benefits, nor welfare dependence decline significantly. We can rule out negative employment effects among low-income households as an alternative explanation. The counterfactual scenarios reveal that neither full compliance nor a substantial increase to 12€ per hour would make the uniform minimum wage a more efficient tool for income redistribution and poverty reduction.

The remainder of this paper is organized as follows: Section 1.2 discusses the related distributional minimum-wage literature. Section 3.3 provides institutional details of the German minimum wage. Section 2.2.1 informs about the data set and sample. Section 3.5 discusses our methodological approach. Section 2.4 provides empirical results on wages, disposable household incomes, and the several mechanisms behind the distributional effects. Section 3.7 discusses our findings and concludes.

3.2 Related literature

This study is related to two branches of the minimum wage research. First, we relate to the research concerned with effects on individuals' gross wages, as we start our analysis with the investigation of the effects of the German minimum wage on the low-wage sector and wage inequality. The literature concurs that minimum wages mitigate inequalities at the bottom of the wage distribution, albeit to a varying extent (Autor et al., 2016; Dolton et al., 2012; Stewart, 2012b,a; Neumark et al., 2004; Dickens and Manning, 2004; Teulings, 2003; Lee, 1999; DiNardo et al., 1996). Applications for Germany confirm wage increases at the bottom of the distribution (Burauel et al., 2019b; Bossler and Gerner, 2019; Ahlfeldt et al., 2018; Caliendo et al., 2018; Bruttel et al., 2018; Caliendo et al., 2017). Evidence on wage spillovers is mixed (Autor et al., 2016; Stewart, 2012b; Dickens and Manning, 2004).

We mainly contribute to a second branch of the distributional minimum wage

[5]Note, that we require the tax-transfer simulation model as the reported disposable household incomes are not available for simulated scenarios and top-up benefits are not reported in SOEP.

literature investigating whether gross-wage increases induced by a minimum wage translate to disposable household incomes and reduce (in-work) poverty and income inequality. Income redistribution is jointly determined by wage and employment changes and interactions with the tax and transfer system (MaCurdy, 2015). One approach are ex-ante simulations that mimic certain adjustment channels. Incorporating tax interactions and employment effects, Johnson and Browning (1983) find a marginal redistributive impact of the U.S. minimum wage (see Freeman, 1996 for the UK). As low-wage employment and low household incomes are only loosely related in the U.S., workers in households above the poverty line benefit more from the minimum wage in relative terms (Burkhauser and Finegan, 1989; Burkhauser et al., 1996; Burkhauser and Sabia, 2007; Sabia and Burkhauser, 2010; Neumark, 2015). Richer households bear most of the burden from price increases induced by the minimum wage, yet poor households lose more in relative terms because of higher consumption rates (Macurdy and McIntyre, 2001; Gosling, 1996; Atkinson et al., 2017; Müller and Steiner, 2009, 2013; Campolieti et al., 2012; Maloney and Pacheco, 2012).

Ex-post studies often use exogenous variation in minimum-wage regulations within a reduced-form regression framework. Except for Neumark et al. (2005), they use panel estimators exploiting regional variation in minimum wages. Several studies do not identify a significant reduction of poverty (Vedder and Gallaway, 2002; Neumark and Wascher, 2002; Burkhauser and Sabia, 2007; Sabia, 2008; Sabia and Burkhauser, 2010; Sabia and Nielsen, 2013). Other studies find moderate reductions in the incidence (Addison and Blackburn, 1999; Morgan and Kickham, 2001; Stevans and Sessions, 2001; Gundersen and Ziliak, 2004; DeFina, 2008; Sen et al., 2011) and depth of poverty (Dube, 2019) in the U.S.. Neumark et al. (2012) find a slight poverty-reducing effect of city-wide living wage laws. Godøy and Reich (2019) find significant reductions of household and child poverty in low-wage areas across the U.S.

Our study provides first evidence on the disposable income inequality and poverty after the federal minimum-wage introduction in Germany. It closes a gap in the literature, as previous studies on this topic mostly focused on the U.S..[6] The German case is relevant as a federal minimum wage with significant bite has been introduced in a comprehensive European welfare state, and mixed evidence from existing studies has underlined the importance of the institutional context for the effectiveness of the minimum wage as a tool for income redistribution. We further contribute to the literature by providing evidence on several underlying mechanisms (position of low-wage earners in the income distribution, benefit withdrawal, changes in employment) that may impact the pass-through of wage increases to disposable incomes, and by combining the ex-post analysis with simulations of counterfactual scenarios.

[6] There is some evidence for the Pacific region (Kawaguchi and Mori, 2009) and South America (Sotomayor, 2021).

3.3 Minimum wage institutions in Germany

Set at a gross wage of 8.50€ per hour the federal minimum wage in Germany came into effect on the 1st of January 2015. At that time a number of sectoral minimum wages had already been put in place and many were still effective in 2015 and 2016. Since 2017 sectoral minimum wages are required to pay at least the statutory level or more, all sectoral minima below the federal minimum wage increased upon introduction of the federal minimum wage.[7] During the transition period in 2015–2016 the existing minimum wages were allowed to undercut the national level.

Generally, all employees are eligible for the federal minimum wage, except explicitly exempted groups: workers aged under 18 without formal training; trainees and certain types of interns; the long-term unemployed in the first six months of a new job and unemployed people who are working only few hours; and employees working under collectively bargained sectoral minimum wages below 8.50€ during the transition period after the minimum-wage introduction. The self-employed are also not eligible for the minimum wage. The only exemptions that significantly reduce the number of employees eligible for the minimum wage concern trainees and minors (vom Berge et al., 2016). Thus, there are no 'natural' control groups available among regularly employed individuals for evaluation purposes. We will use the term *eligible employees* throughout the paper when referring to employees who are not exempted and who do not work in a sector temporarily exempted from the minimum wage.

The German Minimum Wage Commission (MWC) consists of employer and employee representatives as well as scientific advisors. Its members are solely responsible for negotiating and recommending adjustments to the minimum wage level, which is then legally codified by the German government (chancellor and labor secretary). In 2016, the minimum wage remained at the level of 8.50€. Thereafter, it has been raised following proposals by the MWC according to §8 German Minimum Wage Law.[8]

The minimum wage is enforced by the German Customs Administration. It regularly conducts inspections of firms and enforces compliance with social security laws and the Minimum Wage Law. In the event of non-compliance, penalties of up to 500,000€ can be imposed. However, not least because of personnel shortages due to the refugee crisis, enforcement was widely regarded as weak, especially in the first year after the introduction of the minimum wage (Deutscher Bundestag, 2016; Burauel et al., 2017).

[7] Sector-specific minimum wages are only allowed if they exceed the statutory level. As of January 1st, 2019 the full list in descending order by minimum wage levels varying from 17.25€ per hour to 9.49€ per hour and for West and East Germany includes money transports, vocational education and training services, skilled construction workers, commercial cleaning, painting (skilled workers), chimney sweeping, roofing, unskilled construction workers, scaffolding, stone masonry, electro trade, elderly care, painting (unskilled workers), and temporary agency work (Amlinger et al., 2016).

[8] As of 1 January 2017 the minimum wage was raised to 8.84€, as of 1 January 2019 to 9.19€, and to 9.35€ and 9.60€ per hour in the following years with further steps being scheduled for 2022. We focus here on the large wage-shock in first two post reform years 2015 and 2016 in order to allow for clear interpretation of our results.

3.4 Data and sample

The empirical analysis is based on unbalanced panels from the German Socio-Economic Panel (SOEP) for the years 2012–16. We analyze wages for eligible working-age individuals and disposable incomes for all households with household members up to age 65, including the non-employed.

3.4.1 Data

The SOEP is a representative longitudinal household study. It contains information of roughly 30,000 individuals living in about 15,000 households (Goebel et al., 2019; Wagner et al., 2007). The SOEP provides detailed information on individuals' labor market status, e.g. the type of employment relationship, contractual and actual weekly working hours, and monthly labor earnings. It distinguishes earnings for the main and potential side jobs. A wide range of individual and household characteristics (including non-labor income) shed light on the economic and socio-demographic background of individuals in our samples. This allows us to analyze interactions of the minimum wage with the German tax and transfer system and to simulate disposable incomes and transfers at the household level.

We use SOEP version 33.1.[9] For specific variables, in particular for the labor market status, we utilize the SOEP EVA-MIN data set. This is a specific data set based on the SOEP that provides information for evaluation purposes and aims to establish certain standards for the preparation of the data to ensure the comparability of results among different studies. The EVA-MIN project included the collection of additional variables on various topics related to the introduction of the minimum wage.[10]

3.4.2 Sample

For the wage analysis we use a sample of individuals and for the income analysis a sample of households. The focus of this paper is on the working-age population. Therefore, we exclude individuals above age 65 and households with such individuals. A minimum wage also affects old-age incomes through lifetime labor earnings that determine retirement benefits and through the supplementary earnings of retirees (e.g. during partial retirement, or from marginal jobs). We do not consider these margins of income redistribution here.

The *individual sample* for the wage analysis consists of full-time, part-time, and marginally employed individuals as well as civil servants eligible for the minimum wage. We exclude non-eligible individuals, the self-employed and retirees from the individual sample. The *household sample* comprises all households with working-age members and children – irrespective of employment status and eligibility because we

[9] See `https://www.diw.de/en/diw_01.c.572910.en/1984_2016_v33.html`, last accessed on 15 December 2021.

[10] See `https://eva-min.soep.de/` for further information, last accessed on 15 December 2021.

are interested in the impact of the minimum wage on the overall income distribution and poverty. Therefore, we only exclude households with at least one household member who is aged over 65 to prevent our results from being influenced by changes in retirement benefits. The household sample also contains self-employed, unemployed, or inactive individuals.

We use observations from 2012–2016 in unbalanced panels. This way we observe two pre-reform years that are not affected by anticipation of the reform, since the minimum-wage introduction became common knowledge in 2014. We winsorize the bottom and top percentiles of the hourly wage, the total wage, the hours, and the income distributions to cope with outliers in our sample. In line with other studies (e.g. Caliendo et al., 2018, 2017), values below the bottom and above the top percentiles are replaced with the threshold values. All SOEP sub-samples are used to keep the overall size of our individual and household samples roughly constant. We use sampling weights provided by SOEP throughout the empirical analysis to ensure representativity.[11]

3.5 Methods

We use a descriptive approach investigating distributions, moments of these distributions, and distributional measures over time to assess whether outcomes changed significantly after the introduction of the minimum wage. Year-to-year changes before the minimum wage was introduced are used as a reference for comparison. Further, we compare observed outcomes with simulated counterfactual scenarios, such as full compliance and a 30% increase in the minimum wage level, to establish more general results for a minimum wage in Germany's institutional set-up.

3.5.1 Measurement of hourly wages

The SOEP questionnaire does not contain a direct query on hourly wages. Yet, respondents are asked questions, both, about their monthly gross earnings as well as their contractual and actual weekly hours of work. Based on this information different concepts of hourly wages can be computed (see, e.g., Brenke and Müller, 2013, Caliendo et al., 2017, or Dütsch et al., 2019), where monthly gross labor earnings are divided by weekly working hours extrapolated to a monthly figure.

We employ the arguably most reliable measure of *contractual working hours* that are fixed in the contract the employee signed and do not fluctuate or change in the short-run. Although a minimum wage policy intends that employee's receive the minimum wage for all the hours they work, which would be represented by *actual* working hours in the SOEP, there are problems attached to this wage concept. Actual work-

[11] Robustness checks for a samples without migrants who have been increasingly oversampled during the observation period are provided upon request. The results do not depend on the inclusion of these samples.

ing hours are more likely to suffer from measurement error or strong fluctuations and therefore lack precision. Moreover, wages and overtime hours do not have the same reference month in the survey. However, we must keep in mind that many employees supply unpaid overtime hours, which might have increased due to the minimum wage reform. The wage measure based on contractual hours thus represents an upper bound for gross hourly wages. Wages are not deflated.

3.5.2 Simulated and observed incomes

The primary interest of this study is to investigate whether the minimum wage improved the living standard of low-wage earners. Therefore, we consider *disposable household incomes* that take into account the size and composition of households and interactions with the tax and transfer system. Disposable household incomes in our study are defined as the equivalence weighted household income, including all income sources, including transfers minus the taxes.

To compare income measures not only for observed wages before and after the minimum-wage introduction, but also consistently with counterfactual scenarios based on hypothetical hourly wages and labor earnings, we compute *disposable household incomes* as main outcome. Employing a microsimulation model (Steiner et al., 2012), we simulate the disposable household incomes on the basis of various earnings and income components as observed in the SOEP: hourly wages, contractual hours of work, and other types of income by all household members. This model incorporates the features of the German tax and transfer system.[12] Gross household income is composed of earnings from dependent employment, income from capital, property rents and other income. Earnings from dependent employment is the main income component for the most households. Taxable income is calculated by deducting various expenses from gross income. According to German tax law, joint income taxation is applied to married couples. Employees' social security contributions and income tax are deducted from gross income and social transfers are added to compute net-household income. Social transfers include child allowances, child-rearing benefits, educational allowances for students and apprentices, unemployment benefits, housing allowance, and social assistance. The micro-simulation model is also used to calculate top-up benefits and transfer eligibility.

The computation of disposable household incomes is based on perfect compliance and full take-up assumptions. It is assumed that people fully comply with the tax law; tax avoidance and non-take up of benefits are not considered. Therefore, calculated welfare-benefits are based on the neediness of households and not the actual take-up. This way we can abstract from potential problems regarding enforcement of the tax-transfer system. We check the robustness of our results based on the simulated income measure by comparing them to outcomes based on *reported disposable household incomes* as directly reported by SOEP respondents before and after the

[12] Vandelannoote and Verbist (2020) and Leventi et al. (2019) follow a similar methodological approach in a comparative perspective.

introduction of the minimum wage.[13] Distributional moments and quantiles as well as inequality and poverty measures prove to be similar for simulated and observed disposable incomes. Throughout the income analysis we use equivalence-weighted household incomes based on the new OECD equivalence scale. Equivalence incomes are not deflated.

3.5.3 Assumptions on employment effects and wage spillovers

Different parts of the distributional analyses, e.g. hourly wages vs. disposable incomes or observed differences in pre- and post-reform years vs. comparisons with counterfactual scenarios, require different assumptions. Since the wage analysis is based on hourly wages of *eligible* employees (sub-section 3.4.2), it does not consider *changes in employment*. In the counterfactual scenarios, we modify certain wage rates based on the same number of total jobs as in the status quo.

The analysis of disposable incomes is based on the *overall* distribution of households with working-age adults (sub-section 3.4.2). When individuals become unemployed, change their jobs, or the number of hours worked as a result of the minimum wage, this affects disposable household incomes and is thus included in the distributional analysis. No assumptions on employment effects are needed here. However, comparisons with counterfactual scenarios require assumptions on employment. We do not change any other variables besides hourly wages in the simulation of counterfactual scenarios (sub-section 3.5.4), that is we assume no changes in employment. Assuming that potential employment effects tend to be negative, these scenarios provide an upper bound for the redistributive potential of the minimum wage if there were no downsides.

We do not need assumptions on *wage spillovers* when analyzing observed changes in wages and incomes. Should the minimum wage induce spillover effects, they are captured in observed wage and income distributions. We assume zero wage spillovers for the simulation of counterfactual scenarios. Should spillover effects primarily benefit medium to high-wage individuals or high-income households, then our scenarios must be interpreted as upper bounds for redistributive effects of the minimum wage also in this regard.

3.5.4 Counterfactual scenarios

We simulate counterfactual scenarios assuming full compliance to assess the redistributive potential of the minimum wage, irrespective of compliance or measurement problems during the implementation of the minimum wage. We construct two 'ideal world' scenarios: First, we lift observed hourly wages below 8.50€ to this threshold in post-reform years simulating full compliance ceteris paribus (*scenario A*). Wages above the minimum wage level and other variables remain unchanged. In the second

[13] As mentioned, incomes of counterfactual scenarios and top-up benefits are not observed and must be computed with the tax-transfer microsimulation model.

scenario, we repeat this exercise for a markedly higher minimum wage level of 12€ per hour. Assuming full compliance all observed hourly wages below 12€ per hour are set to this threshold value (*scenario B*). In both scenarios we assume zero labor supply and zero labor demand effects.[14] By construction, scenarios A and B provide upper bounds for the redistributive effects of the minimum wage, in the absence of secondary effects (wage spillovers or employment) diminishing income redistribution.

3.5.5 Inequality and poverty measures

In order to reduce wage inequality, income inequality and (in-work) poverty, a minimum wage needs to lift wages at the bottom of the hourly wage distribution and increase incomes at the bottom of the disposable income distribution. Besides comparing distributions, moments, and quantiles of these distributions, we also study inequality and poverty measures (Cowell, 2011) to assess whether the minimum wage reduces poverty and income inequality.

Despite its straightforward interpretation and widespread use, the poverty rate only describes how many households are below or above a certain income threshold – the poverty line. It is insensitive to changes in low incomes that do not push households above the poverty line. Therefore, we use additional *poverty measures* from the *Foster-Greer-Thorbeke class* to get more information on the income situations of poor households:

$$FGT(\alpha) = \frac{1}{n} \sum_{i=1}^{q} \left(\frac{z - y_i}{z} \right)^{\alpha} \tag{3.1}$$

Parameters z and q denote the poverty line and the number of households below this line, respectively. For parameter $\alpha = 0$ we get the *Poverty Rate*, for $\alpha = 1$ the *Poverty Gap*. This measure is based on the distance of incomes to the poverty line for poor households and can hence change, even if households are not lifted above the poverty line. For $\alpha = 2$, the *FGT(2) measure* puts more weight on poorer households that are further away from the poverty line. Both, the Poverty Gap and the FGT(2) satisfy the monotonicity axiom by (Sen, 1976), which states that the measure must rise whenever income of a poor person is reduced. The FGT(2) measure further satisfies the transfer axiom, which requires that the poverty measure must increase whenever money is transferred from a poor to a less poor household, ceteris paribus.

To analyze minimum wage effects on *overall* distributions we use the *Atkinson inequality measure* with an inequality aversion parameter $\varepsilon = 2$ (Atkinson, 1970; Cow-

[14] This is a strong assumption, especially for the 12€ per hour-scenario which would affect around 30% of the employees in our sample. It is further possible that non-complying jobs in the observed data would be at risk when compliance is enforced. Yet, the purpose of these simulated scenarios is not to compute a realistic outcome under full compliance but to provide a counterfactual of the potential impact that the minimum wage could have if there were no negative side effects.

ell, 2011).

$$A_{\varepsilon=2} = 1 - \left[\frac{1}{n} \sum_{i=1}^{n} \left[\frac{y_i}{\bar{y}} \right]^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}} = 1 - \left[\frac{1}{n} \sum_{i=1}^{n} \frac{\bar{y}}{y_i} \right]^{-1} \tag{3.2}$$

where y_i and $\bar{y}$ are individual and mean incomes (or wages) and we sum over the entire distribution. In addition to its sound theoretical foundation based on social welfare and its favorable statistical properties (e.g. sub-group consistency), the Atkinson index is sensitive to inequality at the lower end of the distribution. Thus, the Atkinson measure is particularly suited for a distributional analysis of the minimum wage that disproportionately affects lower parts, but may also influence the middle of wage and income distributions.

3.5.6 Definition of people affected by the minimum wage

To investigate different mechanisms behind the minimum wage effect on household income inequality (sub-section 3.6.3), we need to define the group of affected people. A common approach in ex-ante studies (e.g. Lesch et al., 2014; Kalina and Weinkopf, 2014; Falck et al., 2013) and ex-post evaluations (e.g. Bonin et al., 2019; Burauel et al., 2019b; Garloff, 2019) of the minimum wage is to determine affected individuals based on their hourly wages in a single 'pre-reform' period. Applying this approach here would create substantial problems that are rarely discussed. In the bottom parts of the wage distribution there is a lot of year-to-year fluctuation between jobs and employment states. As a result, the hourly wages of low-wage employees vary substantially between years and are subject to mean reversion. Wages of a fixed group would therefore entail positive wage trends, even in the absence of minimum wage reforms. This fluctuation is clearly present in the pre-reform years in our sample. More than 40% of people working in jobs paying below 8.50€ in 2012 earn more than 8.50€ in the subsequent year (Table C.1, Appendix).

This pattern is in many instances driven by job changes. Transitions to new jobs are particularly frequent in lower deciles of the wage distribution: In the pre-reform years 2011–2014 on average 39% of employees in the bottom decile and 33% of employees in the second decile of our sample state that they had changed jobs since the last year (Table C.2, Appendix). Mean reversion contributes to positive average wage trends for such people (see also Dustmann et al., 2019).

Given job fluctuation and variation in hourly wages that are unrelated to the minimum wage, we do not use pre-reform work conditions to define the treatment group. Instead, we define employees as being 'affected' by the minimum wage, if their wage is within a certain range at the bottom of the hourly wage distribution and if they comply – according to their employment status – with eligibility criteria. The chosen range is determined by the share of eligible employees who earned less than 8.50€ per hour prior to the minimum wage reform. We take 2013 as the baseline year to avoid bias through anticipation effects. In 2013 11% of eligible employees earned less than

8.50€. Therefore, we denote the group of employed people whose employment status complies with the eligibility criteria of the minimum wage and who belong to the bottom 11% of the hourly wage distribution of a respective year as affected.[15]

Eligibility and "affectedness" are determined at the individual level. Wage effects are, by construction, primarily driven by employees with hourly wages at the bottom of the wage distribution in a given year, i.e. those targeted and affected by the minimum wage. For the analysis of disposable incomes, households are defined as being affected by the minimum wage, if at least one household member is individually affected (eligible and in the bottom 11% of the hourly wage distribution).

3.6 Empirical findings

As wage effects are a necessary condition for a minimum wage-induced redistribution of disposable incomes, we first assess the impact of the minimum wage on individuals' hourly wages. Second, we analyze distributional effects of the minimum wage on disposable household incomes. Third, we investigate several mechanisms that potentially affect the transmission of wage increases to household incomes.

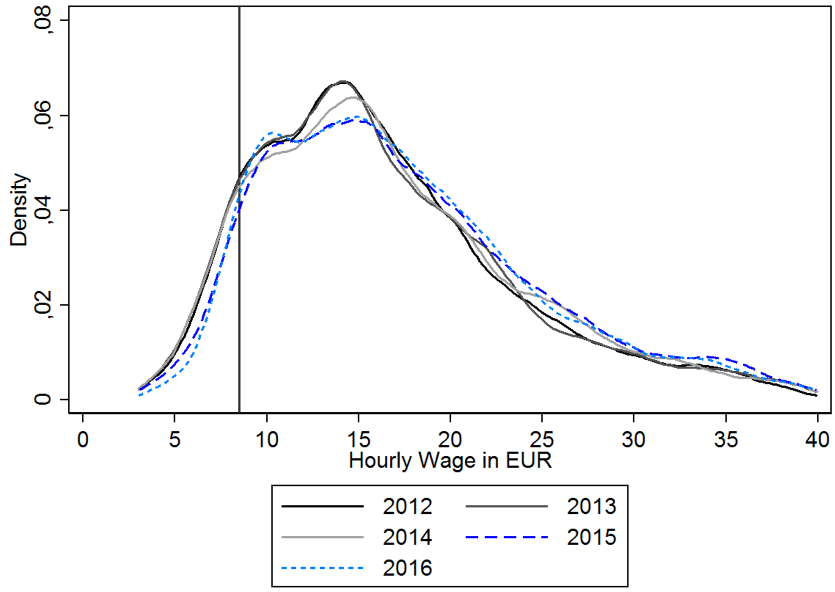
3.6.1 Wage effects

Figure 3.1 shows kernel density estimates for hourly wages of eligible employees between 2012 and 2016. Distributions are indistinguishable at the bottom in the pre-reform years 2012–2014. In contrast, we observe a distinct shift to the right after the minimum wage was introduced in 2015, followed by an additional shift in 2016. A Kolmogorov-Smirnov test confirms that the post-reform wage distributions differ significantly from the pre-reform distribution. The minimum wage reform had a substantial impact at the bottom end of the wage distribution. However, there is still a lot of probability mass to the left of the statutory minimum wage level of 8.50€ per hour (represented by the vertical line), even in 2016. This points to possible measurement issues and reporting errors with respect to hourly wages as well as non-compliance with the minimum wage law, potentially to a considerable extent (see also Caliendo et al., 2017; Burauel et al., 2017).

To shed light on potential non-compliance, we take a look at the share of employees who receive wages below the minimum wage over time (Table 3.1). The share of employees below the threshold decreases significantly in 2015, persisting in 2016. However, the share remains markedly positive in 2015 (7.5%). In 2016 this number drops only slightly. This confirms the observations from the distributional graph. It remains unclear to what extent this is a measurement or compliance problem. Evidence on insufficient enforcement of the minimum wage suggests that non-compliance was a significant factor (see Caliendo et al., 2017).

[15]Robustness checks with 9% and 13% thresholds are available upon request. Results are not driven by the precise definition of this threshold.

Figure 3.1: Distributions of hourly wages, eligible employees, 2012-2016



Notes: Kernel densities of the hourly wages of eligible employees by year. Wages not deflated, individual frequency weights used. The vertical line depicts the minimum wage level of 8.50€ per hour. *Source:* SOEP, waves 2012-2016; weighted; own calculations.

Table 3.1: Share of eligible employees with wages below 8.50€ per hour in %, 2012-2016

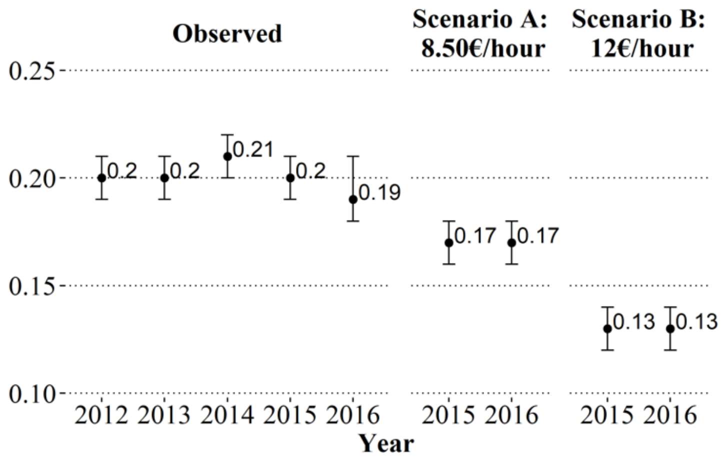
Year	2012	2013	2014	2015	2016
Share eligible	10.3	10.4	10.1	7.5	6.9
CI	[9.8;10.9]	[9.9;11.0]	[9.5;10.6]	[7.0;8.0]	[6.4;7.4]

Notes: 53,143 observations per year for those eligible; 95% confidence intervals in parentheses. *Source:* SOEP, waves 2012-2016; own calculations.

The wage growth observed in the lower quantiles does not impact overall inequality of gross hourly wages (Figure 3.2). Due to the general wage-growth across the distribution in post-reform years, the Atkinson inequality index does not change significantly after the introduction of the federal minimum wage. Under full compliance, however, the statutory minimum wage of 8.50€ per hour would have significantly decreased wage inequality (scenario A).

Given full compliance, a markedly higher minimum wage level of 12€ would even reduce the wage inequality among the employed by 40% (scenario B). Comparisons with full-compliance scenarios show that the minimum wage did by far not reach its full potential in reducing inequality at the bottom of the hourly-wage distribution. Under full compliance reductions would be substantially larger than for the observed

Figure 3.2: Atkinson inequality measure for the hourly gross wage distribution, eligible employees, 2012-2016



Notes: Individual frequency weights used. Bootstrapped confidence intervals based on 500 replications. For inequality and poverty measures see definition in sub-section 3.5.5. In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. For exact values of the confidence intervals and poverty lines, and for results of additional counterfactual scenarios see Table C.8; for significance of differences see Table C.9, Appendix. *Source:* SOEP, waves 2012-2016; own calculations.

outcomes (Figure 3.2).

3.6.2 Income effects

The distributional analysis of disposable incomes is based on a sample of all households in the SOEP without household members exceeding age 65. Given the moderate wage effects and insignificant reductions in wage inequality, we expect even smaller redistributive effects on incomes: The analysis of disposable household incomes takes adjustments of employment, partners' earnings, and interactions with the tax and transfer system into account that potentially reduce the redistributive impact of wage increases. Therefore, the counterfactual scenarios A and B – representing full compliance under the statutory level and a considerably higher minimum wage level of 12 € per hour – provide a benchmark for the redistributive potential the minimum wage would have in the best case, i.e. without negative employment and price effects.[16] Comparisons with these scenarios require the use of simulated incomes in the main analysis (sub-section 3.5.2). We provide robustness checks by comparing our simulated outcomes with outcomes based on reported incomes in the appendix.

[16]Assuming that potential spillovers on other wages are of minor importance regarding the reduction of disposable household income inequality. The assumption of no employment losses becomes more restrictive with higher minimum wage levels.

In a first step, we compare specific quantiles and moments of the disposable income distribution over time and with the counterfactual scenarios (Figure 3.3). The 5th percentile of the income distribution does not reveal any changes in post-reform compared to pre-reform years. There is income growth for the 10th percentile and for the mean over time which stagnates, however, after the minimum-wage introduction. Only median incomes keep increasing after the minimum wage is introduced; the 2016 median is significantly above its 2014 level. This points rather at a divergence than a convergence in incomes. Full-compliance scenarios A and B would not change these patterns. Incomes in the 5th or 10th percentile would hardly increase. Even under the substantial increase in the minimum wage to 12€ with full-compliance (scenario B), the incomes would not converge. On the contrary, the median income increase would be even larger compared the increase in the 5th and 10th percentiles and fortify divergence. That means households in the middle of the distribution would benefit more from a higher minimum wage level. We will further elaborate on this finding in sub-section 3.6.3 below.[17]

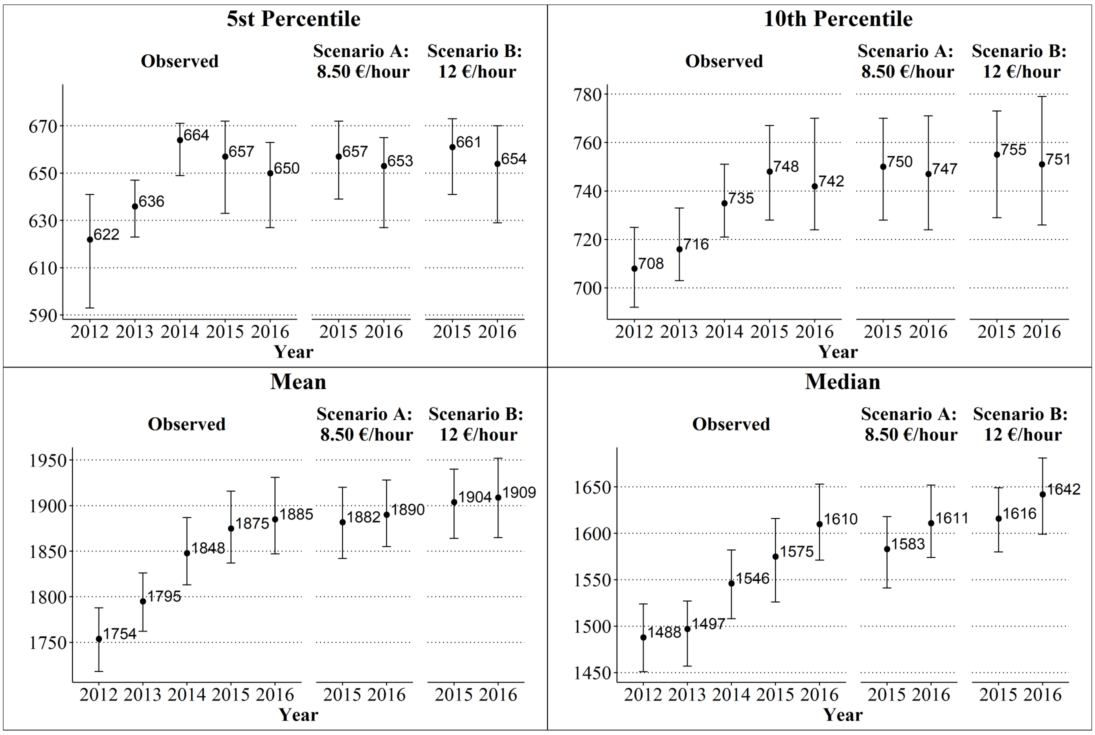
The longitudinal analysis of inequality and poverty measures sheds more light on the distributional consequences of these findings for disposable household incomes (Figure 3.4). We do not observe any changes in the Atkinson inequality measure after the minimum-wage introduction. Instead, we find a rise in poverty measures. The poverty gap increases by 0.5 in 2016 compared to 2014 but all changes remain insignificant. Full-compliance scenario A would diminish the increase in the poverty rate and poverty gap slightly but insignificantly. The measures would still increase compared to 2014. Under the 12 € full-compliance scenario , in turn, the poverty measures would increase as much as for observed incomes compared to 2014, with differences being insignificant (see also tables C.12 and C.13 for differences, Appendix).

Differential income growth across the distribution raises the poverty line while incomes in bottom quantiles remain largely constant. Absolute poverty did not increase: When we keep the poverty line fixed to 2014 levels and do not deflate equivalence incomes, we observe even a slight decrease in the poverty rate in 2016 and decreases in the poverty gap and the FGT(2) measure over the years (Table C.14, Appendix). The patterns with respect to the minimum wage reform are robust to using reported household incomes. Neither inequality, nor poverty decreased significantly after the minimum wage introduction in 2015 (Figure C.2, Appendix).

Our counterfactual scenarios show that neither full compliance with the statutory minimum wage, nor raising its level to 12€ per hour would have decreased disposable household income inequality or poverty (Figure 3.4, scenarios A and B). The Atkinson index would have remained at the same level, while the poverty measures rather increased than decreased. A higher minimum wage at 12€ would even lift the poverty line and thereby increase relative income poverty, albeit insignificantly, compared to a full compliance under a minimum wage level of 8.50€ per hour.

[17] The growth patterns at the different moments of the income distribution can be replicated with reported household incomes (Figure C.1, Appendix).

Figure 3.3: Quantiles and moments of the monthly disposable household equivalence income distribution (in €), working-age households, 2012-2016



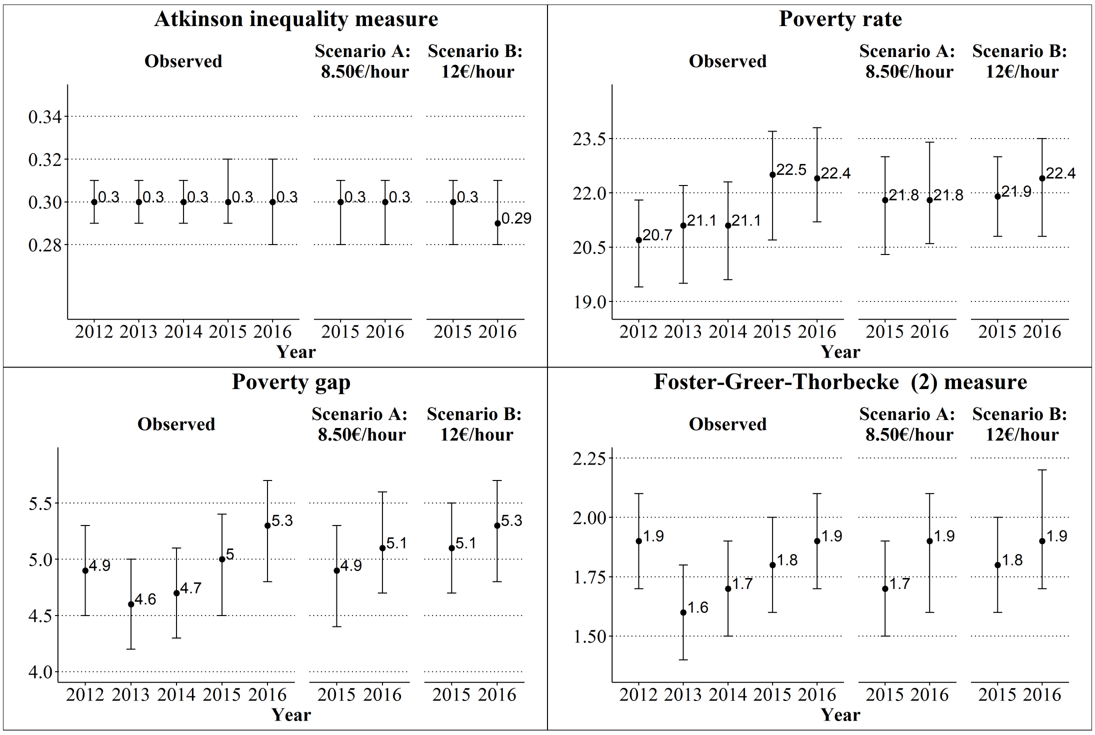
Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. For exact values of the confidence intervals and for results of additional counterfactual scenarios see Table C.10, for significance of differences see Table C.11, Appendix. *Source:* SOEP, waves 2012-2016; own calculations.

Results based on a fixed poverty line show that even the maximum minimum wage effect on income levels of the poor, i.e. under full compliance and with a substantially higher minimum-wage level and no negative employment effects, would be very small with a maximum of 9% less people below the poverty line compared to 2014 (Table C.14, Appendix). To conclude, the minimum wage in Germany has proven to be an ineffective redistributive tool with respect to disposable household incomes. In fact, an increase of the minimum-wage level could even amplify income inequality and poverty, as households at the very bottom would benefit less in relative terms (due to their lower labor market attachment). To explain these findings, we turn to the analysis of different mechanisms.

3.6.3 Mechanisms

There are several channels which potentially affect a low pass-through of wage changes to incomes. Previous studies point out that the correlation between gross hourly wages and disposable household incomes is limited (Neumark, 2015; Müller and Steiner,

Figure 3.4: Inequality and poverty measures for the monthly disposable household equivalence income distribution, working-age households, 2012-2016



Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. For inequality and poverty measures see definition in sub-section 3.5.5. Poverty line refers to respective year (flexible poverty line). In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. For exact values of the confidence intervals and poverty lines, and for results of additional counterfactual scenarios see Table C.12; for significance of differences see Table C.13, for number of observations Table C.10 Appendix. For results with a fixed poverty line see Table C.14, Appendix. *Source:* SOEP, waves 2012-2016; own calculations.

2013; Burkhauser and Finegan, 1989; Johnson and Browning, 1983). Low-wage employees often provide only secondary wage earnings to overall household incomes. Various types of welfare transfers may also contribute to a weak relationship between the hourly wage and disposable income distributions. We elaborate on the mechanisms that could drive our results, by investigating the distribution of affected individuals across the household-income distribution, potential welfare-benefit withdrawal, and employment effects.

Position of affected individuals within the disposable household income distribution

To analyze the relationship between low hourly wages and low disposable incomes, we investigate which kind of households are affected by the minimum wage. Almost two thirds of all affected individuals in our sample live in households with an additional wage earner and about 53% of affected individuals earn less than their partner. These numbers already indicate that affected individuals must not necessarily live in the poorest households. To be more precise, we display the distributional position of affected households, breaking down their shares by deciles of the disposable household income distribution (Table 3.2, left panel). Note, 'affected households' comprise households with at least one person earning an hourly wage in the bottom 11% of the gross hourly wage distribution in the respective year (sub-section 3.5.6). The share of affected households in the bottom decile is less than 3%. The largest shares of affected households are in deciles 3 to 5. Even in the 6th and 7th deciles shares around 10% are reached. Not even in the top decile the share of affected households is smaller than at the bottom of the distribution in all years. Shares are stable over time for most deciles. Hence, there is conclusive evidence that the minimum wage does not effectively target households at the bottom of the income distribution.

Table 3.2: Shares of affected and average incomes by deciles of the household income distribution, 2012-2016

Decile	**Share affected in %**					**Average disposable househ. income**				
	2012	2013	2014	2015	2016	2012	2013	2014	2015	2016
1	2.35	2.56	2.68	2.49	2.04	553	579	592	596	590
2	8.99	8.25	7.40	8.33	7.95	795	802	826	829	840
3	20.14	18.87	19.44	19.22	19.18	966	959	996	994	1012
4	15.17	15.32	18.60	17.23	19.28	1158	1147	1194	1204	1235
5	13.11	13.39	12.91	13.65	12.14	1372	1369	1417	1446	1486
6	9.77	10.61	10.53	9.25	12.83	1611	1617	1671	1696	1737
7	10.85	5.67	5.83	8.28	7.05	1868	1887	1947	1986	2014
8	4.52	5.06	5.32	5.23	8.90	2182	2233	2299	2358	2348
9	3.48	2.78	3.62	4.01	2.65	2660	2776	2840	2921	2869
10	1.70	1.89	3.16	2.04	2.75	4384	4585	4701	4727	4728
Total	9.01	8.44	8.95	8.97	9.47	1754	1795	1848	1875	1885

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Share of affected defined as share of households with at least one member earning wages in the bottom 11% of the wage distribution of respective year. Equivalence weights according to the new OECD scale and household frequency weights used. For confidence intervals see Tables C.19 and C.20, Appendix. *Source:* SOEP, waves 2012-2016; own calculations.

We also break down average disposable household incomes by deciles of the income distribution (Table 3.2, right panel). Income growth differs across deciles of the household income distribution. We do not observe income growth in the bottom decile, not even in 2016. The largest growth between 2014 and 2016 occurred in the middle of the distribution (deciles 5 with 4.8% , 6 with 3.9%, 4 and 7 with 3.4%), while there was less growth at the upper end. This explains why poverty measures increased while the Atkinson inequality measure remained constant.

The limited impact on the distribution of disposable household incomes is partly driven by the fact that many households at the bottom are not affected by the minimum wage as they are not working, they are not eligible, or they are working at higher wage rates. To see how large the effect of the minimum wage would be *within* the group of affected households, we replicate the distributional income analysis only for affected households, i.e. with at least one member affected by the minimum wage (Tables C.21 and C.22, Appendix).[18] The poverty measures are based on the poverty line of the entire household income distribution from above.

We observe a modest increase in median incomes over time. The mean income fluctuates with a decrease in 2016 as does the poverty rate. The poverty gap and the FGT(2) measure display an increase in post-reform years. However, none of these changes are significant. In the full-compliance scenario A the mean and median incomes would increase slightly and the poverty rate would decrase below the 2014 level. Still, poverty gap and FGT(2) would stay above the 2014 level. In the 12€ full-compliance scenario B, the mean and median incomes would increase significantly above the 2014 level. Poverty rate and poverty gap would undercut the 2014 level, but insignificantly, and the FGT(2) measure would still be higher than in 2014.

In summary, even in this selective sub-sample, where we only focus on households that are actually affected by the minimum wage, and even with a 12€ minimum wage without negative side effects, the minimum wage proves to be ineffective in poverty reduction. This holds especially with respect to the severity of poverty, measured by the poverty gap and the FGT(2) measure.

Benefit withdrawal: top-up benefits and welfare dependence

One redistributive goal of the minimum wage stated by policymakers is the reduction of in-work poverty. Individuals with regular jobs should not depend on welfare transfers, namely on top-up benefits in addition to labor earnings (European Commission, 2020b; Coalition, 2021; Deutscher Bundestag, 2014). Therefore, we analyze changes in top-up benefits (in-work transfers) after the minimum wage reform. We, further analyze overall social assistance transfers (ALG II) of all households in our sample (Table 3.3), as these include welfare transfers of people who are not employed and employment may interact with the minimum wage.[19] We simulate eligibility and amount of these transfers with the tax-transfer simulation-model, while assuming that eligibility for benefits below 10€ per month are not taken up. As a robustness we also show transfer receipt as stated by the SOEP respondents, which is typically lower due to non-take-up and under-reporting. The simulated transfers represent the eligibility by the law and hence represent the neediness of the households. Therefore, they are more informative regarding the policy goal to reduce in-work poverty.[20]

[18] Note that a 12€ minimum wage would affect almost 30% of the eligible employees. However, we still refer to the bottom 11% as affected for scenario B to allow for comparability between the results.

[19] Arbeitslosengeld II (ALG II) is a means tested transfer for employable individuals and their households which applies if they working age individuals are not, or no longer eligible for unemployment insurance benefits.

[20] The actual transfer take-up might be more important for fiscal considerations.

Table 3.3: Top-up benefits and welfare receipt, working-age households, 2012-2016

	Top-up benefits (only working)[2]				**Social assistance transfer (all households)**							
					Calculated eligibility[2]				**Stated take-up**[3]			
Year	eligibility	CI	avg. transfer €/year[1]	CI	eligibility	CI	avg. transfer €/year[1]	CI	take-up	CI	avg. transfer €/year[1]	CI
2012	10.7	[9.8;11.5]	590	[533;644]	25.0	[23.8;26.1]	1975	[1864;2081]	9.4	[8.6;10.3]	723	[655.1;784.6]
2013	11.3	[10.4;12.1]	639	[582;692]	26.9	[25.8;28.3]	2175	[2074;2281]	10.0	[9.2;10.9]	795	[730.3;862.7]
2014	11.3	[10.3;12.2]	623	[566;680]	25.6	[24.3;27.0]	2074	[1946;2199]	10.1	[9.2;10.9]	826	[745.0;908.8]
2015	10.8	[10.0;11.8]	635	[576;702]	26.1	[24.8;27.7]	2187	[2067;2322]	9.7	[8.8;10.7]	801	[718.3;892.4]
2016	11.1	[10.2;12.1]	620	[571;677]	27.0	[25.5;28.5]	2220	[2077;2340]	10.6	[9.4;11.8]	870	[780.8;958.2]
Scenario A *Full compliance scenario, minimum wage level: 8.50€ per hour*												
2015	9.9	[9.1;10.9]	557	[499;612]	25.2	[23.9;26.6]	2103	[1985;2228]				
2016	10.6	[9.7;11.5]	563	[511;619]	26.5	[25.2;27.8]	2158	[2025;2275]				
Scenario B *Full compliance scenario, minimum wage level: 12€ per hour*												
2015	8.7	[7.9;9.6]	479	[429;538]	23.9	[22.5;25.3]	2005	[1885;2130]				
2016	9.5	[8.6;10.3]	486	[441;533]	25.2	[23.6;26.8]	2066	[1934;2198]				

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications.

[1] Average transfer per year is an average over the entire sample, i.e. reflecting both, the number of households eligible and the amount eligible households receive.

[2] The number of households eligible and average transfer as calculated in our model. We exclude minor transfer eligibility of less than 120€ per year.

[3] The number of households eligible and average transfer as stated in the survey (SOEP).

For significance of differences see Table C.18, Appendix. *Source:* SOEP, waves 2012-2016; own calculations.

We do not observe any significant reductions of top-up benefit eligibility and average benefits in the post-reform years. Under full compliance eligibility would have been reduced significantly in 2015. However, the simulated reduction in average top-up transfers is not significant (scenario A).

For average social-assistance transfers of all households we neither see a reduction in eligibility nor in average transfers after the minimum wage introduction – both numbers increase slightly, but not significantly. The patterns for stated take-up are similar – we do not observe any significant changes.[21] In the full compliance scenario, eligibility and average transfers would be lower than in the observed post-reform years but compared to the pre-reform year 2014 they would not decrease significantly. These results are in line with administrative statistics on welfare receipt and top-up benefits (Figure C.3, Appendix) and previous findings (Bruckmeier and Wiemers, 2015; Mindestlohnkommission, 2016, 2018). Thus, benefit withdrawal due to higher earnings induced by the minimum wage cannot explain the negligible impact of the minimum wage on the income distribution.

Only under a higher minimum-wage level of 12€ per hour with full compliance (and zero employment effects), top-up benefit eligibility and hence in-work poverty could be reduced significantly. Compared to 2014 eligibility would decrease by 16% and the average transfers by 22%. However, this scenario neglects potential (dis-) employment effects and focuses only on people who are already in employed. If we look at the overall welfare dependence, measured by social assistance transfers, we see that in the 12€-scenario, the eligibility and average transfers in 2016 would not decrease significantly compared to 2014. Again, this scenario represents an upper bound for the redistributive potential of the minimum wage as it does not incorporate potentially negative employment effects. These findings confirm that the minimum wage is an inefficient tool to reduce overall and in-work poverty to a large extent, given that such a steep rise of its level yields only minor reductions in benefit dependence.

Changes in employment and working hours

Reductions in employment or working hours counteracting wage gains could be an alternative mechanism behind limited income redistribution and persistent transfer dependence in post-reform years. The outcomes of the counterfactual scenarios in our previous analysis, that omit potentially negative employment effects, indicate that this channel cannot be the main driver of the limited redistributive impact. Nevertheless, we want to discuss this channel in our analysis, as it makes up a large part in the minimum-wage literature. As explained above, the observed incomes in our distributional analysis incorporate employment as a potential adjustment channel (subsection 3.5.3). Therefore, we assess whether employment changes at the extensive and intensive margin contribute to this finding. First, we analyze full-time, part-time, and marginal employment shares of household members aged 18-65 by deciles of the household income distribution (Table C.23, Appendix) and then turn to the working

[21] Stated transfer take-up amounts to roughly 40% of the simulated eligibility. The actual transfer take-up will lie slightly above this figure, see (Bruckmeier et al., 2014, 2019).

hours in these categories. Full-time shares increase almost monotonically over the household income distribution in all years, with the bottom two deciles having full-time employment rates below 25%. Across years the shares remain stable for most of the deciles. In the bottom two deciles the shares fluctuate more across years with a significant reduction in the 2nd decile in 2016 but a significant increase in the first decile. The total full-time employment share does not change significantly.

The part-time employment share increases up to the 3rd decile and then slowly decreases again. Across years these shares fluctuate in all deciles. For some deciles we observe a significant increase, and for others significant decreases in part-time employment in post-reform years. However, these changes are not correlated with the share of households affected by the minimum wage. Overall, shares of households with part-time employees increased significantly compared to pre-reform years. Marginal employment is observed in all deciles of the household income distribution, but mostly in deciles 2 and 3. It is lowest in the top two deciles. The overall share of marginal employment remained roughly stable across years. There are no clear trends across the distribution that correlate with households affected by the minimum wage.

We next investigate the intensive margin of employment by breaking down aggregate working hours of each household by the three employment categories and taking means over households by deciles of the income distribution (Table C.24, Appendix). We observe a significant increase in overall working hours for full-time employment in 2016 compared to 2014. There is no significant reduction in hours in any decile compared to 2014. In 2015 only the 7th decile experienced a significant dip in full-time hours of work which was recovered in the following year. Among part-time employees hours of work are lowest in the bottom deciles and the top decile of the disposable income distribution. We find a significant increase in overall part-time hours between 2013 and 2014, i.e. before reform. There is no significant change in part-time hours after the minimum wage came into effect. Mean hours of work in marginal employment are relatively evenly distributed across income deciles, except for the top decile where they are below average in most years. Moreover, mean marginal hours fluctuate in most deciles without clear trends over time. Overall, marginal hours decreased significantly in 2016 compared to 2014. However, the decrease is smaller than the significant jump from 2013 to 2014 before the minimum wage reform.

In summary, changes in employment levels provide no indication for significant disemployment effects due to the minimum-wage reform, neither overall nor differentially across deciles. This is consistent with previous studies that found short-run employment effects to be insignificant or limited to inflows (Bruttel, 2019; Caliendo et al., 2019). We have limited evidence for a substitution from marginal to part-time employment which also confirms previous findings (Garloff, 2019; Schmitz, 2019; Bonin et al., 2019; Bachmann et al., 2017; vom Berge and Weber, 2017), albeit only significant for the rise in part-time work in 2016. Different from Burauel et al. (2019a) and Caliendo et al. (2017), we do not find decreases in working hours in our sample, neither overall nor differentially across deciles.[22] Adjustments at the extensive or

[22]This is not necessarily a contradiction, as we do not consider any positive employment effects

intensive margin of employment induced by the minimum wage cannot explain the limited pass-through of wage increases to disposable outcomes limiting the impact of the minimum wage on income redistribution and poverty reduction.

3.7 Discussion and conclusion

This paper on the redistributive impact on disposable household incomes closes a gap in the minimum wage literature on European welfare states. The case is of general interest as the minimum wage introduction in Germany offers one of the more sizable policy experiments among European labor markets in recent years. A statutory minimum wage with substantial bite, particularly in certain regions and for specific groups of employees, was introduced in an economy with a generous welfare state. In recent years policy-makers increasingly state redistributive motives in support of harmonizing or increasing minimum wage levels (European Commission, 2020b; Council of the European Union, 2021).

We show that a uniform federal minimum wage is not an effective tool for income redistribution and the reduction of (in-work) poverty when the correlation between low hourly wages and disposable incomes is as weak as in Germany. Under these circumstances the minimum wage does not target poor households because low-wage earners are not concentrated at the bottom, but spread out over the middle and higher parts of the household income distribution. This means that the minimum wage reduces wage inequality at the the bottom of the individual wage distribution, but not poverty and income inequality. Consequently, we see only marginal reductions in top-up benefits and no decrease in welfare dependence in the data. The withdrawal of welfare transfers does hardly contribute to the limited pass-through of wage effects to disposable incomes. The same holds for employment levels and working hours of low-income households which did not decrease systematically and significantly. We further show that, under those conditions, a higher minimum wage level would not increase its efficiency for poverty and inequality reduction, even if we abstract from potentially negative employment effects. These findings on a weak link between low-wage earners and low-income households confirm studies for the U.S. (Burkhauser and Finegan, 1989; Burkhauser et al., 1996; Burkhauser and Sabia, 2007; Sabia and Burkhauser, 2010; Neumark, 2015) and other Non-European countries (Kawaguchi and Mori, 2009; Sotomayor, 2021).

What do our results mean for the policy discussion? A uniform federal minimum wage cannot reduce income inequality and poverty in a labor market where low-wage earners are distributed across the entire household income distribution and non-employment is prevalent among the lowest household incomes. Raising the federal minimum wage level does not improve its redistributive efficiency with respect to disposable household incomes. In light of current plans about substantial minimum wage increases, our findings serve as a cautionary tale. Results on the underlying

which could have been there in absence of a reform.

mechanisms rather indicate severe employability problems for individuals in households with the lowest incomes and job insecurity among low-wage earners (Halleröd et al., 2015). In order to strengthen the relationship between low wages and incomes, the labor market attachment of individuals in the bottom deciles of the income distribution must be improved, for example by strengthening their employability (Rovny, 2014), by enhancing work incentives (Vandelannoote and Verbist, 2020), or by addressing labor market risks driven by long-term processes like skill-biased technological change (Brülle et al., 2019). Sustainable labor market attachment of low-wage earners is a necessary (pre-)condition for minimum wages to become more effective in reducing income inequality and (in-work) poverty.

Appendix A

Appendix to Chapter 1

A.1 Econometric approach for the strategy estimation

Recall that a subject using a pure strategy acts equivalently whenever a given state is reached and she uses the same pure strategy across all supergames. A subject using a mixed strategy uses a pure strategy within supergames but randomizes over pure strategies prior to supergames. A subject using a behavior strategy may randomize each round and thus deviate from pure strategies even within supergames. These definitions provide a basis for identification, but identification is made difficult by the standard assumption that choice is stochastic. For example, a single deviation from a given pure strategy, over say 20 observations, is intuitively not considered sufficient evidence against purity of strategies. Otherwise, the case for behavior strategies would be trivial, but how can this intuition be made formally precise—in a manner that allows us to econometrically distinguish "noisy" pure, mixed, and behavior strategies?

The distinction is achieved efficiently using the Markov-switching models known from empirical finance and empirical macroeconomics in conjunction with the robust likelihood-ratio tests of Schennach and Wilhelm (2017). Markov-switching models generalize the finite-mixture and random-switching models used in previous analyses of repeated game strategies.[1] They allow us to capture a potentially heterogeneous group of agents (in our case, subjects potentially playing different strategies), where each agent is characterized by a "state of mind" (the strategy to be played), and agents may change their states of mind over the course of time, but both states and transitions are latent and thus not directly observable. Let us refer to Ansari et al. (2012), Breitmoser et al. (2014) and Shachat et al. (2015) for earlier applications in behavioral analyses. The identifying assumption is that state transitions follow a Markov process. This generalizes the finite mixture model, with degenerate transition prob-

[1]The approach of using mixture models in order to uncover decision rules in experimental data has been established by Stahl and Wilson (1994) and El-Gamal and Grether (1995) and subsequently used in many analyses of level-k reasoning and stochastic choice, see e.g. Houser and Winter (2004) and Houser et al. (2004), to unravel individual decision rules. A special case of finite mixture modeling is the Strategy Frequency Estimation Method (SFEM) employed by Dal Bó and Fréchette (2011), Fudenberg et al. (2012), Rand et al. (2015), Dal Bó and Fréchette (2015), Fréchette and Yuksel (2017).

abilities, and the random switching model, with constant choice probabilities for the strategies. Given this, estimation proceeds by maximum likelihood using an EM algorithm. Model adequacy is evaluated using ICL-BIC (Biernacki et al., 2000), and model differences are evaluated using the Schennach-Wilhelm test, which captures that all models may be arbitrarily nested and misspecified. Finally, we allow for stochastic choice in the form of trembles (after all histories of play) following Harless and Camerer (1994), i.e. in each round the minimal probability of any action is equal to $\gamma \geq 0$ where γ is a free (noise) parameter in the estimation.

A.1.1 Markov-switching models and ICL-BIC

The Markov-switching model builds on the simpler and more restrictive finite mixture model, which has been established in the experimental literature by Stahl and Wilson (1994) and can be used to empirically identify a finite number K of strategies with parameter vectors θ_k. The log-likelihood function to be maximized for the finite mixture model is

$$\ln \mathcal{L}(\theta, \rho | O) = \log \left(\prod_{s \in S} p(o_s | \theta, \rho) \right) = \sum_{s \in S} \ln \sum_{k \in K} \rho_k \, p_k(o_s | \theta_k), \tag{A.1}$$

with observations O, ρ_k denoting the relative frequency of strategy k, and $p_k(o_s|\theta_k)$ denoting the probability that player s chooses action o_s given he plays strategy k [2].

A way to model regime switches is to replace the implicit latent indicator variable in finite mixture models (indicating the discrete types) with a hidden Markov chain (Frühwirth-Schnatter, 2006). The central assumption characterizing the learning process in Markov models is that the type of a player (or its strategy in our context) in the next period can only depend on its type in this period. More precisely if k_t is the type in period t then: $Pr(k_{t+1}|k_t, k_{t-1}, k_{t-2}, ..., k_1) = Pr(k_{t+1}|k_t)$, where the type is hidden and cannot be observed directly.[3] What we do observe is the action o_t, which in turn depends on the type k_t in t only: $Pr(o_t|k_t, o_{t-1}, k_{t-1}, ..., k_1, o_1) = Pr(o_t|k_t)$ (c.f Bilmes et al. (1998)). It implies that transitions between states are independent of time t. This assumption might be quite restrictive. For example if we want to assume that the probability of switching to a new strategy is more likely later in the game than at the beginning. Nevertheless, we can use memory-2 or memory-3 strategies if we define the state ω as a history of more than one past outcome and condition the strategy on this history of outcomes. Moreover, it is possible to interact time dependent components with switching probabilities.

Let K_t denote the state at time $t \in 1, 2, ..., T$ and $\sigma_{kk'} = Pr(K_{t+1} = k'|K_t = k)$ define the transition probability from k to k' which is independent from t, as pointed. So σ is a $(K \times K)$ transition matrix containing transition probabilities for every pair of

[2] For the memory-1 case $p_k(o_s|\theta_k) = \prod_t (\sigma_{\omega_{s,t}}(k))^{o_{s,t}} (1 - \sigma_{\omega_{s,t}}(k))^{1-o_{s,t}}$ with strategy $\sigma_{\omega_{s,t}}(k)^{o_{s,t}}$ for state $\omega_{s,t}(k)^{1-o_{s,t}}$.

[3] Therefore also known as the Hidden Markov Model (HMM).

states, where all entries are positive and each row sums up to 1. Moreover, the state-paths are denoted by $\kappa \in K^T$ with $Pr(\kappa)$ conditional on initial weights ρ and transition probabilities σ. The probability of observing $o_{s,t}$ conditional on subject s being type k in this period is $Pr(o_{s,t}|\theta,k)$. The likelihood function is:

$$\ln \mathcal{L}(\rho,\sigma,\theta|O) = \sum_{s\in S} \ln \sum_{\kappa\in K^T} Pr(\kappa) \prod_{t\leq T} Pr(o_{s,t}|\theta,\kappa(t),t) \tag{A.2}$$

Due to the introduction of the transition matrix σ the number of parameters to be estimated increases dramatically. Moreover, with a naive estimation approach we would have to consider all possible state paths and be very time consuming. Therefore we choose to apply a backward-forward algorithm to calculate posteriors for estimation with the expectation maximization (EM) algorithm.

The idea of the EM-algorithm is to conduct two steps the E-step and the M-step iteratively. This way we split up every optimization step into many steps which simplifies complexity and consequently speeds up computations. In the E-step we evaluate the conditional expectation of the log-likelihood given our data O and the current parameter vector and then maximize over a reduced set of free parameters in the M-Step. The number of possible types k is pre-defined as well as the structure of their mixing parameters θ_k.

In the E-step we need to compute for all subjects for all time periods the posterior probability of component inclusion (being a specific type) and the probability to switch between two types. An efficient way to calculate those posterior probabilities is to built up on the backward-forward. First, we have the forward procedure, where we define the (joint) probability of observing the partial sequence $o_{s1},...,o_{st}$ and ending up with type k at time t:

$$\alpha_{sk}(t) = Pr(O_{s1} = o_{s1},...,O_{st} = o_{st}, K_t = k) \tag{A.3}$$

Recursively, we can then define:

$$1.\quad \alpha_{sk}(1) = \rho_k Pr(o_{s1}|\theta,k) \tag{A.4}$$

$$2.\quad \alpha_{sk'}(t+1) = \left[\sum_k \alpha_{sk}(t)\sigma_{kk'}\right] Pr(o_{st+1}|\theta,k')$$

$$3.\quad Pr(o_s) = \sum_{k\in K} \alpha_{sk}(T)$$

Second, for the backward procedure we define the probability of ending in the partial sequence $o_{st+1},...o_{sT}$ given that we have started at type k at time t.

$$\beta_{sk}(t) = Pr(O_{st+1} = o_{st+1},...,O_T = o_T|K_t = k) \tag{A.5}$$

Again we can define $\beta_{sk}(t)$ efficiently (Bilmes et al., 1998)

$$\begin{aligned} &1. \quad \beta_{sk}(T) = 1 \\ &2. \quad \beta_{sk}(t) = \sum_{k' \in K} \sigma_{kk'} Pr(o_{st+1}|\theta, k')\beta_{sk'}(t+1) \\ &3. \quad Pr(o_s) = \sum_{k \in K} \beta_{sk}(1)\rho_k Pr(o_{s1}|\theta, k) \end{aligned} \tag{A.6}$$

We then take advantage of the fact that the unconditional probability $Pr(o_s)$ can be defined using $\alpha_{sk}(t)$ or $\beta_{sk}(t)$ to calculate the posterior probabilities γ_{sk} and $\zeta_{skk'}$. The former is the conditional probability of being type k at time t given observations o_s:

$$\gamma_{sk}(t) = Pr(K_t = k|o_s) = \frac{Pr(o_s, K_t = k)}{Pr(o_s)} = \frac{Pr(o_s, K_t = k)}{\sum_{k' \in K} Pr(o_s, K_t = k)} = \frac{\alpha_{sk}(t)\beta_{sk}(t)}{\sum_{k' \in K} \alpha_{sk'}(t)\beta_{sk'}(t)}, \tag{A.7}$$

Using γ_{sk} we can define the probability of having type k in t and type k' in $t+1$ conditional on our observations as

$$\begin{aligned} \zeta_{skk'}(t) = Pr(K_t = k, K_{t+1} = k'|o_s) &= \frac{Pr(K_t = k|o_s)Pr(o_{t+1,\dots,T}, K_{t+1} = k'|K_t = k')}{Pr(o_{t+1,\dots,T}|K_t = k)} \\ &= \frac{\gamma_{sk}(t)\sigma_{kk'}Pr(o_{s,t+1}|\theta, k')\beta_{sk'}(t+1)}{\beta_{sk}(t)} \end{aligned} \tag{A.8}$$

(cf. Bilmes et al. (1998)).

In the M-step we maximize for each k and $t \leq T$ the function

$$LL_{kt}(\theta'_k) = \sum_{s \in S} \gamma_{sk}(t) \ln Pr(o_{st}|\theta') \to \max_{\theta'_{kt}}! \tag{A.9}$$

to yield the updated θ^{+1} when assuming that θ_{kt} does not affect the likelihood of other components k. If it does, we need to maximize $\sum_{k' \in K} LL_{kt}(\theta') \to \max_{\theta'}!$ and yield θ^{+1}.[4] Moreover, we update ρ and σ using the posteriors from above and yield

$$\rho_k^{+1} = \frac{1}{n}\sum_{s \in S} \gamma_{sk}(1) \quad \text{and} \quad \sigma_{kk'}^{+1} = \frac{\sum_{s \in S}\sum_{t<T} \zeta_{skk'}(t)}{\sum_{s \in S}\sum_{t<T} \gamma_{sk}(t)} \tag{A.10}$$

The two steps are iterated until the distance between (θ, ρ, σ) and $(\theta^{+1}, \rho^{+1}, \sigma^{+1})$ gets small.

Estimation proceeds by a maximum likelihood, as usual, but as is well-known, the larger the number of parameters, the larger a model's capacity to fit data—and implicitly, the larger its fallacy to overfit the data. This is conventionally captured by

[4] θ may depend on t but does not have to.

evaluating model adequacy based on information criteria such as BIC, which penalize for the degrees of freedom in a theoretically adequate manner. Mixture and switching models additionally contain freedom in defining the components of the subject pool, i.e. the number of subject types, which provides an additional source for overfitting aside from the number of parameters used. Following (Biernacki et al., 2000), these concerns are addressed using the information-classification likelihood Bayes-information criterion (ICL-BIC), a criterion that penalizes both model complexity and the failure of the mixture model to provide a classification in well-separated strategy clusters. We address the observation that modeling mixtures of pure, mixed, and behavior strategies induces sophisticated nesting structures, and the concern that indeed all models may be misspecified by evaluating model differences using the novel Schennach-Wilhelm likelihood ratio tests (Schennach and Wilhelm, 2017). Finally, we capture the intuition that choice is stochastic by allowing for trembles in the sense of Selten (1975): Each agent of a player picks any given action with probability no less than $e > 0$. This approach follows (Breitmoser, 2015) and, in relation to the logistic-error approach proposed by (Dal Bó and Fréchette, 2011), it has the advantage that it does not perturb choice probabilities of subjects that originally randomize already.

A.1.2 Validity

To demonstrate the validity of our approach to distinguish pure, mixed, and behavior strategies, we first run it on different sets of simulated data: For each of the three conjectures, we simulate corresponding data sets and verify if we can identify the underlying conjecture based on model-fit evaluations using ICL-BIC. As for pure strategies, we consider a population where AD, Grim, and TFT have share 0.25 each, AC has share 0.15, and WSLS has share 0.1.[5] Drawing from this population, we simulate for three different discount factors $\delta = 0.6$, $\delta = 0.75$, and $\delta = 0.9$ each 100 data-sets with 50 subjects[6] and enough supergames to have 40 decisions per subject past round 1.

Here, $\delta = 0.75$ corresponds to the average supergame in our sample, $\delta = 0.6$ and $\delta = 0.9$ serve as robustness check approaching the upper and lower bound of δ in our data. The tremble parameter is $\gamma = 0.1$, which is of the proportion typically estimated in the literature. Then we determine the average ICL-BICs of the three basic econometric models, finite-mixture, random-switching, and semi-grim[7], across those 100 data-sets and compare their performance using simple matched-pairs Wilcoxon tests of the ICL-BICs. Table A.1 reports the results.

Under the pure-strategy conjecture, the true model of the population is the finite-mixture model. Our analysis should therefore identify it as the best fitting model if

[5]We include WSLS here and in the analysis below, as a number of studies established its evolutionary robustness, see Nowak and Sigmund (1993) and Imhof et al. (2007), indicating that it should be considered a promising candidate.

[6]Robustness-checks with 100 and 200 subjects are provided in Table A.2.

[7]In this case, without allowing for subject heterogeneity, the semi-grim model simply determines the average cooperation rates in each state.

Table A.1: Can we econometrically distinguish pure, mixed and behavior strategies?

	Model fitted to the data				
	Finite Mixture		Random Switching		Semi-Grim
Pure-Strategy Conjecture					
$\delta = 0.6$	**1227.92**	$\ll$	1706.67	$\ll$	1862.09
$\delta = 0.75$	**1045.68**	$\ll$	1329.11	$\ll$	1412.36
$\delta = 0.9$	**950.68**	$\ll$	1061.13	$\gg$	1011.52
Mixed-Strategy Conjecture					
$\delta = 0.6$	1842.11	$\gg$	**1725.16**	$\ll$	1875.59
$\delta = 0.75$	1472.24	$\gg$	**1334.32**	$\ll$	1415.32
$\delta = 0.9$	1228.48	$\gg$	1073.86	$\gg$	**1023.88**
Behavior-Strategy Conjecture					
$\delta = 0.6$	2068.31	$\gg$	**1720.06**	$\approx$	1728.46
$\delta = 0.75$	1521.77	$\gg$	1262.84	$\gg$	**1202.79**
$\delta = 0.9$	1049.64	$\gg$	944.11	$\gg$	**732.88**

Note: Analysis based on simulated data sets comprising 50 subjects and 40 observations (past round 1) per subject, reporting the average ICL-BIC of the classes of fitted models. Here, $\gg, \ll$ indicate significance of differences (in Wilcoxon matched-pairs tests of the simulated ICL-BICs) at $\alpha = 0.01$ and $>, <$ indicate significance at $\alpha = 0.05$.

and only if the simulated subjects play pure strategies. The first three rows of Table A.1 show, that this is clearly the case: We obtain significantly (at $\alpha = 0.01$) lower ICL-BICs for the finite-mixture model than for the other two models for all three values of δ. We can therefore identify pure strategies with our approach.

We repeat the same exercise for simulated subject pools playing mixed strategies and pools playing semi-grim strategies. The mixed strategy population is based on the same pure strategies and prior probabilities as above but assuming subjects redraw a pure strategy prior to each supergame. The semi-grim strategy is of the form $(0.4, 0.9, 0.3, 0.3, 0.1)$, which approximates the average cooperation probabilities across all experiments in our data set.

The results displayed in the bottom rows of Table A.1 indicate that distinguishing between mixed-strategy and semi-grim populations is more difficult. When analyzing long supergames ($\delta = 0.9$), there appears be to a bias towards detecting semi-grim, and analyzing short supergames ($\delta = 0.6$) there appears to be a bias towards the random-switching model (mixed strategies). Our data set contains more observations for short supergames satisfying $\delta \leq 0.6$ than for long supergames satisfying $\delta \geq 0.9$, see Tables A.9 and A.10 in the appendix. Moreover, the average δ weighed by individual observations is around 0.73 in the first halves of sessions and 0.74 in the second halves, approximating the case where all conjectures are well-identified. Thus, in aggregate there may be a slight bias against semi-grim in the analysis, but aggregating across a large number of subject pools with $\delta = 0.75$ on average, our method seems suitable to reliably identify the correct model.

Table A.2: Can we econometrically distinguish pure, mixed and behavior strategies? Robustness check for larger data

(a) Intermediate data set: 100 subjects

	Model fitted to the data				
	Finite Mixture		Random Switching		Semi-Grim
Pure-Strategy Conjecture					
$\delta = 0.6$	**2450.06**	$\ll$	3430.25	$\ll$	3746.59
$\delta = 0.75$	**2093.11**	$\ll$	2669.43	$\ll$	2841.81
$\delta = 0.9$	**1891.42**	$\ll$	2120.93	$\gg$	2042.6
Mixed-Strategy Conjecture					
$\delta = 0.6$	3693.23	$\gg$	**3454.03**	$\ll$	3762.16
$\delta = 0.75$	2948.44	$\gg$	**2673.63**	$\ll$	2835.13
$\delta = 0.9$	2457.96	$\gg$	2146.63	$\gg$	**2058.91**
Behavior-Strategy Conjecture					
$\delta = 0.6$	4132.82	$\gg$	**3436.66**	$\ll$	3463.7
$\delta = 0.75$	3047.1	$\gg$	2521.5	$\gg$	**2406.99**
$\delta = 0.9$	2105.78	$\gg$	1888.58	$\gg$	**1468.14**

(b) Large data set: around 200 subjects

	Model fitted to the data				
	Finite Mixture		Random Switching		Semi-Grim
Pure-Strategy Conjecture					
$\delta = 0.6$	**4908.54**	$\ll$	6870.11	$\ll$	7498.08
$\delta = 0.75$	**4175.89**	$\ll$	5329.73	$\ll$	5675.49
$\delta = 0.9$	**3791.25**	$\ll$	4252.75	$\gg$	4103.17
Mixed-Strategy Conjecture					
$\delta = 0.6$	7385.62	$\gg$	**6909.42**	$\ll$	7521.3
$\delta = 0.75$	5923.99	$\gg$	**5371.1**	$\ll$	5693.22
$\delta = 0.9$	4926.83	$\gg$	4298.72	$\gg$	**4120.77**
Behavior-Strategy Conjecture					
$\delta = 0.6$	8266.47	$\gg$	**6877.24**	$\ll$	6927.44
$\delta = 0.75$	6092.37	$\gg$	5037.9	$\gg$	**4805.57**
$\delta = 0.9$	4220.99	$\gg$	3787.16	$\gg$	**2938.41**

Note: Analysis based on simulated data sets comprising 50 subjects and 40 observations (past round 1) per subject, reporting the average ICL-BIC of the classes of fitted models. Here, $\gg, \ll$ indicate significance of differences (in Wilcoxon matched-pairs tests of the simulated ICL-BICs) at $\alpha = 0.01$ and $>, <$ indicate significance at $\alpha = 0.05$.

A.2 Robustness check: Memory-2

We investigate memory length using a data mining approach similar to above. To this end, we extend the set of pure strategies to capture possible interdependence of actions with choices in $t-2$ and determine the best-fitting specification for each treatment. We then evaluate these best fitting specifications, treatment by treatment, against the above memory-1 model AD+SG, i.e. against the conjecture that all cooperating subjects homogeneously play a simple behavior strategy.

Specifically, we allow for two alternative approaches of extending the set of memory-1 strategies to memory-2. One approach follows Fudenberg et al. (2012), who introduced lenient and resilient variants of the pure memory-1 strategies, i.e., strategies that punish only after the second deviation or that punish for two rounds instead of one, respectively. Let us note that such variations in punishment behavior also follow if punishment is random as in memory-1 behavior strategies, which were not considered by Fudenberg et al. (2012). This first approach is applicable in particular to generalize pure memory-1 strategies, by providing a specific list of memory-2 generalizations. The other approach is novel and more generally allows the cooperation probabilities in round t to depend on the behavior of one or both players in $t-2$. Here, we allow for three different specifications: cooperation probabilities may be a function of the opponent's choice in $t-2$ (*TFT-Scheme*), a function of whether both players cooperated in $t-2$ or not (*Grim-Scheme*), or a function of the entire choice profile in $t-2$ (*General scheme*). This approach is parametric and suitable in particular to extend generalized pure strategies of type II (or, behavior strategies) from memory-1 to memory-2. As indicated, we set up this deliberately large number of ways to model memory-2 only to post-hoc pick the best of them for an evaluation against the memory-1 semi-grim specification.

Table A.3 summarizes the results. First, we mine for mixtures of pure strategies, based on the list of 10 strategies[8] of Fudenberg et al. (2012). Given the above results, we assume that subjects do not switch strategies within half-sessions, as this comes without loss of descriptive adequacy for experienced subjects and only little loss for inexperienced subjects (for whom, however, memory-2 will turn out to be of negligible relevance). For each treatment, we determine the most adequate combination of strategies from a list of five possible combinations of Fudenberg et al.'s strategies, thus providing a selection of the best of 5^{32} models overall. The resulting model (Column "Best Pure M1&M2" in Table A.3) fits highly significantly worse than the selection of pure and generalized-pure strategies with memory-1 defined above ("M1" in Table A.3). We may therefore discard the possibility that subjects play pure strategies (with noise) of either memory-1 or memory-2, in favor of the possibility that they play generalized-pure strategies allowing for non-trivial randomization in at least one state.

Second, we take the above memory-1 model ("M1" in Table A.3) as our benchmark and ask if equipping the pure or generalized pure strategies of type II with memory-

[8]These strategies are TFT, Grim, AD, Grim2, TF2T, T2, 2TFT, 2PTFT as defined in Fudenberg et al. (2012) and also in Table A.7 in the Appendix.

Table A.3: **Memory-1 or Memory-2, and semi-grim, pure or generalized pure?** Strategy mixtures are estimated treatment-by-treatment. The resulting ICL-BICs are pooled within experiments and overall (less is better, relation signs point to better models)

	Memory-2 Generalizations of Semi-Grim + AD								Best Mixtures of Generalized Pure Strategies						Best Pure
	M2"General"		M2"TFT"		M2"Grim"		AD+SG		M1+M2"TFT"		M1+M2"Grim"		M1		M1 & M2
Specification															
# Models evaluated	1		1		1		1		22^{32}		22^{32}		13^{32}		5^{32}
# Pars estimated (by treatment)	12		6		6		5		160		160		80		32
# Parameters accounted for	12		6		6		5		6–15		6–15		6–10		3–8
First halves per session															
Aoyagi and Frechette (2009)	756.04	≈	764.13	≈	749.99	≈	781.86	≈	756.95	≈	756.95	≈	756.95	≪	884.86
Blonski et al. (2011)	1244.76	≫	1121.17	≈	1120.87	≫	1069.28	≈	1069.56	≈	1069.56	≈	1069.58	≈	1105.98
Bruttel and Kamecke (2012)	807.47	≈	802.89	≈	804.16	≈	800.12	≈	817.89	≈	817.89	≈	817.89	≈	839.97
Dal Bó (2005)	660.68	>	641.34	≈	642.26	≈	629.17	≈	635.04	≈	635.04	≈	635.04	≈	653.05
Dal Bó and Fréchette (2011)	6671.28	≈	6616.44	≈	6604.7	≈	6597.93	≪	6904.79	≈	6904.79	≈	6904.79	≪	7391.89
Dal Bó and Fréchette (2015)	8068.37	≈	8028.83	≈	8031.59	≈	8017.59	≪	8423.8	≈	8431.51	≈	8434.93	≪	8893.78
Dreber et al. (2008)	805.74	>	785.48	≈	785.6	≈	782.37	≈	787.71	≈	787.71	≈	787.71	<	863.47
Duffy and Ochs (2009)	1361.84	≈	1377.17	≈	1369.86	≈	1372.97	≈	1395.4	≈	1395.4	≈	1395.4	≈	1426.34
Fréchette and Yuksel (2017)	305.9	≈	299.72	≈	296.93	≈	299.62	≈	300.87	≈	300.87	≈	300.87	≈	317.35
Fudenberg et al. (2012)	387.8	≈	379.84	≈	378.07	≈	381.01	<	432.32	≈	432.32	≈	432.32	≈	463.4
Kagel and Schley (2013)	2542.02	≈	2556.45	≈	2552.09	≈	2561.76	≈	2679.23	≈	2685.4	≈	2685.4	≈	2730.66
Sherstyuk et al. (2013)	1311.64	≈	1307.45	≈	1303.94	≈	1303.8	≈	1322.6	≈	1322.6	≈	1322.6	<	1398.69
Pooled	**25434.21**	≫	**24972.71**	≈	**24931.86**	≈	**24779.85**	≪	**25750.84**	≈	**25757.44**	≈	**25758.38**	≪	**27115.39**
Second halves per session															
Aoyagi and Frechette (2009)	415.47	≈	421.18	>	409.19	≈	423.68	≈	416.51	≈	416.51	≈	416.51	≪	540.47
Blonski et al. (2011)	1518.54	≫	1395.94	≈	1393.41	≫	1346.79	≈	1398.5	≈	1398.5	≈	1398.5	<	1564.48
Bruttel and Kamecke (2012)	536.19	≈	532.08	≈	529.47	≈	536.77	≈	538.17	≈	538.17	≈	538.17	≈	567.99
Dal Bó (2005)	727.25	≈	710.88	≈	708.32	≈	699.05	≈	726.04	≈	731.81	≈	732.27	≈	741.2
Dal Bó and Fréchette (2011)	5201.05	≈	5137.82	≈	5132.96	≈	5128.69	≈	5195.88	≈	5195.88	≈	5195.88	≪	5960.78
Dal Bó and Fréchette (2015)	7840.87	≈	7829.51	≈	7808.63	≈	7825.98	≪	8172.63	≈	8177.46	≈	8177.46	≪	9143.98
Dreber et al. (2008)	597.17	≈	580.63	≈	570.33	≈	589.84	≈	618.5	≈	618.89	≈	619.9	≈	648.55
Duffy and Ochs (2009)	1706.1	≈	1753.41	≈	1719.86	≈	1761.6	≈	1857.06	≈	1876.72	≈	1883.52	≈	2003.41
Fréchette and Yuksel (2017)	422.32	≈	424.41	≈	419.44	≈	423.34	≈	433.18	≈	433.18	≈	433.18	<	464.23
Fudenberg et al. (2012)	452.64	≈	450.08	≈	447.25	≈	452.6	<	484.5	≈	477.91	≈	514.87	≈	534.47
Kagel and Schley (2013)	1782.43	≈	1777.83	≈	1773.55	≈	1775.62	≈	1751.81	≈	1751.81	≈	1751.81	≈	1830.26
Sherstyuk et al. (2013)	959.21	≈	952.56	≈	949.46	≈	951.34	≈	955.73	≈	955.73	≈	955.73	≈	1023.43
Pooled	**22669.91**	≫	**22258.14**	≈	**22153.69**	≈	**22097.67**	≪	**22811.34**	≈	**22828.13**	≈	**22848.49**	≪	**25177.57**

Note: Results treatment-by-treatment are in the appendix. The main body contains ICL-BICs aggregated at paper level. Relation signs and p-values are exactly as above, see Table 1.3. "M2" ("M1") denotes strategies, whose actions may depend on actions in $t-2$ and $t-1$ ($t-1$ only). The supplements "General", "TFT", "Grim" indicate whether parameters of behavior strategies may depend on: all four possible histories in $t-2$ (M2 "General"), whether the opponent cooperated in $t-2$ (M2 "TFT"), or whether there was joint cooperation in $t-2$ (M2 "Grim"). Pure M2 strategies do not have such free parameters. Columns 1-3 contain one memory-2 version of semi-grim each. Column 4 is memory-1 semi-grim. Columns 5-7 are memory-2 and memory-1 versions of generalized prototypical strategies. The last column contains the best fitting combinations of a set of pure memory-1 and memory-2 strategies from the literature (TFT, Grim, AD, Grim2, TF2T, T2, 2TFT, 2PTFT) for definitions see Table A.7 in the Appendix.

2 improves goodness-of-fit. Again, we do so treatment by treatment. That is, for each treatment, we take the best-fitting of the 13 memory-1 models discussed above, the best of the five pure memory-2 strategy combinations following Fudenberg et al. (2012), and the best of the four generalized pure strategies (type II) after allowing for them to be of memory-2 following either the TFT scheme or the Grim scheme, and then take the best of these 22 models overall. The results are provided in the columns *M1+M2"TFT"* and *M1+M2"Grim"* of Table A.3: After allowing for generalized pure strategies as done here, allowing for memory-2 has virtually zero impact for inexperienced subjects and some but only insignificant impact for experienced subjects.[9] This indicates that the appearance of memory-2 is indistinguishable from the parametrically simpler notion of randomization as in generalized-pure strategies. Further, all of these data-mined models still fit significantly worse than the simple AD+SG that stays free from post-hoc modeling choices (column 4 of Table A.3). Considering that the best of 22^{32} models, comprising all of the key ideas expressed in behavioral analyses of repeated games, does not improve on this single model now strongly indicates that subjects actually play behavior strategies.

Third, we evaluate whether these behavior strategies possibly have memory-2. That is, we compare the simple AD+SG memory-1 version with the three generalizations to memory-2 introduced above. The TFT-scheme allows the cooperation probabilities to be functions of the opponent's action in $t-2$, the Grim-scheme allows them to be functions of whether both subjects cooperated in $t-2$, and the General scheme of all four possible states in $t-2$. The results are report in the three left-most columns of Table A.3 and appear clear-cut: None of the memory-2 extensions improves on describing behavior by the simple memory-1 semi-grim strategy. Indeed, the finer the memory-2 ramifications, the worse the model adequacy (after accounting for the additional degrees of freedom). These results are additionally compatible with a result of Breitmoser (2015) who verified the Markov assumption by testing whether subjects systematically deviate from memory-1 strategies after particular histories in memory-2. We summarize these observations as follows.

Result 6 (Memory-2)**.** *Model adequacy does not improve by equipping subjects with memory-2, neither for (generalizations of) pure strategies nor for semi-grim.*

A.3 Further details and results on the structural analysis of preferences and beliefs

Our objective is to examine to what extent received models are compatible with the observation that the (sub-)population of cooperating subjects consists of two compo-

[9] One reason for the good performance of generalized memory-1 strategies compared to the generalized memory-2 strategies is that allowing for first round randomization seems essential. However, when we abstract from first rounds, as done in an earlier draft (available from the authors), we obtained a similarly bad fit for generalized memory-2 strategies compared to generalized memory-1 strategies (both type-II generalization).

nents, cautious cooperators and strong cooperators, who play the mildly treatment-dependent strategies estimated above. For clarity, the estimated strategies are listed in Table A.4. In the structural analysis, we do not include defecting subjects, as their behavior is easily rationalizable across treatments. Further, we do not seek to model the relative shares of cautious cooperators and strong cooperators, since the shares seem closely related to existing predictors of cooperation. The actual strategies leave us with the remaining part of our original research question to understand behavior in the repeated PD: How can we rationalize this behavior?

In order to introduce the requisite notation in a general setting, let us consider a player using strategy σ (as above, a mapping from memory-1 states to probabilities of cooperation) with initially arbitrary beliefs about the possibly types of opponents. The set of opponents' types is K, and opponents of type $k \in K$ play strategy τ_k. The prior belief of facing opponent type $k \in K$ is denoted ρ_k, and given history h, the posterior belief that the opponent is of type $k \in K$ is denoted as $\Pr(k|h)$. Obviously, this posterior is a function of the prior belief (K, ρ, τ), which we shall make explicit in the notation below. Define $\tau = \{\tau_k\}_k$. The expected payoff of playing $a \in \{c, d\}$ after history h, over the present and all subsequent rounds of the indefinitely repeated game, given one's own continuation strategy σ and the opponent's strategy τ_k, is denoted as $\Pi(a|h, \sigma, \tau_k)$. Holding the belief $\Pr(k|h)$ fixed, the expected payoff of playing $a \in \{c, d\}$, given σ and τ, can be written as

$$\Pi^0(a|h, \sigma, K, \rho, \tau) = \sum_{k \in K} \Pr(k|h, K, \rho, \tau) \cdot \Pi(a|h, \sigma, \tau_k). \tag{A.11}$$

Assuming logistic errors and precision $\lambda \geq 0$, the probability of observing action $a \in \{c, d\}$ in state ω is thus

$$\Pr(a, \omega|\sigma, K, \rho, \tau) = \frac{\exp\{\lambda \cdot \Pi^0(a|\omega, \sigma, K, \rho, \tau)\}}{\exp\{\lambda \cdot \Pi^0(c|\omega, \sigma, K, \rho, \tau)\} + \exp\{\lambda \cdot \Pi^0(d|\omega, \sigma, K, \rho, \tau)\}}. \tag{A.12}$$

Now, let the estimated population be described by the two types $(\hat{\rho}_{\text{cautious}}, \hat{\sigma}_{\text{cautious}})$ and $(\hat{\rho}_{\text{strong}}, \hat{\sigma}_{\text{strong}})$, and let the underlying data set consist of $n(a, \omega)$ observations of action a in state ω. Allowing cautious and strong cooperators to hold different beliefs, the log-likelihood of a belief model (ρ, τ, K) with respect is

$$\begin{aligned} LL(\rho, \tau, K) = \hat{\rho}_{\text{cautious}} \sum_{\omega} \sum_{a \in \{c,d\}} n(a, \omega) \cdot \log \Pr(a, \omega|\hat{\sigma}_{\text{cautious}}, K_c, \rho_c, \tau_c) \\ + \hat{\rho}_{\text{strong}} \sum_{\omega} \sum_{a \in \{c,d\}} n(a, \omega) \cdot \log \Pr(a, \omega|\hat{\sigma}_{\text{strong}}, K_s, \rho_s, \tau_s). \end{aligned}$$

We maximize this log-likelihood using the same algorithms as above (first NEWUOA and Newton-Raphson), where the free parameters are those of the utility models described below.

Table A.4: Estimated cooperation probabilities and shares of the identified player types

		Defectors		Cautious Coop.		Strong Coop.		Continuation of Coop.		
Experiment/Treatment	$\delta - \delta^*$	Share	ε	Share	$\sigma_\emptyset$	Share	$\sigma_\emptyset$	σ_{cc}	$\sigma_{cd/dc}$	σ_{dd}
First halves per session										
DF11–6	-0.32	0.487	0.016	0.47	0.181	0.05	0.887	0.922	0.398	0.078
DF15–4	-0.32	0.591	0.026	0.39	0.263	0.02	0.99	0.895	0.356	0.105
BOS11–9	-0.3	0.366	0	0.59	0.304	0.05	0.99	0.946	0.201	0.054
BOS11–15	-0.15	0.839	0.008	0.08	0.196	0.08	0.197	0.999	0.224	0.001
DF11–7	-0.11	0.308	0.018	0.4	0.123	0.29	0.43	0.894	0.324	0.106
DF11–22	-0.07	0.316	0.013	0.42	0.212	0.27	0.568	0.916	0.383	0.084
DF15–20	-0.07	0.276	0.01	0.61	0.247	0.11	0.882	0.921	0.322	0.079
BOS11–14	-0.05	0.189	0.203	0.73	0.069	0.08	0.478	0.991	0.123	0.009
BOS11–26	-0.05	0.174	0.222	0.62	0.112	0.21	0.831	0.984	0.171	0.016
DRFN08–10	-0.05	0.188	0.036	0.62	0.438	0.19	0.965	0.948	0.178	0.052
BOS11–30	0.07	0.648	0.062	0.21	0.484	0.14	0.99	1	0	0
BOS11–31	0.07	0.33	0.027	0.27	0.256	0.4	0.895	0.977	0.512	0.023
BOS11–16	0.08	0.051	0.5	0.49	0.251	0.46	0.898	0.95	0.178	0.05
BOS11–27	0.08	0.502	0.01	0.35	0.373	0.15	0.99	0.887	0.448	0.113
D05–18	0.08	0.096	0.045	0.36	0.144	0.55	0.782	0.86	0.286	0.14
D05–19	0.08	0.233	0.01	0.44	0.289	0.33	0.956	0.914	0.335	0.086
DF15–33	0.08	0.279	0.025	0.55	0.291	0.17	0.898	0.929	0.368	0.071
DRFN08–11	0.08	0.271	0.052	0.39	0.468	0.34	0.908	0.931	0.329	0.069
DF11–8	0.11	0.251	0.01	0.32	0.204	0.43	0.699	0.906	0.419	0.094
DF15–5	0.11	0.296	0.095	0.31	0.458	0.39	0.947	0.933	0.309	0.067
BK12–28	0.13	0.143	0.077	0.47	0.262	0.39	0.867	0.916	0.289	0.084
DF15–35	0.13	0.169	0.167	0.3	0.076	0.54	0.833	0.972	0.417	0.028
DF11–23	0.14	0.21	0.08	0.25	0.288	0.54	0.817	0.951	0.458	0.049
KS13–12	0.15	0.224	0.022	0.31	0.431	0.47	0.911	0.932	0.335	0.068
BOS11–17	0.18	0.569	0.298	0.14	0.036	0.29	0.75	1	0.383	0
STS13–13	0.19	0.152	0.074	0.33	0.275	0.52	0.892	0.919	0.409	0.081
DO09–32	0.23	0.22	0.1	0.31	0.283	0.47	0.905	0.901	0.373	0.099
FY17–25	0.31	0.119	0.01	0.32	0.581	0.56	0.984	0.926	0.245	0.074
DF11–24	0.36	0.112	0.189	0.37	0.597	0.51	0.948	0.949	0.356	0.051
DF15–21	0.36	0.186	0.088	0.24	0.407	0.58	0.926	0.942	0.467	0.058
FRD12–29	0.48	0.062	0.023	0.3	0.417	0.63	0.983	0.97	0.469	0.03
AF09–34	0.59	0.15	0.5	0.53	0.648	0.32	0.988	0.911	0.41	0.089
Second halves per session										
DF11–6	-0.32	0.687	0.01	0.27	0.093	0.05	0.643	0.937	0.553	0.063
DF15–4	-0.32	0.635	0.009	0.28	0.102	0.08	0.72	0.94	0.234	0.06
BOS11–9	-0.3	0.166	0.074	0.53	0.01	0.3	0.718	0.999	0.129	0.001
BOS11–15	-0.15	0.008	0.007	0.9	0.001	0.09	0.001	0.998	0.001	0.002
DF11–7	-0.11	0.399	0.009	0.41	0.178	0.19	0.615	0.864	0.473	0.136
DF11–22	-0.07	0.313	0.01	0.46	0.158	0.23	0.818	0.963	0.465	0.037
DF15–20	-0.07	0.392	0.01	0.4	0.179	0.21	0.856	0.943	0.42	0.057
BOS11–14	-0.05	0.002	0.01	0.95	0	0.05	0.491	0.987	0.3	0.013
BOS11–26	-0.05	0.43	0.008	0.39	0.365	0.18	0.748	0.935	0.291	0.065
DRFN08–10	-0.05	0.455	0.01	0.4	0.342	0.14	0.908	0.968	0.252	0.032
BOS11–30	0.07	0.339	0.01	0.57	0.356	0.09	0.99	0.963	0.201	0.037
BOS11–31	0.07	0.449	0.017	0.23	0.139	0.33	0.88	0.979	0.484	0.021
BOS11–16	0.08	0.11	0.371	0.43	0.271	0.46	0.977	0.966	0.208	0.034
BOS11–27	0.08	0.355	0.01	0.34	0.109	0.3	0.887	0.951	0.495	0.049
D05–18	0.08	0.071	0.009	0.38	0.048	0.55	0.83	0.878	0.396	0.122
D05–19	0.08	0.21	0.018	0.16	0.051	0.63	0.825	0.947	0.295	0.053
DF15–33	0.08	0.219	0.01	0.38	0.159	0.4	0.841	0.964	0.476	0.036
DRFN08–11	0.08	0.091	0.01	0.3	0.309	0.61	0.92	0.951	0.327	0.049
DF11–8	0.11	0.37	0.01	0.24	0.231	0.39	0.896	0.971	0.446	0.029
DF15–5	0.11	0.291	0.021	0.3	0.345	0.41	0.948	0.963	0.322	0.037
BK12–28	0.13	0.236	0.015	0.42	0.275	0.34	0.969	0.948	0.323	0.052
DF15–35	0.13	0.156	0.01	0.31	0.127	0.53	0.93	0.967	0.51	0.033
DF11–23	0.14	0.079	0.01	0.16	0.151	0.76	0.967	0.956	0.508	0.044
KS13–12	0.15	0.165	0.01	0.12	0.175	0.71	0.954	0.964	0.359	0.036
BOS11–17	0.18	0.311	0.009	0.53	0.504	0.16	0.908	0.95	0.256	0.05
STS13–13	0.19	0.125	0.021	0.25	0.237	0.63	0.925	0.953	0.55	0.047
DO09–32	0.23	0.047	0.01	0.3	0.173	0.66	0.953	0.954	0.392	0.046
FY17–25	0.31	0.139	0.024	0.14	0.514	0.73	0.956	0.957	0.352	0.043
DF11–24	0.36	0	0.053	0.11	0.647	0.89	0.99	0.98	0.334	0.02
DF15–21	0.36	0.089	0.01	0.16	0.337	0.75	0.958	0.965	0.373	0.035
FRD12–29	0.48	0.083	0.06	0.09	0.119	0.83	0.967	0.965	0.536	0.035
AF09–34	0.59	0.133	0.498	0.05	0.259	0.81	0.984	0.968	0.461	0.032

Modeling prior beliefs We consider the following three types of prior beliefs. The "naive" prior assumes that opponents are homogeneous and play an average strategy, the "correct" prior assumes that all three types of opponents exist, and the "consensus" prior assumes that opponents are of the same type as oneself. Using $(\tilde{K}, \tilde{\rho}, \tilde{\tau})$ to denote the true type distributions, the beliefs (K, ρ, τ) of the two playe types (c, s), i.e. cautious and strong cooperators, are formally defined as follows.

$$\begin{array}{rrll}
\text{Naive:} & K_c = K_s = \{A\} & \rho_A = 1 & \tau_A = \sum_{k \in \tilde{K}} \tilde{\rho}_k \tilde{\tau}_k \\
\text{Correct:} & K_c = K_s = \tilde{K} & \rho_k = \tilde{\rho}_k & \tau_k = \tilde{\tau}_k \; \forall k \in \tilde{K} \\
\text{Consensus:} & K_c = \{c\} & \rho_c = 1 & \tau_c = \tilde{\tau}_{\text{cautious}} \\
 & K_s = \{s\} & \rho_s = 1 & \tau_s = \tilde{\tau}_{\text{strong}}
\end{array}$$

Bayesian updating of beliefs Players with correct beliefs understand that subjects are not homogeneous and therefore update their beliefs given their observations. Using Bayes' rule, the posterior belief after history h is

$$\Pr(k|h, K, \rho, \tau) = \frac{\rho_k \Pr(h|\sigma, \tau_k)}{\sum_{k' \in K} \rho_{k'} \Pr(h|\sigma, \tau_{k'})},$$

where $\Pr(h|\sigma, \tau_k)$, with $k \in \{A, B\}$, denotes the probability that history h is reached if the own strategy is σ and the opponent's strategy is τ_k. As estimated above, subjects in experiments seem to condition their actions on memory-1 Markov states, as opposed to more complex subsets of the history or even entire histories. This form of bounded rationality (i.e., imperfect recall) needs to be acknowledged, but can be expressed straightforwardly also in belief formation. Given the own strategy σ and the two opponent types' strategies τ_k, the **memory-1 posterior** that the opponent's type is $k \in K$ given memory-1 state ω is

$$\Pr(k|\omega, K, \rho, \tau) = \frac{\rho_k \sum_{h \in H(\omega)} \Pr(h|\sigma, \tau_k)}{\sum_{k' \in K} \rho_{k'} \sum_{h \in H(\omega)} \Pr(h|\sigma, \tau_{k'})},$$

where $H(\omega)$ is the set of histories leading to the memory-1 state ω.

Interdependent preferences As discussed above, we also examine to what extent received models of interdependent preferences allow us to capture behavior—having observed that pure payoff concerns are inevitably insufficient to capture behavior across treatments. The extension of the above definitions from expected payoffs to expected utilities is straightforward using the following definitions of stage game utilities. To begin with, all models of interdependent preferences are defined such that they allow for two free parameters. In **altruism**, we allow for the payoff of the other player to be relevant, and to obtain two free parameters as in other models, the other payoff's weight is allowed to depend on the relation of the own payoff to any reference point in $[0, 1]$. In **inequity aversion**, we use a standard implementation of Fehr-Schmidt preferences. In **conditional cooperation**, we allow the utility to express an aversion against unilateral cooperation and unilateral defection (i.e. a preference for matching the opponent's action). In **generalized fairness**, we generalize the parameter-free fairness concerns fo Rabin (1993) to contain two free parameters just like the other models.

$$\begin{aligned}
\text{Altruism:}\quad & u(\pi_1,\pi_2,a_1,a_2) = \pi_1 + I_{\pi_1\geq 0.5}\cdot\alpha\pi_2 + I_{\pi_1<0.5}\cdot\beta\pi_2\\
\text{Inequity aversion:}\quad & u(\pi_1,\pi_2,a_1,a_2) = \pi_1 - I_{\pi_1\geq\pi_2}\cdot\alpha\pi_2 - I_{\pi_1<\pi_2}\cdot\beta\pi_2\\
\text{Cond. cooperation:}\quad & u(\pi_1,\pi_2,a_1,a_2) = \pi_1 - I_{a_1=d\wedge a_2=c}\cdot\alpha g - I_{a_1=c\wedge a_2=d}\cdot\beta l
\end{aligned}$$

Our definition of **generalized fairness concerns** requires additional notation. Recall that Rabin (1993) definitions imply that in a one-shot PD with probabilities of cooperation $(s_1,s_2)\in[0,1]^2$, player i's utility is

$$\begin{aligned}
U_i(s_i,s_j) &= \pi_i(s_i,s_j) + \overline{f}_j(s_j,s_i)\cdot f_i(s_i,s_j)\\
&= s_j\cdot(1+g) - s_i\cdot l - s_is_j\cdot(g-l) + (s_j-1/2)(s_i-1/2).
\end{aligned}$$

We generalize this towards

$$U_i(s_i,s_j) = s_j\cdot(1+g) - s_i\cdot l - s_is_j\cdot(g-l) + \alpha(s_j-\beta)(s_i-\beta) \tag{A.13}$$

and as for the implicit stage game payoffs, this implies

$$\begin{aligned}
U_i(1,1) &= 1+\alpha(1-\beta)^2 = 1+\alpha(1-2\beta+\beta^2) && \hat{=}\, 1+\alpha(1-2\beta)\\
U_i(1,0) &= -l-\alpha\beta(1-\beta) = -l-\alpha\beta+\alpha\beta^2 && \hat{=} -l-\alpha\beta\\
U_i(0,1) &= 1+g-\alpha\beta(1-\beta) = 1+g-\alpha\beta+\alpha\beta^2 && \hat{=}\, 1+g-\alpha\beta\\
U_i(0,0) &= \alpha\beta^2 && \hat{=}\, 0,
\end{aligned}$$

i.e. that the players play a constituent game resembling a "PD" with the parameters $l^* = \frac{l+\alpha\beta}{1+\alpha(1-2\beta)}$ and $g^* = \frac{1+g-\alpha\beta}{1+\alpha(1-2\beta)} - 1$.

Discounting We allow for the perceived discount factor $\tilde{\delta}$ to be a function of the true discount factor as in $\tilde{\delta} = \delta^x$. If $x = 1$, subjects correctly perceive the discount factor (or, break-up probability), for $x < 1$ they underestimate it, with the limiting case $x \to 0$ where they simply disregard the break-up probabibility and simply play the game as if it had an infinite time horizon (or, without impatience). In turn, if $x > 1$, subjects overestimate the break-up probability, and in the limiting case $x \to \infty$, subjects are myopic and play a sequence of one-shot games. In the estimation x is limited to 100 for viability.

Parametrization Overall, all models thus have up to three parameters, exponent X characterizing the perceived discount factor δ^X and (α,β) characterizing the extent of social preferences.

Benchmarks We provide results for the standard benchmark of *uniform randomization*, i.e. the goodness-of-fit of predicting 50-50 randomization in all states, and for the benchmark *clairvoyance* predicting the actually estimated probabilities of cooperation in all states. The first one is a lower bound of the goodness-of-fit and the second one is an upper bound, and in relation to those we can estimate the extent to which behavior is explained by the various model components.

$$LL_{\text{Random}}(\rho,\tau,K) = \hat{\rho}_{\text{cautious}} \sum_{\omega} \sum_{a\in\{c,d\}} n(a,\omega)\cdot \log 1/2 + \hat{\rho}_{\text{strong}} \sum_{\omega} \sum_{a\in\{c,d\}} n(a,\omega)\cdot \log 1/2$$

$$\begin{aligned} LL_{\text{Clairvoyance}}(\rho,\tau,K) = {} & \hat{\rho}_{\text{cautious}} \sum_{\omega} \sum_{a\in\{c,d\}} n(a,\omega)\cdot \log \hat{\sigma}_{\text{cautious}}(a,\omega) \\ & + \hat{\rho}_{\text{strong}} \sum_{\omega} \sum_{a\in\{c,d\}} n(a,\omega)\cdot \log \hat{\sigma}_{\text{strong}}(a,\omega). \end{aligned}$$

BIC Instead of looking at the pure log-likelihoods, we evaluate models based on their Bayes information criteria $BIC = -LL + \#pars \cdot \log \#obs/2$, reported in Tables 1.5 in the paper, and Tables A.5 and A.6 in the appendix. As for the two benchmark models, whose specification remains the same across the three column sets, we evaluate the BIC using the numbers of parameters and observations for the models that are compared to the respective benchmark.This way, we obtain upper and lower bounds for the reported BIC.

Figure A.1: Relation of observed and predicted probabilities of cooperation (second halves of sessions)

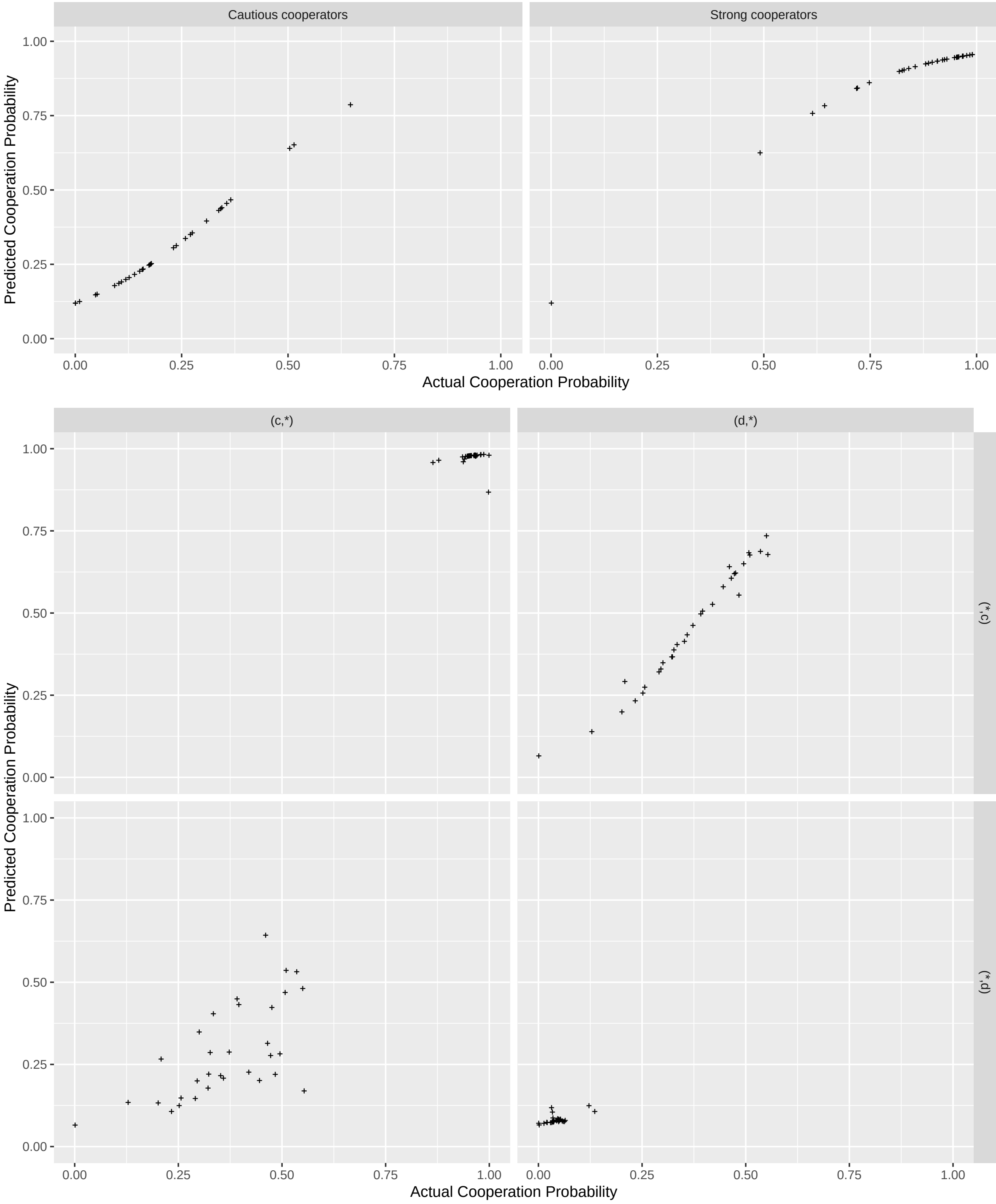
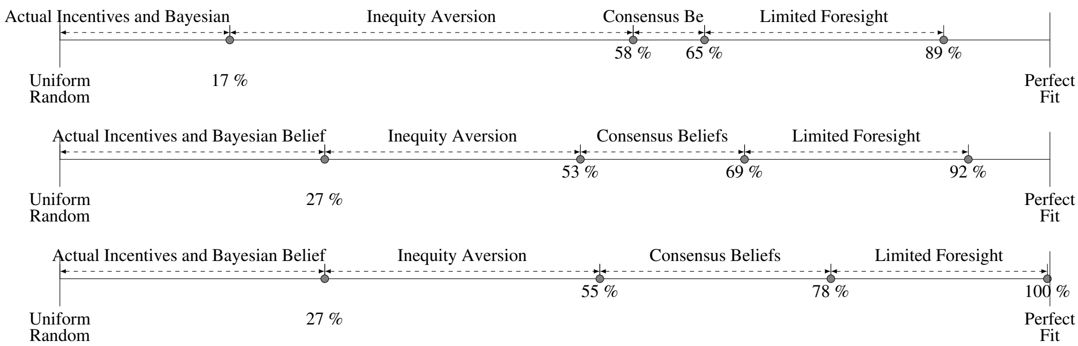


Figure A.2: Decomposition of the structural model components
Top graph in each half: with constant preference parameters and constant variance of noise;
Middle graph in each half: with constant preference parameters and treatment-dependent variance of noise;
Bottom graph in each half: with treatment-dependent preference parameters and variance of noise

(a) First halves



(b) Second halves

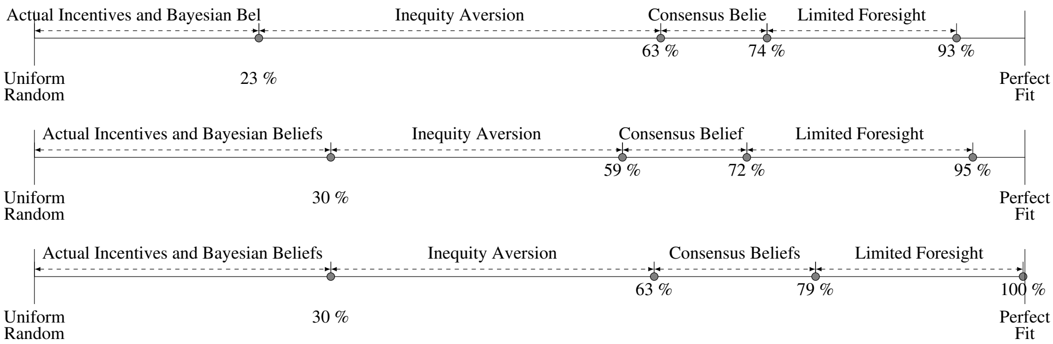


Table A.5: Testing interdependence of preferences (both halves)

	Fit to pooled data					
	Homogeneous variance		Heterogeneous variance		Fit to each treatment	
Model (free parameters)	*BIC*	Estimates	*BIC*	Estimates	*BIC*	Average Estimates
Upper bound BIC (Clairvoyance)	45129.7		45361.8		46058	
Lower bound BIC (Uniform Random)	94380.8		94612.8		95309.1	
False Consensus Beliefs						
True supergame (g,l,δ), no free par $(-)$	83654.6	$(-,-,-)$	79175.3	$(-,-,-)$	79871.6	$(-,-,-)$
True stage game g,l, free $(\delta^X,-,-)$	83455	$(1.19,-,-)$	78282.6	$(1.35,-,-)$	74836.7	$(1.3,-,-)$
True δ, inequity aversion $(-,\alpha,\beta)$	61047.3	$(-,1.01,0.5)$	60561.3	$(-,1.28,0.6)$	55375.4	$(-,15.44,0.43)$
Inequity Aversion (δ^X,α,β)	49685.8	$(100,0.79,0.12)$	48920.5	$(19.85,0.75,0.1)$	46200.5	$(46.62,0.7,-0.05)$
Cond Cooperation (δ^X,α,β)	55923	$(100,1.48,-0.37)$	54269.2	$(5.96,1.6,-0.05)$	46599.6	$(20.26,2.01,-0.03)$
Altruism (δ^X,α,β)	53154.9	$(74.75,1.37,-0.27)$	51208.9	$(21.84,1.33,-0.22)$	46187.8	$(9.72,0.89,0.24)$
Gen Fairness Equilibrium (δ^X,α,β)	57075.3	$(7.4,38.23,0.22)$	54040.5	$(6.57,43.25,0.22)$	47108.2	$(9.12,33.11,0.02)$
Naive Beliefs						
True supergame (g,l,δ), no free par $(-)$	83743.8	$(-,-,-)$	81266.6	$(-,-,-)$	81962.8	$(-,-,-)$
True stage game g,l, free $(\delta^X,-,-)$	83437	$(1.14,-,-)$	80676.1	$(1.21,-,-)$	77696.3	$(3.62,-,-)$
True δ, inequity aversion $(-,\alpha,\beta)$	61994.4	$(-,-100,-3.67)$	62929.2	$(-,-100,-2.69)$	60135	$(-,-100,-2.36)$
Inequity Aversion (δ^X,α,β)	56552	$(100,26.11,1.09)$	56390.1	$(87.42,3.36,1.09)$	56398.5	$(49.69,14.98,0.82)$
Cond Cooperation (δ^X,α,β)	67945.9	$(100,30.4,0.22)$	63489.7	$(4.24,8.45,0.47)$	56398.5	$(100,20.26,-0.05)$
Altruism (δ^X,α,β)	59484.3	$(87.42,15.46,-0.96)$	58236.5	$(19.53,44.06,-0.8)$	56398.5	$(34.4,15.85,-0.59)$
Gen Fairness Equilibrium (δ^X,α,β)	59345.5	$(4.13,-6.15,0.53)$	57955.1	$(3.93,-6.09,0.54)$	56398.5	$(40.1,9.13,0.41)$
Bayesian Beliefs						
True supergame (g,l,δ), no free par $(-)$	83891.8	$(-,-,-)$	80092.5	$(-,-,-)$	80788.7	$(-,-,-)$
True stage game g,l, free $(\delta^X,-,-)$	83746	$(0.9,-,-)$	80091.6	$(1.01,-,-)$	77163.4	$(1.39,-,-)$
True δ, inequity aversion $(-,\alpha,\beta)$	62553.9	$(-,11.84,1.21)$	65804.6	$(-,2.23,0.86)$	65085.3	$(-,100,100)$
Inequity Aversion (δ^X,α,β)	56374.2	$(100,9.72,0.98)$	56319.6	$(87.42,11.68,0.95)$	56706	$(6.83,100,0.9)$
Cond Cooperation (δ^X,α,β)	68640.9	$(100,100,0.11)$	63818.6	$(3.69,14.65,0.33)$	56704.2	$(22.88,5.08,-0.22)$
Altruism (δ^X,α,β)	58022.9	$(100,-100,5.74)$	57485.5	$(11.32,-100,5.53)$	56704.8	$(20.47,100,-0.7)$
Gen Fairness Equilibrium (δ^X,α,β)	66459.5	$(5.83,17.42,0.21)$	63148	$(5.52,7.93,0.2)$	56704.1	$(9.02,81.49,-0.26)$

Table A.6: Testing interdependence of preferences (first halves)

	Fit to pooled data				Fit to each treatment	
	Homogeneous variance		Heterogeneous variance			
Model (free parameters)	*BIC*	Estimates	*BIC*	Estimates	*BIC*	Average Estimates
Upper bound BIC (Clairvoyance)	22650.9		22883		23579.2	
Lower bound BIC (Uniform Random)	42075.3		42307.3		43003.5	
False Consensus Beliefs						
True supergame (g,l,δ), no free par $(-)$	38037.9	$(-,-,-)$	36156.8	$(-,-,-)$	36853	$(-,-,-)$
True stage game g,l, free $(\delta^X,-,-)$	37892.6	$(1.28,-,-)$	35739.7	$(1.36,-,-)$	34543.1	$(0.4,-,-)$
True δ, inequity aversion $(-,\alpha,\beta)$	29429.8	$(-,1.02,0.49)$	28878	$(-,1.32,0.66)$	27879.8	$(-,11.37,0.54)$
Inequity Aversion (δ^X,α,β)	24738.5	$(100,0.81,0.14)$	24486.5	$(24.6,0.76,0.12)$	23632.4	$(57.13,0.61,-0.02)$
Cond Cooperation (δ^X,α,β)	27236.5	$(100,1.48,-0.32)$	26859.8	$(100,1.55,-0.32)$	23848.4	$(2.8,2.04,0)$
Altruism (δ^X,α,β)	26204.3	$(77.34,1.32,-0.27)$	25520.2	$(28.27,1.29,-0.23)$	23633.4	$(10.43,3.43,0.12)$
Gen Fairness Equilibrium (δ^X,α,β)	27087.2	$(8.91,2.95,0.22)$	25933.4	$(6.24,3.07,0.24)$	24047.4	$(5.89,6.9,0.04)$
Naive Beliefs						
True supergame (g,l,δ), no free par $(-)$	39017.8	$(-,-,-)$	37922	$(-,-,-)$	38618.3	$(-,-,-)$
True stage game g,l, free $(\delta^X,-,-)$	38910.2	$(1.14,-,-)$	37674	$(1.22,-,-)$	36580.1	$(0.6,-,-)$
True δ, inequity aversion $(-,\alpha,\beta)$	30817.9	$(-,-87.62,-3.64)$	31187.3	$(-,-87.77,-2.91)$	30333.6	$(-,-69.79,-2.46)$
Inequity Aversion (δ^X,α,β)	28610.8	$(100,8.31,1.04)$	28622.1	$(87.42,4.61,1.04)$	28969.7	$(55.54,100,0.72)$
Cond Cooperation (δ^X,α,β)	33552.7	$(100,26.39,0.31)$	31888	$(3.34,4.55,0.57)$	28967.9	$(62.27,9.96,-0.08)$
Altruism (δ^X,α,β)	29758.9	$(100,17.51,-0.95)$	29435.6	$(22.6,46.57,-0.77)$	28969.7	$(40.36,34.44,-0.47)$
Gen Fairness Equilibrium (δ^X,α,β)	29944.2	$(3.81,-7.36,0.53)$	29358.2	$(3.64,-6.03,0.53)$	28967.6	$(100,100,0.29)$
Bayesian Beliefs						
True supergame (g,l,δ), no free par $(-)$	38912.9	$(-,-,-)$	37205.4	$(-,-,-)$	37901.7	$(-,-,-)$
True stage game g,l, free $(\delta^X,-,-)$	38784.8	$(0.84,-,-)$	37202.4	$(0.98,-,-)$	36329.7	$(1.27,-,-)$
True δ, inequity aversion $(-,\alpha,\beta)$	30829.4	$(-,2.04,1.16)$	32096.1	$(-,2,0.92)$	32411.5	$(-,10.71,0.84)$
Inequity Aversion (δ^X,α,β)	28534.6	$(100,60.49,0.99)$	28609.6	$(58.38,14.71,0.97)$	29106.3	$(2.13,64.75,0.83)$
Cond Cooperation (δ^X,α,β)	33762.8	$(100,1.91,0.15)$	32161.8	$(2.88,2.04,0.5)$	29106	$(11.55,14.75,-0.18)$
Altruism (δ^X,α,β)	29003.9	$(100,-10.62,5.7)$	29047.6	$(17.9,-9.93,5.6)$	29105.4	$(100,-51.77,-0.37)$
Gen Fairness Equilibrium (δ^X,α,β)	32044.4	$(6.93,2.96,0.2)$	30760.7	$(4.79,2.91,0.22)$	29105.3	$(27.06,100,0.28)$

A.4 Information on the experiments re-analyzed

This section provides some background information on the experiments re-analyzed in this paper. Table A.7 summarizes and defines the strategies considered by previous studies. Table A.8 reviews focus and main results (in terms of identified strategies) of these studies. Table A.9 reviews the numbers of subjects and observations, average parameters, and average cooperation rates for all experiments, and Table A.10 provides the detailed overview by treatments.

Table A.7: Pure strategies considered in behavioral analyses

Strategy	Abbreviation	Description	$(\sigma_{cc},\sigma_{cd},\sigma_{dc},\sigma_{dd})^{\dagger}$	References
Pure Strategies Non-responsive or Memory-1				
Always Defect	AD	Always defects independent of previous outcome	(0,0,0,0)	DF11, DF15, FRD12, FY17, STS13
Always Cooperate	AC	Always cooperates independent of previous outcome	(1,1,1,1) (1,1,0,0)	DF11, DF15, FRD12, B15 FY17, STS13
Grim	G	Only cooperates after cc was last outcome	(1,0,0,0)	AF09, DF11, DF15 FRD12, FY17, STS13
Tit-for-Tat	TFT	Only plays C if opponent did last period	(1,0,1,0)	AF09, DF11, DF15 FRD12, FY17, STS13
Win-stay-Lose-Shift (aka Perfect TFT)	WSLS	Plays same strategy if it was successful, otherwise shifts	(1,0,0,1)	DF11, DF15, FRD12, FY17
False cooperator	C-to-AD	Play c in first round then AD	–	FRD12, FY17
Explorative TFT	D-TFT	Play d in first round then TFT	–	DF15, FRD12, FY17
Alternator	DC-Alt	Play d in first round then alternate c and d	–	FRD12, FY17
Trigger-with-Reversion	GwR	Like Grim but revert to cooperation after cc[‡]	(1,0,0,0)	STS13
Pure Strategies Memory-2/3				
Trigger 2 periods	T2	Player punishes defection for max. 2 periods, otherwise cooperates	$(1,0,\theta_1^*, 0)$	DF11, FY17
Tit-for-2(3)-Tats	TF2T	Defects after 2 defections	$(1,\theta_2,1,\theta_2)$	FRD12, FY17
2-Tits-for-2-Tats	2TF2T	Defects twice after 2 defections	$(1,\theta_3,\theta_3,\theta_3)$	FRD12, FY17
2-Tits-for-1-Tats	2TFT	Defects twice after each defections	$(1,0,\theta_4,0)$	FRD12, FY17
Grim2(3/4)	G2(3)	After 2(3) defections will play D forever	$(1,\theta_5,0,0)$	FRD12, FY17, STS13
Win-stay-Lose-Shift-2	WSLS2	cooperate after (dd,dd),(cc,cc), (dd,cc) otherwise defect	–	FRD12
Explorative TF2(3)T	D-TF2(3)T	Play D in first round then TF2(3)T	–	FRD12, FY17
Explorative Grim2(3)	D-Grim2(3)	Play D in first round then Grim2(3)	–	FRD12, FY17
Behavior Strategies				
Semi-Grim**	SG	Similar to Grim but may cooperate after CD or DC.	$(1,\theta_{SG},\theta_{SG},0)$	B15
Generous TFT	GTFT	Like TFT but cooperate with prob α after CD or DD	$(1,\theta_{GT},1,\theta_{GT})$	FRD12, B15

† σ assigns cooperation probabilities after joint cooperation (cc), unilateral defection by opponent (cd), unilateral defection (dc), and joint defection (dd).
‡ possible if players make mistakes.
* Vector assigning cooperation probabilities $\in \{0,1\}$ depending on the state 2 periods ahead.
** θ_{SG} and θ_{GT} are mixing parameters $\in (0,1)$.

References: **AF09** (Aoyagi and Frechette, 2009), **B15** (Breitmoser, 2015), **DF11** (Dal Bó and Fréchette, 2011), **DF15** (Dal Bó and Fréchette, 2015), **FRD12** (Fudenberg et al., 2012), **FY17** (Fréchette and Yuksel, 2017), **STS13** (Sherstyuk et al., 2013)

Table A.8: Overview literature

Reference	Focus	Investigation of Strategies	Strategies found
Aoyagi and Frechette (2009)	Imperfect public monitoring in PD	Mainly avg. coop. rates Mem-1, Mem-2, Threshold	Threshold strat S_0 (same threshold in state 1 & 0)
Blonski et al. (2011)	New δ^* with sucker's payoff	Avg. coop rates	–
Bruttel and Kamecke (2012)	Endgame effects	Elicitation of pure strategies discuss avg. coop. rates	– *
Camera et al. (2012)	Player's strat using finite automata	All possible pure mem-1	large share play unconditional
Dal Bó (2005)	Finitely vs infinitely repeated PD	Avg. cooperation rates	–
Dal Bó and Fréchette (2011)	Players' strategies learning model	selected mem-1 strategies SFEM	AC, AD, TFT
Dal Bó and Fréchette (2015) upd (2017)	Players' strategies	SFEM, elicitation, pure Mem-1, Mem-2 mainly preselected	AD, TFT, Grim
Dreber et al. (2008)	PD extended with punishment option	Agg. cooperation behavior	(AD, Grim, TFT)**
Duffy and Ochs (2009)	Fixed matching of players in PD	Round 1 and avg. coop. rates	–
Fréchette and Yuksel (2017)	De-coupling of expected length of game and discount factor	Avg. coop. rates, SFEM Mem-1, Mem2/3 preselected	Grim, TFT
Fudenberg et al. (2012)	Effect of noise/ uncertainty on leniency	Avg. coop. rate, SFEM, 20 pure Mem-1, Mem-2(3)	AC, AD, Grim, (D)-TFT, 2TFT, Grim2
Kagel and Schley (2013)	Linear payoff transformations	Fist round coop. rates	–
Sherstyuk et al. (2013)	Payment schemes	Avg. cooperation rates, share of correctly predicted actions by selected pure strats	AD, TFT, GwR
Dal Bó and Fréchette (2018)	Determinants of cooperation (meta)	Mainly first round coop	–

* Table 4 column "Strategy" in their study indicating SG in coefficients for cd_{t-1} & cd_{t-2}.
** Reported by Fudenberg et al. (2012).

Table A.9: Overview of the data sets used in the analysis

Experiment	Logistics		Parameters			Average cooperation rates							
	#Subj	#Dec	δ	g	l	$\hat{\sigma}_{\emptyset}$	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$
First halves per session													
Aoyagi and Frechette (2009)	38	1650	0.9	0.333	0.111	0.465	0.917	$\gg$	0.45	$\approx$	0.408	$\approx$	0.336
Blonski et al. (2011)	200	3040	0.756	1.345	2.602	0.295	0.89	$\gg$	0.279	$\approx$	0.193	$\gg$	0.034
Bruttel and Kamecke (2012)	36	1920	0.8	1.167	0.833	0.481	0.91	$\gg$	0.286	$\approx$	0.228	$\gg$	0.08
Dal Bó (2005)	102	1320	0.75	0.939	1.061	0.342	0.922	$\gg$	0.212	$<$	0.342	$\gg$	0.089
Dal Bó and Fréchette (2011)	266	17772	0.622	1.062	1.072	0.31	0.951	$\gg$	0.334	$\approx$	0.331	$\gg$	0.063
Dal Bó and Fréchette (2015)	672	22112	0.743	1.579	1.341	0.451	0.94	$\gg$	0.297	$\approx$	0.335	$\gg$	0.057
Dreber et al. (2008)	50	2064	0.75	1.488	1.488	0.488	0.904	$\gg$	0.217	$\approx$	0.213	$\gg$	0.036
Duffy and Ochs (2009)	102	3128	0.9	1	1	0.53	0.904	$\gg$	0.301	$\approx$	0.33	$\gg$	0.111
Fréchette and Yuksel (2017)	50	800	0.75	0.4	0.4	0.737	0.943	$\gg$	0.141	$\approx$	0.266	$\approx$	0.091
Fudenberg et al. (2012)	48	1452	0.875	0.333	0.333	0.756	0.982	$\gg$	0.4	$\approx$	0.427	$\gg$	0.066
Kagel and Schley (2013)	114	7600	0.75	1	0.5	0.573	0.935	$\gg$	0.263	$\approx$	0.295	$\gg$	0.051
Sherstyuk et al. (2013)	56	3052	0.75	1	0.25	0.56	0.945	$\gg$	0.328	$\approx$	0.371	$\gg$	0.117
Pooled	1734	65910	0.728	1.207	1.083	0.389	0.938	$\gg$	0.304	$\approx$	0.322	$\gg$	0.065
Second halves per session													
Aoyagi and Frechette (2009)	38	1400	0.9	0.333	0.111	0.424	0.958	$\gg$	0.398	$\approx$	0.517	$\approx$	0.375
Blonski et al. (2011)	200	5460	0.766	1.282	2.554	0.279	0.923	$\gg$	0.287	$\approx$	0.231	$\gg$	0.02
Bruttel and Kamecke (2012)	36	1632	0.8	1.167	0.833	0.447	0.947	$\gg$	0.221	$\approx$	0.297	$\gg$	0.041
Dal Bó (2005)	102	1650	0.75	0.961	1.039	0.297	0.92	$\gg$	0.242	$<$	0.388	$\gg$	0.064
Dal Bó and Fréchette (2011)	266	19270	0.62	1.122	1.103	0.355	0.979	$\gg$	0.376	$\approx$	0.362	$\gg$	0.041
Dal Bó and Fréchette (2015)	672	29480	0.766	1.666	1.386	0.469	0.976	$\gg$	0.315	$<$	0.402	$\gg$	0.035
Dreber et al. (2008)	50	1838	0.75	1.533	1.533	0.461	0.917	$\gg$	0.128	$\ll$	0.39	$\gg$	0.009
Duffy and Ochs (2009)	102	6018	0.9	1	1	0.684	0.977	$\gg$	0.367	$\approx$	0.391	$\gg$	0.082
Fréchette and Yuksel (2017)	50	1568	0.75	0.4	0.4	0.763	0.97	$\gg$	0.233	$\approx$	0.398	$\gg$	0.069
Fudenberg et al. (2012)	48	1800	0.875	0.333	0.333	0.829	0.971	$\gg$	0.487	$\approx$	0.412	$\gg$	0.083
Kagel and Schley (2013)	114	7172	0.75	1	0.5	0.704	0.966	$\gg$	0.262	$\approx$	0.332	$\gg$	0.025
Sherstyuk et al. (2013)	56	2604	0.75	1	0.25	0.646	0.973	$\gg$	0.482	$\approx$	0.437	$\gg$	0.078
Pooled	1734	79892	0.744	1.271	1.172	0.404	0.971	$\gg$	0.327	$<$	0.376	$\gg$	0.039

Note: The "average cooperation rates" are the relative frequencies estimated directly from the data. The relation signs encode bootstrapped p-values (resampling at the subject level with 10,000 repetitions) where $<, >$ indicate rejection of the Null of equality at $p < .05$ and $\ll, \gg$ indicating $p < .002$. Following Wright (1992), we accommodate for the multiplicity of comparisons within data sets by adjusting p-values using the Holm-Bonferroni method (Holm, 1979). Note that all details here exactly replicate Breitmoser (2015). As a result, if a data set is considered in isolation, the .05-level indicated by "$>, <$" is appropriate. If all 24 treatments are considered simultaneously, the corresponding Bonferroni correction requires to further reduce the threshold to $.002 \approx .05/24$, which corresponds with "$\gg, \ll$".

Table A.10: Table A.9 by treatments – Overview of the data sets used in the analysis

(a) First halves per session

	Logistics		Parameters			Average cooperation rates							
Treatment	#Subj	#Dec	δ	g	l	$\hat{\sigma}_{\emptyset}$	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$
Aoyagi and Frechette (2009)													
AF09–34	38	1650	0.9	0.333	0.111	0.729	0.917	≫	0.45	≈	0.408	≈	0.336
Blonski et al. (2011)													
BOS11–9	20	220	0.5	2	2	0.23	-		0.182		0.182		0.031
BOS11–14	20	340	0.75	0.5	3.5	0.16	-		0.188		0.062		0.029
BOS11–15	20	320	0.75	1	8	0.04	-		0.167		0		0.005
BOS11–16	20	400	0.75	0.75	1.25	0.56	0.915	≫	0.206	≈	0.206	>	0.073
BOS11–17	20	180	0.75	0.833	0.5	0.42	0.5	≈	0.235	≈	0.471	≈	0.125
BOS11–26	40	760	0.75	2	2	0.285	0.833	≫	0.235	≈	0.196	≫	0.03
BOS11–27	20	240	0.75	1	1	0.28	0.917	>	0.316	≈	0.211	>	0.056
BOS11–30	20	140	0.875	0.5	3.5	0.275	-		0		0		0.058
BOS11–31	20	440	0.875	2	2	0.437	0.968	≫	0.513	≈	0.154	>	0.023
BOS11–All	200	3040	0.756	1.345	2.602	0.295	0.89	≫	0.279	≈	0.193	≫	0.034
Bruttel and Kamecke (2012)													
BK12–28	36	1920	0.8	1.167	0.833	0.481	0.91	≫	0.286	≈	0.228	≫	0.08
Dal Bó (2005)													
D05–18	42	420	0.75	1.167	0.833	0.484	0.806	≫	0.239	≈	0.304	>	0.114
D05–19	60	900	0.75	0.833	1.167	0.443	0.958	≫	0.2	<	0.36	≫	0.074
D05–All	102	1320	0.75	0.939	1.061	0.342	0.922	≫	0.212	<	0.342	≫	0.089
Dal Bó and Fréchette (2011)													
DF11–6	44	2748	0.5	2.571	1.857	0.134	0.792	≫	0.32	≈	0.272	≫	0.036
DF11–7	50	3290	0.5	0.667	0.867	0.18	0.673	≫	0.299	≈	0.258	≫	0.061
DF11–8	46	3092	0.5	0.087	0.565	0.365	0.973	≫	0.421	>	0.263	≫	0.081
DF11–22	44	2842	0.75	2.571	1.857	0.248	0.891	≫	0.303	≈	0.355	≫	0.05
DF11–23	38	2656	0.75	0.667	0.867	0.511	0.965	≫	0.39	≈	0.386	≫	0.073
DF11–24	44	3144	0.75	0.087	0.565	0.74	0.961	≫	0.266	≈	0.399	≫	0.11
DF11–All	266	17772	0.622	1.062	1.072	0.31	0.951	≫	0.334	≈	0.331	≫	0.063
Dal Bó and Fréchette (2015)													
DF15–4	50	1438	0.5	2.571	1.857	0.137	0.562	>	0.164	<	0.327	≫	0.031
DF15–5	140	4094	0.5	0.087	0.565	0.58	0.921	≫	0.254	≈	0.241	≫	0.082
DF15–20	114	4054	0.75	2.571	1.857	0.25	0.912	≫	0.223	<	0.336	≫	0.052
DF15–21	164	4740	0.75	0.087	0.565	0.658	0.952	≫	0.388	≈	0.369	≫	0.083
DF15–33	168	6438	0.9	2.571	1.857	0.307	0.928	≫	0.297	≈	0.344	≫	0.054
DF15–35	36	1348	0.95	2.571	1.857	0.5	0.974	≫	0.324	≈	0.432	≫	0.05
DF15–All	672	22112	0.743	1.579	1.341	0.451	0.94	≫	0.297	≈	0.335	≫	0.057
Dreber et al. (2008)													
DRFN08–10	28	1008	0.75	2	2	0.468	0.888	≫	0.188	≈	0.139	≫	0.02
DRFN08–11	22	1056	0.75	1	1	0.507	0.917	≫	0.245	≈	0.283	≫	0.051
DRFN08–All	50	2064	0.75	1.488	1.488	0.488	0.904	≫	0.217	≈	0.213	≫	0.036
Duffy and Ochs (2009)													
DO09–32	102	3128	0.9	1	1	0.53	0.904	≫	0.301	≈	0.33	≫	0.111
Fréchette and Yuksel (2017)													
FY17–25	50	800	0.75	0.4	0.4	0.737	0.943	≫	0.141	≈	0.266	≈	0.091
Fudenberg et al. (2012)													
FRD12–29	48	1452	0.875	0.333	0.333	0.756	0.982	≫	0.4	≈	0.427	≫	0.066
Kagel and Schley (2013)													
KS13–12	114	7600	0.75	1	0.5	0.573	0.935	≫	0.263	≈	0.295	≫	0.051
Sherstyuk et al. (2013)													
STS13–13	56	3052	0.75	1	0.25	0.56	0.945	≫	0.328	≈	0.371	≫	0.117
Pooled	1734	65910	0.728	1.207	1.083	0.389	0.938	≫	0.304	≈	0.322	≫	0.065

(b) Second halves per session

	Logistics		Parameters			Average cooperation rates							
Treatment	#Subj	#Dec	δ	g	l	$\hat{\sigma}_{\emptyset}$	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$
Aoyagi and Frechette (2009)													
AF09–34	38	1400	0.9	0.333	0.111	0.873	0.958	≫	0.398	≈	0.517	≈	0.375
Blonski et al. (2011)													
BOS11–9	20	300	0.5	2	2	0.233	0.917	>	0.062	≈	0.188	≈	0.007
BOS11–14	20	280	0.75	0.5	3.5	0.025	-		0.2		0.4		0.013
BOS11–15	20	640	0.75	1	8	0	-		0		0		0.002
BOS11–16	20	340	0.75	0.75	1.25	0.633	0.846	≫	0.2	≈	0.233	≫	0.024
BOS11–17	20	680	0.75	0.833	0.5	0.417	0.917	≫	0.182	≈	0.255	≫	0.026
BOS11–26	40	1100	0.75	2	2	0.283	0.959	≫	0.241	≈	0.203	≫	0.032
BOS11–27	20	800	0.75	1	1	0.308	0.875	≫	0.447	≈	0.318	≫	0.023
BOS11–30	20	560	0.875	0.5	3.5	0.3	0.8	≈	0.167	≈	0.139	≈	0.02
BOS11–31	20	760	0.875	2	2	0.338	1	≫	0.423	≈	0.173	>	0.021
BOS11–All	200	5460	0.766	1.282	2.554	0.279	0.923	≫	0.287	≈	0.231	≫	0.02
Bruttel and Kamecke (2012)													
BK12–28	36	1632	0.8	1.167	0.833	0.447	0.947	≫	0.221	≈	0.297	≫	0.041
Dal Bó (2005)													
D05–18	42	630	0.75	1.167	0.833	0.476	0.86	≫	0.274	<	0.476	≫	0.098
D05–19	60	1020	0.75	0.833	1.167	0.533	0.952	≫	0.21	≈	0.296	≫	0.046
D05–All	102	1650	0.75	0.961	1.039	0.297	0.92	≫	0.242	<	0.388	≫	0.064
Dal Bó and Fréchette (2011)													
DF11–6	44	2988	0.5	2.571	1.857	0.064	1	≫	0.352	≈	0.477	≫	0.022
DF11–7	50	3614	0.5	0.667	0.867	0.194	0.922	≫	0.377	≈	0.364	≫	0.078
DF11–8	46	3398	0.5	0.087	0.565	0.414	1	≫	0.409	>	0.189	≫	0.027
DF11–22	44	3606	0.75	2.571	1.857	0.264	0.96	≫	0.357	≈	0.408	≫	0.024
DF11–23	38	2524	0.75	0.667	0.867	0.708	0.974	≫	0.405	≈	0.5	≫	0.088
DF11–24	44	3140	0.75	0.087	0.565	0.957	0.984	≫	0.302	≈	0.372	≫	0.083
DF11–All	266	19270	0.62	1.122	1.103	0.355	0.979	≫	0.376	≈	0.362	≫	0.041
Dal Bó and Fréchette (2015)													
DF15–4	50	1638	0.5	2.571	1.857	0.101	0.833	>	0.067	<	0.267	>	0.017
DF15–5	140	4656	0.5	0.087	0.565	0.539	0.976	≫	0.27	≈	0.231	≫	0.038
DF15–20	114	4370	0.75	2.571	1.857	0.24	0.948	≫	0.305	≈	0.37	≫	0.03
DF15–21	164	6090	0.75	0.087	0.565	0.775	0.98	≫	0.313	≈	0.313	≫	0.062
DF15–33	168	9718	0.9	2.571	1.857	0.384	0.975	≫	0.314	≪	0.542	≫	0.032
DF15–35	36	3008	0.95	2.571	1.857	0.539	0.981	≫	0.478	≈	0.427	≫	0.039
DF15–All	672	29480	0.766	1.666	1.386	0.469	0.976	≫	0.315	<	0.402	≫	0.035
Dreber et al. (2008)													
DRFN08–10	28	980	0.75	2	2	0.269	0.75	≫	0.121	<	0.276	≫	0.002
DRFN08–11	22	858	0.75	1	1	0.653	0.942	≫	0.133	≪	0.47	≫	0.028
DRFN08–All	50	1838	0.75	1.533	1.533	0.461	0.917	≫	0.128	≪	0.39	≫	0.009
Duffy and Ochs (2009)													
DO09–32	102	6018	0.9	1	1	0.684	0.977	≫	0.367	≈	0.391	≫	0.082
Fréchette and Yuksel (2017)													
FY17–25	50	1568	0.75	0.4	0.4	0.763	0.97	≫	0.233	≈	0.398	≫	0.069
Fudenberg et al. (2012)													
FRD12–29	48	1800	0.875	0.333	0.333	0.829	0.971	≫	0.487	≈	0.412	≫	0.083
Kagel and Schley (2013)													
KS13–12	114	7172	0.75	1	0.5	0.704	0.966	≫	0.262	≈	0.332	≫	0.025
Sherstyuk et al. (2013)													
STS13–13	56	2604	0.75	1	0.25	0.646	0.973	≫	0.482	≈	0.437	≫	0.078
Pooled	1734	79892	0.744	1.271	1.172	0.404	0.971	≫	0.327	<	0.376	≫	0.039

Table A.11: Expected and observed realizations in two round 2s per subject after outcome CD in round 1

		Cooperators			Defectors		
		iid	observed	difference	iid	observed	difference
Half 1		(Obs	518)		(Obs	108)	
	Defecting twice	0.557	0.627	-0.07	0.522	0.583	-0.061
	One of each	0.379	0.237	0.142	0.401	0.278	0.123
	Cooperating twice	0.064	0.135	-0.071	0.077	0.139	-0.062
Half 2		(Obs	455)		(Obs	84)	
	Defecting twice	0.557	0.684	-0.116	0.545	0.631	-0.086
	One of each	0.379	0.141	0.23	0.387	0.214	0.173
	Cooperating twice	0.064	0.176	-0.115	0.069	0.155	-0.086

Note: “Cooperators” and “Defectors” are determined by their average cooperation rate in round 1. If above median, they are cooperators. Average cooperation behavior in round 2 if the state is CD of the last two supergames with such an observation by halves and round1-cooperation rates.

Table A.12: Overview of cooperation rates in the data

	Cooperators							Defectors						
			Average cooperation rates							Average cooperation rates				
Experiment	#Subj	#Dec	$\hat{\sigma}_{\emptyset}$	$\hat{\sigma}_{cc}$	$\hat{\sigma}_{cd}$	$\hat{\sigma}_{dc}$	$\hat{\sigma}_{dd}$	#Subj	#Dec	$\hat{\sigma}_{\emptyset}$	$\hat{\sigma}_{cc}$	$\hat{\sigma}_{cd}$	$\hat{\sigma}_{dc}$	$\hat{\sigma}_{dd}$
First halves per session														
Aoyagi and Frechette (2009)	35	1509	0.783	0.936	0.45	0.402	0.313	3	141	0.143	0.575	0.444	0.441	0.486
Blonski et al. (2011)	74	1145	0.685	0.896	0.31	0.356	0.056	126	1895	0.066	0.714	0.192	0.123	0.027
Bruttel and Kamecke (2012)	20	1062	0.75	0.926	0.253	0.267	0.113	16	858	0.144	0.806	0.375	0.198	0.055
Dal Bó (2005)	52	675	0.807	0.947	0.21	0.37	0.133	50	645	0.087	0.762	0.22	0.326	0.064
Dal Bó and Fréchette (2011)	108	7382	0.699	0.969	0.337	0.415	0.113	158	10390	0.108	0.807	0.328	0.28	0.045
Dal Bó and Fréchette (2015)	311	10133	0.819	0.954	0.326	0.499	0.084	361	11979	0.124	0.87	0.239	0.239	0.048
Dreber et al. (2008)	31	1272	0.711	0.909	0.189	0.245	0.05	19	792	0.129	0.846	0.326	0.181	0.022
Duffy and Ochs (2009)	63	1886	0.807	0.913	0.302	0.403	0.14	39	1242	0.097	0.866	0.298	0.25	0.087
Fréchette and Yuksel (2017)	41	652	0.886	0.941	0.133	0.394	0.136	9	148	0.056	1	0.25	0.129	0.039
Fudenberg et al. (2012)	39	1185	0.905	0.985	0.418	0.518	0.06	9	267	0.091	0.947	0.316	0.333	0.077
Kagel and Schley (2013)	76	5066	0.814	0.939	0.262	0.419	0.069	38	2534	0.089	0.872	0.268	0.168	0.033
Sherstyuk et al. (2013)	34	1920	0.828	0.968	0.33	0.518	0.119	22	1132	0.152	0.78	0.323	0.266	0.115
Pooled	884	33887	0.778	0.951	0.312	0.43	0.098	850	32023	0.111	0.843	0.283	0.242	0.049
Second halves per session														
Aoyagi and Frechette (2009)	34	1245	0.959	0.968	0.382	0.578	0.328	4	155	0.211	0.75	0.448	0.371	0.469
Blonski et al. (2011)	66	1761	0.75	0.926	0.322	0.398	0.036	134	3699	0.049	0.91	0.189	0.164	0.015
Bruttel and Kamecke (2012)	15	656	0.893	0.954	0.136	0.613	0.031	21	976	0.129	0.922	0.351	0.211	0.044
Dal Bó (2005)	60	974	0.838	0.927	0.24	0.434	0.063	42	676	0.042	0.852	0.25	0.348	0.065
Dal Bó and Fréchette (2011)	111	7984	0.892	0.982	0.358	0.579	0.055	155	11286	0.081	0.948	0.406	0.286	0.038
Dal Bó and Fréchette (2015)	319	14330	0.897	0.978	0.312	0.585	0.067	353	15150	0.089	0.965	0.322	0.315	0.024
Dreber et al. (2008)	22	830	0.847	0.929	0.1	0.479	0.027	28	1008	0.125	0.833	0.195	0.344	0.002
Duffy and Ochs (2009)	69	4206	0.943	0.978	0.376	0.408	0.083	33	1812	0.124	0.968	0.348	0.373	0.081
Fréchette and Yuksel (2017)	42	1322	0.909	0.973	0.227	0.507	0.115	8	246	0	0.8	0.333	0.194	0.014
Fudenberg et al. (2012)	41	1542	0.957	0.969	0.465	0.456	0.106	7	258	0.065	1	0.6	0.325	0.053
Kagel and Schley (2013)	82	5176	0.949	0.968	0.242	0.505	0.035	32	1996	0.067	0.937	0.426	0.194	0.015
Sherstyuk et al. (2013)	37	1674	0.907	0.978	0.489	0.558	0.124	19	930	0.123	0.946	0.456	0.382	0.053
Pooled	898	41700	0.898	0.974	0.318	0.525	0.063	836	38192	0.084	0.954	0.347	0.292	0.03

Note: "Cooperators" and "Defectors" are determined by their average cooperation rate in round 1. If above median, they are cooperators. The "average cooperation rates" are the relative frequencies estimated directly from the data. The relation signs encode bootstrapped p-values (resampling at the subject level with 10,000 repetitions) where $<, >$ indicate rejection of the Null of equality at $p < .05$ and $\ll, \gg$ indicating $p < .002$. Following Wright (1992), we accommodate for the multiplicity of comparisons within data sets by adjusting p-values using the Holm-Bonferroni method (Holm, 1979). Note that all details here exactly replicate Breitmoser (2015). As a result, if a data set is considered in isolation, the .05-level indicated by "$>, <$" is appropriate. If all 24 treatments are considered simultaneously, the corresponding Bonferroni correction requires to further reduce the threshold to $.002 \approx .05/24$, which corresponds with "$\gg, \ll$".

A.5 Robustness checks for section 1.4

The tables in this section provide robustness checks on the results presented in Section 1.4. Specifically, we show results by treatment, different strategy combinations, and results considering only continuation strategies (excluding first rounds)

- Table A.13 compares the "best mixtures" analyzed in the main text to the models allowing for all 1-memory types that correspond with those analyzed in the literature, e.g. Dal Bó and Fréchette (2011). Recall that the 2-memory strategies analyzed in other strings of literature are examined in Section 4. This table clarifies that focussing on the "best mixtures" for each treatment improves the goodness-of-fit of these models substantially (i.e. by at least 100 likelihood points).
- Table A.15 shows a comparison of the best mixtures of pure and generalized pure continuation strategies.
- Table A.16 shows a comparison of the best mixtures of pure and generalized pure strategies as discussed in the main text.
- Table A.18 is similar to Table 1.3 in the main text but focussing on the prototypical strategies in their pure form only.
- Table A.20 is similar to Table 1.3 in the main text but focussing on the prototypical strategies in their generalized form only.
- Table A.22 is shows a robustness for to Table 1.3 in the main text, showing strategy combinations with AD and one or two generalized Semi-Grim strategies.
- Table A.25 is a robustness check for Table A.3 by focussing on continuation strategies.
- Table A.26 is a robustness for Table 1.4 in the main text, showing the additional stratgey combination SG+AD.
- Table A.28 shows aggregate state-wise cooperation rates for different lagged histories (cooperation or defection of the opponent in $t-2$) *TFT-Scheme*.
- Table A.29 shows aggregate state-wise cooperation rates for different lagged histories (joint cooperation or not in $t-2$) *Grim-Scheme*.
- Table A.31 compares different models containing semi-grim to models containing pure strategies assuming no-switching behavior.
- Table A.33 compares different models containing semi-grim to models containing pure strategies assuming random-switching behavior.
- Table A.35 compares different models containing modifications of semi-grim.

- Table A.37 compares different models containing prototypical strategies derived from strategies discussed in previous literature in a No-Switching model.
- Table A.39 compares different two parameter versions of semi-grim with models containing prototypical strategies. The memory-2 level follows a *Grim-Scheme* if applicable
- Table A.40 compares different two parameter versions of semi-grim with models containing prototypical strategies. The memory-2 level follows a *TFT-Scheme* if applicable
- Table A.41 examines all mixtures of Semi-Grim with pure or generalized pure strategies as secondary components.

Table A.13: Pure, mixed, or switching strategies? (ICL-BIC of the models, less is better and relation signs point toward better models)

	Best w/o SG					All but SG				
	No Switching		Random Switching		Markov Switching	No Switching		Random Switching		Markov Switching
Specification										
Models evaluated	5^{32}		5^{32}		5^{32}	1		1		1
Pars est. (by treat.)	16		16		82	5		5		30
Pars accounted for	3–5		3–5		12–30	5		5		30
First halves per session										
Aoyagi and Frechette (2009)	843.08	≈	834.4	≈	845.51	886.44	≈	866.95	≈	892.7
Blonski et al. (2011)	1069.58	≈	1104.85	≪	1221.28	1114.69	≈	1157.02	≪	1615.75
Bruttel and Kamecke (2012)	845.41	≈	845.05	>	785.49	845.41	≈	846.82	>	811.17
Dal Bó (2005)	651.88	<	689.58	>	652.36	666.1	<	702.56	≈	729
Dal Bó and Fréchette (2011)	7164.32	≪	7557.8	≫	6422.83	7423.23	<	7705.11	≫	6913.83
Dal Bó and Fréchette (2015)	8756.15	≪	9253.62	≫	8275.74	8880.62	≪	9330.5	≫	8571.44
Dreber et al. (2008)	863.26	≈	864.49	≫	752.16	871.32	≈	880.55	≫	809.71
Duffy and Ochs (2009)	1396.68	<	1467.36	≫	1372.99	1448.71	<	1497.48	>	1444.51
Fréchette and Yuksel (2017)	313.03	≈	337.5	>	301.74	321.32	≈	337.5	≈	332.73
Fudenberg et al. (2012)	451.47	≈	435.83	≈	435.86	454.09	≈	437.74	≈	455.21
Kagel and Schley (2013)	2685.4	≪	3010.1	≫	2439.06	2735.02	≪	3041.29	≫	2581.96
Sherstyuk et al. (2013)	1346.41	<	1481.65	≫	1296.85	1389.33	<	1483.17	≫	1333.21
Pooled	**26525.91**	≪	**28023.06**	≫	**25411.21**	**27218.66**	≪	**28469.06**	≫	**27585.46**
Second halves per session										
Aoyagi and Frechette (2009)	492.28	≈	484.05	≈	482.82	534.29	≈	514.94	≈	547.48
Blonski et al. (2011)	1462.41	≈	1513.92	<	1604.87	1503.41	≈	1554.93	≪	1973.56
Bruttel and Kamecke (2012)	561.63	≈	627.74	≫	516.71	588.33	≈	632.75	>	584.4
Dal Bó (2005)	741.2	<	790.21	>	743.74	751.82	≪	814.54	≈	823.78
Dal Bó and Fréchette (2011)	5646.38	≪	6634.92	≫	5110.1	6065.93	≪	6783.93	≫	5634.97
Dal Bó and Fréchette (2015)	8951.57	≪	9835.77	≫	8264.26	9085.4	≪	9876.09	≫	8601.02
Dreber et al. (2008)	648.55	≈	681.35	>	588.62	656.38	≈	702.27	≈	672.66
Duffy and Ochs (2009)	1925.24	≈	1992.71	≫	1883.22	2010.01	≈	2038.28	>	1977.9
Fréchette and Yuksel (2017)	433.18	<	474.93	>	427.79	469.85	≈	493.4	≈	474.8
Fudenberg et al. (2012)	528.36	≈	545.76	≈	529.88	530.3	≈	547.36	≈	549.27
Kagel and Schley (2013)	1751.81	≪	2365.94	≫	1678.7	1866.19	≪	2375.6	≫	1777.72
Sherstyuk et al. (2013)	1025.32	≪	1177.96	≫	1008.49	1027.43	≪	1180.11	≫	1025.75
Pooled	**24301.45**	≪	**27269.48**	≫	**23494.22**	**25271.72**	≪	**27696.6**	≫	**25737.55**

Note: Relation signs are used as defined above (Table A.9). "No Switching", "Random Switching" and "Markov Switching" are as defined in the text, but briefly: "No Switching" assumes that each subject randomly chooses a strategy prior to the first supergame and plays this strategy constantly for the entire half session. "Random Switching" assumes that each subject randomly chooses a strategy prior to each supergame (by i.i.d. draws), and "Markov Switching" allows that these switches follow a Markov process. "All but SG" allows subjects to play either AD, Grim, TFT, AC or WSLS, and "Best w/o SG" picks the best mixture model after eliminating AC or WSLS, or both or none of these.

Table A.14: Table A.13 by treatments – Pure, mixed, or switching strategies?

(a) First halves per session

	Best w/o SG					All but SG				
	No Switching		Random Switching		Markov Switching	No Switching		Random Switching		Markov Switching
Specification										
Models evaluated	5^{32}		5^{32}		5^{32}	1		1		1
Pars est. (by treat.)	16		16		82	5		5		30
Pars accounted for	3–5		3–5		12–30	5		5		30
AF09–34	843.08	≈	834.4	≈	845.51	886.44	≈	866.95	≈	892.7
BOS11–9	83.42	≈	83.96	≈	88.41	85.17	≈	86.21	≪	112.66
BOS11–14	97.73	≈	90	≈	92.94	100.72	≈	93	≪	119.36
BOS11–15	34.3	≈	32.69	≪	43.18	37.29	≈	35.69	≪	69.59
BOS11–16	167.3	≈	169.38	≈	170.57	176.55	≈	180.23	<	197.16
BOS11–17	110.57	≈	118.71	≈	121.05	113.57	≈	121.87	≪	147.65
BOS11–26	256.88	≈	262.33	≈	257.54	260.57	≈	270.79	≈	286.48
BOS11–27	102.11	≈	112.76	≈	111.44	103.61	≈	114.26	≈	132.37
BOS11–30	56.81	≈	65.61	≈	64.33	59.81	≈	68.31	<	91.33
BOS11–31	125.82	≈	135.1	≈	142.43	127.32	≈	136.59	<	158.7
BK12–28	845.41	≈	845.05	>	785.49	845.41	≈	846.82	>	811.17
D05–18	235.84	≈	234.95	≈	235.63	241.39	≈	243.54	<	266.02
D05–19	413.65	<	452.05	≫	408.22	421.17	<	455.47	≈	441.71
DF11–6	810.5	<	925.1	>	770.36	880.04	≈	949.19	≈	847.92
DF11–7	1349.47	≈	1364.07	≫	1132.04	1423.93	≈	1388.73	≫	1227.66
DF11–8	1496.25	≪	1712.65	≫	1279.8	1515.51	<	1714.28	≫	1316.15
DF11–22	1154.93	≈	1122.94	≈	1066.33	1192.92	≈	1161.02	≈	1141.85
DF11–23	1142.96	≈	1217.02	≫	1020.09	1144.78	≈	1218.9	≫	1066.21
DF11–24	1188.68	≈	1194.48	≫	1046.5	1239.14	≈	1246.06	>	1152.48
DF15–4	431.07	≈	467.36	>	395.89	460.23	≈	478.56	≈	441.94
DF15–5	1763.19	≪	2211.16	≫	1646.78	1808.3	≪	2212.37	≫	1686.31
DF15–20	1569.49	≈	1543.46	≫	1439.66	1588.62	≈	1571.15	>	1501.57
DF15–21	2012.6	≪	2221.98	≫	1943.68	2015.1	≪	2224.97	≫	1960.65
DF15–33	2552.94	>	2400.56	≈	2336.73	2573.89	>	2423.22	≈	2389.72
DF15–35	403.53	≈	385.77	≈	396.36	405.32	≈	391.08	≪	416.29
DRFN08–10	410.24	≈	390.77	>	334.73	413.58	≈	400.1	>	362.2
DRFN08–11	450.5	≈	470.91	≫	405.73	454.24	≈	476.95	≫	426.5
DO09–32	1396.68	<	1467.36	≫	1372.99	1448.71	<	1497.48	>	1444.51
FY17–25	313.03	≈	337.5	>	301.74	321.32	≈	337.5	≈	332.73
FRD12–29	451.47	≈	435.83	≈	435.86	454.09	≈	437.74	≈	455.21
KS13–12	2685.4	≪	3010.1	≫	2439.06	2735.02	≪	3041.29	≫	2581.96
STS13–13	1346.41	<	1481.65	≫	1296.85	1389.33	<	1483.17	≫	1333.21
AF09	843.08	≈	834.4	≈	845.51	886.44	≈	866.95	≈	892.7
BOS11	1069.58	≈	1104.85	≪	1221.28	1114.69	≈	1157.02	≪	1615.75
BK12	845.41	≈	845.05	>	785.49	845.41	≈	846.82	>	811.17
D05	651.88	<	689.58	>	652.36	666.1	<	702.56	≈	729
DF11	7164.32	≪	7557.8	≫	6422.83	7423.23	<	7705.11	≫	6913.83
DF15	8756.15	≪	9253.62	≫	8275.74	8880.62	≪	9330.5	≫	8571.44
DRFN08	863.26	≈	864.49	≫	752.16	871.32	≈	880.55	≫	809.71
DO09	1396.68	<	1467.36	≫	1372.99	1448.71	<	1497.48	>	1444.51
FY17	313.03	≈	337.5	>	301.74	321.32	≈	337.5	≈	332.73
FRD12	451.47	≈	435.83	≈	435.86	454.09	≈	437.74	≈	455.21
KS13	2685.4	≪	3010.1	≫	2439.06	2735.02	≪	3041.29	≫	2581.96
STS13	1346.41	<	1481.65	≫	1296.85	1389.33	<	1483.17	≫	1333.21
Pooled	**26525.91**	≪	**28023.06**	≫	**25411.21**	**27218.66**	≪	**28469.06**	≫	**27585.46**

(b) Second halves per session

	Best w/o SG					All but SG				
	No Switching		Random Switching		Markov Switching	No Switching		Random Switching		Markov Switching
Specification										
Models evaluated	5^{32}		5^{32}		5^{32}	1		1		1
Pars est. (by treat.)	16		16		82	5		5		30
Pars accounted for	3–5		3–5		12–30	5		5		30
AF09–34	492.28	≈	484.05	≈	482.82	534.29	≈	514.94	≈	547.48
BOS11–9	84.22	≈	96.42	≈	88.85	87.22	≈	99.64	≈	115.59
BOS11–14	40.82	≈	40.83	<	50.24	43.82	≈	43.83	≪	77.2
BOS11–15	15.52	≈	15.52	≪	29.01	18.52	≈	18.52	≪	55.98
BOS11–16	157.48	≈	165.09	≈	157.84	160.48	≈	169.38	≈	183.26
BOS11–17	229.75	≈	225.64	≈	219.73	232.75	≈	230.42	≈	245.01
BOS11–26	366.88	≈	365.76	≈	350.94	369.98	≈	367.47	≈	374.89
BOS11–27	226.92	≈	255.26	≈	243.72	228.41	≈	256.76	≈	258.15
BOS11–30	146.49	≈	137.43	≈	145.96	149.49	≈	143.16	<	172.77
BOS11–31	161.17	≈	174.2	≈	173.52	162.67	≈	175.69	≈	190.25
BK12–28	561.63	≈	627.74	≫	516.71	588.33	≈	632.75	>	584.4
D05–18	350.59	≈	359.16	≈	351.93	355.62	≈	361.11	<	383.77
D05–19	388.49	<	428.21	≫	383.3	392.65	≪	449.88	>	418.75
DF11–6	633.6	≈	693.84	≈	557.16	751.56	≈	723.62	≈	654.48
DF11–7	1427.15	<	1645.34	≫	1268.34	1571.76	≈	1692.09	≫	1428.39
DF11–8	1139.15	≪	1646.78	≫	960.35	1142.1	≪	1648.58	≫	978.71
DF11–22	1196.64	≈	1160.77	≫	1018.52	1198.53	≈	1190.83	>	1068.63
DF11–23	723.5	≪	970.63	≫	737.29	842.37	<	979.34	>	820.55
DF11–24	504.8	≈	496.02	≈	460.73	532.68	≈	522.54	≈	522.66
DF15–4	331.12	≈	402.51	≈	339.15	345.97	≈	407.07	≈	379.36
DF15–5	1666.6	≪	2234.36	≫	1438.87	1686.18	≪	2235.53	≫	1466.72
DF15–20	1572.51	≈	1548.84	≫	1339.13	1572.51	≈	1558.84	≫	1379.3
DF15–21	1664.01	≪	1914.7	≫	1504.63	1754.13	<	1914.7	≫	1620.64
DF15–33	2913.27	≈	2919.03	≫	2735.52	2915.83	≈	2936.72	≫	2771.7
DF15–35	779.84	≈	792.29	≈	790.32	781.64	≈	794.07	≈	808.34
DRFN08–10	301.08	≈	289.13	≈	251.55	304.41	≈	303.62	≈	287.94
DRFN08–11	345.37	≈	389.41	>	323.06	348.47	≈	395.16	≈	363.7
DO09–32	1925.24	≈	1992.71	≫	1883.22	2010.01	≈	2038.28	>	1977.9
FY17–25	433.18	<	474.93	>	427.79	469.85	≈	493.4	≈	474.8
FRD12–29	528.36	≈	545.76	≈	529.88	530.3	≈	547.36	≈	549.27
KS13–12	1751.81	≪	2365.94	≫	1678.7	1866.19	≪	2375.6	≫	1777.72
STS13–13	1025.32	≪	1177.96	≫	1008.49	1027.43	≪	1180.11	≫	1025.75
AF09	492.28	≈	484.05	≈	482.82	534.29	≈	514.94	≈	547.48
BOS11	1462.41	≈	1513.92	<	1604.87	1503.41	≈	1554.93	≪	1973.56
BK12	561.63	≈	627.74	≫	516.71	588.33	≈	632.75	>	584.4
D05	741.2	<	790.21	>	743.74	751.82	≪	814.54	≈	823.78
DF11	5646.38	≪	6634.92	≫	5110.1	6065.93	≪	6783.93	≫	5634.97
DF15	8951.57	≪	9835.77	≫	8264.26	9085.4	≪	9876.09	≫	8601.02
DRFN08	648.55	≈	681.35	>	588.62	656.38	≈	702.27	≈	672.66
DO09	1925.24	≈	1992.71	≫	1883.22	2010.01	≈	2038.28	>	1977.9
FY17	433.18	<	474.93	>	427.79	469.85	≈	493.4	≈	474.8
FRD12	528.36	≈	545.76	≈	529.88	530.3	≈	547.36	≈	549.27
KS13	1751.81	≪	2365.94	≫	1678.7	1866.19	≪	2375.6	≫	1777.72
STS13	1025.32	≪	1177.96	≫	1008.49	1027.43	≪	1180.11	≫	1025.75
Pooled	**24301.45**	≪	**27269.48**	≫	**23494.22**	**25271.72**	≪	**27696.6**	≫	**25737.55**

Note: Notation of treatments and meaning of relation signs are all as defined above, see Table A.9.

Table A.15: Pure, mixed, or switching strategies? Best mixtures of continuation strategies (not including round 1) without Semi-Grim (ICL-BIC of the models, less is better and relation signs point toward better models)

	Best mixture of pure strategies					Best mixture of generalized pure strategies (type II)				
	No Switching		Random Switching		Markov Switching	No Switching		Random Switching		Markov Switching
Specification										
# Models evaluated	4^{32}		4^{32}		4^{32}	4^{32}		4^{32}		4^{32}
# Pars estimated (by treatment) (by treatment)	16		16		82	32		32		98
# Parameters accounted for (by treatment)	3–5		3–5		12–30	6–10		6–10		15–35
First halves per session										
Aoyagi and Frechette (2009)	744.79	≈	733.65	≈	746.14	645.31	≈	646.53	≈	649.53
Blonski et al. (2011)	669.18	≫	621.56	≪	843	713.8	≫	670.62	≪	875.74
Bruttel and Kamecke (2012)	590.68	≈	581	≈	590.89	585.42	≈	570.56	≈	570.87
Dal Bó (2005)	390.88	≫	363.41	≪	393	407.86	≫	378.95	<	404.78
Dal Bó and Fréchette (2011)	3719.86	≈	3729.53	≈	3670.79	3536.73	≈	3589.36	≈	3524.77
Dal Bó and Fréchette (2015)	5494.71	≫	5264.13	≈	5303.29	5259.64	≫	5037.82	≈	5057.54
Dreber et al. (2008)	455.55	≈	461.78	≈	481.64	478.09	≈	466.13	≈	482.86
Duffy and Ochs (2009)	1069.16	≈	1076.16	≈	1069.38	1047.59	≈	1053.04	≈	1049.79
Fréchette and Yuksel (2017)	181.98	≫	158.34	≪	176.5	188.5	≈	183.48	≈	175.59
Fudenberg et al. (2012)	356.73	>	331.44	<	347.07	319.45	≈	308.6	≈	320.55
Kagel and Schley (2013)	1776.53	≈	1837.93	≫	1715.12	1761.98	≈	1780.97	>	1694.94
Sherstyuk et al. (2013)	926.9	≈	953.91	>	912.67	865.67	≈	907.14	>	858.65
Pooled	**16515.74**	>	**16251.31**	≪	**16837.05**	**16077.95**	>	**15853.82**	≪	**16335.33**
Second halves per session										
Aoyagi and Frechette (2009)	448.52	≈	431.35	≈	432.41	363.58	≈	368.23	≈	368.89
Blonski et al. (2011)	967.16	≫	914.28	≪	1140.5	992.44	≈	993.71	≪	1154.56
Bruttel and Kamecke (2012)	342.17	≈	361.38	≈	348.88	344.88	≈	358.12	≈	347.08
Dal Bó (2005)	462.39	≈	445.5	≪	474.71	475.11	≈	456.4	≈	469.98
Dal Bó and Fréchette (2011)	2957.24	≈	3076.88	≈	2979.53	2737.11	<	2875.64	>	2721.88
Dal Bó and Fréchette (2015)	5537.83	>	5419.19	≈	5438.75	5164.78	≈	5105.6	≈	5116.42
Dreber et al. (2008)	287.58	≈	285.34	<	303.79	295.06	≈	297.88	≈	303.03
Duffy and Ochs (2009)	1555.1	≈	1599.27	≈	1561.56	1381.01	≈	1416.71	≈	1392.49
Fréchette and Yuksel (2017)	333.32	≈	309.06	≈	325.58	309.63	≈	304.7	≈	308.78
Fudenberg et al. (2012)	443.13	≈	439.28	≈	444.41	373.44	≈	395.32	≈	376.62
Kagel and Schley (2013)	1191.45	<	1301.1	≫	1187.17	1170.12	≈	1224.37	>	1143.67
Sherstyuk et al. (2013)	587.45	<	640.1	>	597.28	527.09	≈	590.16	≈	567.63
Pooled	**15249.49**	≈	**15361.1**	≪	**15841.93**	**14387.48**	<	**14656.93**	≈	**14961.61**

Note: Relation signs are used as defined above (Table A.9). "No Switching", "Random Switching" and "Markov Switching" are as defined in the text, but briefly: "No Switching" assumes that each subject randomly chooses a strategy prior to the first supergame and plays this strategy constantly for the entire half session. "Random Switching" assumes that each subject randomly chooses a strategy prior to each supergame (by i.i.d. draws), and "Markov Switching" allows that these switches follow a Markov process. "Best mixture of pure strategies" starts with the general mixture model allowing subjects to play AD, Grim, TFT, AC or WSLS and picks the best-fitting model after eliminating AC or WSLS, or both or none of these. The "Best mixture of generalized strategies" additionally allows for randomization based on these proto-typical strategies as defined in the main text.

Table A.16: Pure, mixed, or switching strategies? Best mixtures without Semi-Grim, including first round behavior. (ICL-BIC of the models, less is better and relation signs point toward better models)

			Best mixture of pure strategies					Best mixture of generalized pure strategies				
	Baseline Model		No Switching		Random Switching		Markov Switching	No Switching		Random Switching		Markov Switching
Specification												
# Models evaluated	1		5^{32}		5^{32}		5^{32}	8^{32}		8^{32}		8^{32}
# Pars estimated (by treatment)	5		16		16		82	64		64		196
# Parameters accounted for	5		3–5		3–5		12–30	6–10		6–10		15–35
First halves per session												
Aoyagi and Frechette (2009)	886.44	≈	843.08	≈	834.4	≈	845.51	756.95	≈	763.11	≈	755.97
Blonski et al. (2011)	1114.69	≫	1069.58	≈	1104.85	≪	1221.28	1134.67	≈	1173.15	≪	1272.13
Bruttel and Kamecke (2012)	845.41	≈	845.41	≈	845.05	>	785.49	817.89	≈	835.6	>	787.63
Dal Bó (2005)	666.1	≈	651.88	<	689.58	>	652.36	641.98	<	674.57	≈	653.11
Dal Bó and Fréchette (2011)	7423.23	>	7164.32	≪	7557.8	≫	6422.83	6921.58	≪	7467.72	≫	6465.99
Dal Bó and Fréchette (2015)	8880.62	>	8756.15	≪	9253.62	≫	8275.74	8446	≪	9183.55	≫	8168.2
Dreber et al. (2008)	871.32	≈	863.26	≈	864.49	≫	752.16	787.71	<	865.64	≫	763.43
Duffy and Ochs (2009)	1448.71	≈	1396.68	<	1467.36	≫	1372.99	1395.4	<	1461.01	>	1394.31
Fréchette and Yuksel (2017)	321.32	≈	313.03	≈	337.5	>	301.74	300.87	<	345.74	>	298.53
Fudenberg et al. (2012)	454.09	≈	451.47	≈	435.83	≈	435.86	432.32	≈	432.38	≈	425.54
Kagel and Schley (2013)	2735.02	≈	2685.4	≪	3010.1	≫	2439.06	2709.95	≪	2993.4	≫	2539.99
Sherstyuk et al. (2013)	1389.33	≈	1346.41	<	1481.65	≫	1296.85	1322.6	≪	1450	≫	1298.37
Pooled	**27218.66**	≫	**26525.91**	≪	**28023.06**	≫	**25411.21**	**25933.42**	≪	**27915.32**	≫	**25504.76**
Second halves per session												
Aoyagi and Frechette (2009)	534.29	≈	492.28	≈	484.05	≈	482.82	416.51	≈	437.8	≈	423.05
Blonski et al. (2011)	1503.41	≫	1462.41	≈	1513.92	<	1604.87	1414.39	≪	1553.12	≈	1609.79
Bruttel and Kamecke (2012)	588.33	≈	561.63	≈	627.74	≫	516.71	538.17	<	611.91	≫	525.5
Dal Bó (2005)	751.82	≈	741.2	<	790.21	>	743.74	737.05	<	786.21	>	741.54
Dal Bó and Fréchette (2011)	6065.93	>	5646.38	≪	6634.92	≫	5110.1	5220.17	≪	6378.16	≫	5069.04
Dal Bó and Fréchette (2015)	9085.4	>	8951.57	≪	9835.77	≫	8264.26	8205.77	≪	9401.19	≫	7947.33
Dreber et al. (2008)	656.38	≈	648.55	≈	681.35	>	588.62	619.9	≈	662.24	>	596.78
Duffy and Ochs (2009)	2010.01	≈	1925.24	≈	1992.71	≫	1883.22	1883.52	≈	1914.83	>	1850.35
Fréchette and Yuksel (2017)	469.85	≈	433.18	<	474.93	>	427.79	438.55	<	478.2	≈	434.61
Fudenberg et al. (2012)	530.3	≈	528.36	≈	545.76	≈	529.88	514.87	≈	516.12	≈	515.97
Kagel and Schley (2013)	1866.19	≈	1751.81	≪	2365.94	≫	1678.7	1808.21	≪	2336.29	≫	1718.07
Sherstyuk et al. (2013)	1027.43	≈	1025.32	≪	1177.96	≫	1008.49	955.73	≪	1137.49	≫	958.99
Pooled	**25271.72**	≫	**24301.45**	≪	**27269.48**	≫	**23494.22**	**23009.84**	≪	**26479.73**	≫	**23143.38**

Note: Relation signs are used as defined above (Table A.9). "No Switching", "Random Switching" and "Markov Switching" are as defined in the text, but briefly: "No Switching" assumes that each subject randomly chooses a strategy prior to the first supergame and plays this strategy constantly for the entire half session. "Random Switching" assumes that each subject randomly chooses a strategy prior to each supergame (by i.i.d. draws), and "Markov Switching" allows that these switches follow a Markov process. "Best mixture of pure strategies" starts with the general mixture model allowing subjects to play AD, Grim, TFT, AC or WSLS and picks the best-fitting model after eliminating AC or WSLS, or both or none of these. The "Best mixture of generalized strategies" additionally allows for randomization in the first round.

Table A.17: Table A.16 by treatments – Pure, mixed, or switching strategies? Best mixtures without Semi-Grim

(a) First halves per session

	Baseline Model		Best mixture of pure strategies: No Switching		Random Switching		Markov Switching	Best mixture of generalized pure strategies: No Switching		Random Switching		Markov Switching
Specification												
# Models evaluated	1		5^{32}		5^{32}		5^{32}	8^{32}		8^{32}		8^{32}
# Pars estimated (by treatment)	5		16		16		82	64		64		196
# Parameters accounted for	5		3–5		3–5		12–30	6–10		6–10		15–35
AF09–34	886.44	≈	843.08	≈	834.4	≈	845.51	756.95	≈	763.11	≈	755.97
BOS11–9	85.17	≈	83.42	≈	83.96	≈	88.41	89.7	≈	87.81	≈	91.36
BOS11–14	100.72	≈	97.73	≈	90	≈	92.94	102.27	≈	94.44	≈	96.5
BOS11–15	37.29	≈	34.3	≈	32.69	≪	43.18	38.79	≈	37.18	≈	44.74
BOS11–16	176.55	≈	167.3	≈	169.38	≈	170.57	168.92	≈	176.43	≈	174.73
BOS11–17	113.57	≈	110.57	≈	118.71	≈	121.05	115.07	≈	123.19	≈	123.74
BOS11–26	260.57	≈	256.88	≈	262.33	≈	257.54	257.82	≈	269.17	≈	256.37
BOS11–27	103.61	≈	102.11	≈	112.76	≈	111.44	103.44	≈	114.9	≈	110.81
BOS11–30	59.81	>	56.81	≈	65.61	≈	64.33	60.42	≈	68.55	≈	68.16
BOS11–31	127.32	≈	125.82	≈	135.1	≈	142.43	129.65	≈	137.48	≈	145.13
BK12–28	845.41	≈	845.41	≈	845.05	>	785.49	817.89	≈	835.6	>	787.63
D05–18	241.39	≈	235.84	≈	234.95	≈	235.63	241.44	≈	230.66	≈	238.66
D05–19	421.17	≈	413.65	<	452.05	≫	408.22	396.28	≪	439.65	>	403.81
DF11–6	880.04	≈	810.5	<	925.1	>	770.36	823.69	≈	909.31	>	772.55
DF11–7	1423.93	>	1349.47	≈	1364.07	≫	1132.04	1297.64	<	1370.65	≫	1181.36
DF11–8	1515.51	≈	1496.25	≪	1712.65	≫	1279.8	1422.73	≪	1668.83	≫	1284.25
DF11–22	1192.92	≈	1154.93	≈	1122.94	≈	1066.33	1080.23	≈	1110.68	≈	1056.77
DF11–23	1144.78	≈	1142.96	≈	1217.02	≫	1020.09	1082.68	<	1185.69	≫	1027.3
DF11–24	1239.14	≈	1188.68	≈	1194.48	≫	1046.5	1171.57	≈	1179.6	≫	1022.62
DF15–4	460.23	>	431.07	≈	467.36	>	395.89	439.54	≈	474.37	≫	412.27
DF15–5	1808.3	≈	1763.19	≪	2211.16	≫	1646.78	1762.23	≪	2211.09	≫	1638.92
DF15–20	1588.62	≈	1569.49	≈	1543.46	≫	1439.66	1463.03	<	1547.14	≫	1433.87
DF15–21	2015.1	≈	2012.6	≪	2221.98	≫	1943.68	1974.94	≪	2184.97	≫	1902.95
DF15–33	2573.89	≈	2552.94	>	2400.56	≈	2336.73	2379.17	≈	2350.87	≈	2296.41
DF15–35	405.32	≈	403.53	≈	385.77	≈	396.36	384.6	≈	372.62	≈	382.07
DRFN08–10	413.58	≈	410.24	≈	390.77	>	334.73	374.3	≈	391.56	>	339.73
DRFN08–11	454.24	≈	450.5	≈	470.91	≫	405.73	408.63	<	468.48	≫	413.19
DO09–32	1448.71	≈	1396.68	<	1467.36	≫	1372.99	1395.4	<	1461.01	>	1394.31
FY17–25	321.32	≈	313.03	≈	337.5	>	301.74	300.87	<	345.74	>	298.53
FRD12–29	454.09	≈	451.47	≈	435.83	≈	435.86	432.32	≈	432.38	≈	425.54
KS13–12	2735.02	≈	2685.4	≪	3010.1	≫	2439.06	2709.95	≪	2993.4	≫	2539.99
STS13–13	1389.33	≈	1346.41	<	1481.65	≫	1296.85	1322.6	≪	1450	≫	1298.37
Aoyagi and Frechette (2009)	886.44	≈	843.08	≈	834.4	≈	845.51	756.95	≈	763.11	≈	755.97
Blonski et al. (2011)	1114.69	≫	1069.58	≈	1104.85	≪	1221.28	1134.67	≈	1173.15	≪	1272.13
Bruttel and Kamecke (2012)	845.41	≈	845.41	≈	845.05	>	785.49	817.89	≈	835.6	>	787.63
Dal Bó (2005)	666.1	≈	651.88	<	689.58	>	652.36	641.98	<	674.57	≈	653.11
Dal Bó and Fréchette (2011)	7423.23	>	7164.32	≪	7557.8	≫	6422.83	6921.58	≪	7467.72	≫	6465.99
Dal Bó and Fréchette (2015)	8880.62	>	8756.15	≪	9253.62	≫	8275.74	8446	≪	9183.55	≫	8168.2
Dreber et al. (2008)	871.32	≈	863.26	≈	864.49	≫	752.16	787.71	<	865.64	≫	763.43
Duffy and Ochs (2009)	1448.71	≈	1396.68	<	1467.36	≫	1372.99	1395.4	<	1461.01	>	1394.31
Fréchette and Yuksel (2017)	321.32	≈	313.03	≈	337.5	>	301.74	300.87	<	345.74	>	298.53
Fudenberg et al. (2012)	454.09	≈	451.47	≈	435.83	≈	435.86	432.32	≈	432.38	≈	425.54
Kagel and Schley (2013)	2735.02	≈	2685.4	≪	3010.1	≫	2439.06	2709.95	≪	2993.4	≫	2539.99
Sherstyuk et al. (2013)	1389.33	≈	1346.41	<	1481.65	≫	1296.85	1322.6	≪	1450	≫	1298.37
Pooled	**27218.66**	≫	**26525.91**	≪	**28023.06**	≫	**25411.21**	**25933.42**	≪	**27915.32**	≫	**25504.76**

(b) Second halves per session

	Baseline Model		Best mixture of pure strategies: No Switching		Random Switching		Markov Switching	Best mixture of generalized pure strategies: No Switching		Random Switching		Markov Switching
Specification												
# Models evaluated	1		5^{32}		5^{32}		5^{32}	8^{32}		8^{32}		8^{32}
# Pars estimated (by treatment)	5		16		16		82	64		64		196
# Parameters accounted for	5		3–5		3–5		12–30	6–10		6–10		15–35
AF09–34	534.29	≈	492.28	≈	484.05	≈	482.82	416.51	≈	437.8	≈	423.05
BOS11–9	87.22	≈	84.22	≈	96.42	≈	88.85	78.84	<	103.47	≈	83.98
BOS11–14	43.82	≈	40.82	≈	40.83	<	50.24	45.31	≈	42.43	≈	48.97
BOS11–15	18.52	≈	15.52	≈	15.52	≪	29.01	20.01	≈	20.01	≪	33.5
BOS11–16	160.48	≈	157.48	≈	165.09	≈	157.84	148.98	≈	168.12	≈	158.84
BOS11–17	232.75	≈	229.75	≈	225.64	≈	219.73	211.59	≈	225.1	≈	216.6
BOS11–26	369.98	≈	366.88	≈	365.76	≈	350.94	327.16	≈	352.05	≈	338.09
BOS11–27	228.41	≈	226.92	≈	255.26	≈	243.72	224.85	≈	254.56	≈	233.57
BOS11–30	149.49	>	146.49	≈	137.43	≈	145.96	139.46	≈	139.47	≈	146.9
BOS11–31	162.67	≈	161.17	≈	174.2	≈	173.52	151.87	<	179.31	≈	171.15
BK12–28	588.33	≈	561.63	≈	627.74	≫	516.71	538.17	<	611.91	≫	525.5
D05–18	355.62	≈	350.59	≈	359.16	≈	351.93	340.33	≈	355.81	≈	346.45
D05–19	392.65	≈	388.49	<	428.21	≫	383.3	392.47	<	426.15	>	384.46
DF11–6	751.56	≈	633.6	≈	693.84	≈	557.16	579.84	≈	628.84	≈	565.43
DF11–7	1571.76	>	1427.15	<	1645.34	≫	1268.34	1359.89	≪	1582.11	≫	1299.86
DF11–8	1142.1	≈	1139.15	≪	1646.78	≫	960.35	1028.93	≪	1600.86	≫	904.89
DF11–22	1198.53	≈	1196.64	≈	1160.77	≫	1018.52	1012.26	<	1102.07	≫	973.62
DF11–23	842.37	≈	723.5	≪	970.63	≫	737.29	743.89	<	943.35	≫	739.29
DF11–24	532.68	≈	504.8	≈	496.02	≈	460.73	450.61	≈	477.85	≈	455.62
DF15–4	345.97	≈	331.12	≈	402.51	≈	339.15	301.69	<	385.5	≈	307.03
DF15–5	1686.18	≈	1666.6	≪	2234.36	≫	1438.87	1581.28	≪	2217.39	≫	1435.63
DF15–20	1572.51	≈	1572.51	≈	1548.84	≫	1339.13	1273.14	≪	1441.16	≫	1270.1
DF15–21	1754.13	≈	1664.01	≪	1914.7	≫	1504.63	1688.09	<	1878.92	≫	1544.66
DF15–33	2915.83	≈	2913.27	≈	2919.03	≫	2735.52	2582.61	<	2690.87	≫	2541.5
DF15–35	781.64	≈	779.84	≈	792.29	≈	790.32	733.28	≈	742.93	≈	723.78
DRFN08–10	304.41	≈	301.08	≈	289.13	≈	251.55	276.61	≈	285.26	≈	243.71
DRFN08–11	348.47	≈	345.37	≈	389.41	>	323.06	339.09	≈	371.38	≈	339.95
DO09–32	2010.01	≈	1925.24	≈	1992.71	≫	1883.22	1883.52	≈	1914.83	>	1850.35
FY17–25	469.85	≈	433.18	<	474.93	>	427.79	438.55	<	478.2	≈	434.61
FRD12–29	530.3	≈	528.36	≈	545.76	≈	529.88	514.87	≈	516.12	≈	515.97
KS13–12	1866.19	≈	1751.81	≪	2365.94	≫	1678.7	1808.21	≪	2336.29	≫	1718.07
STS13–13	1027.43	≈	1025.32	≪	1177.96	≫	1008.49	955.73	≪	1137.49	≫	958.99
Aoyagi and Frechette (2009)	534.29	≈	492.28	≈	484.05	≈	482.82	416.51	≈	437.8	≈	423.05
Blonski et al. (2011)	1503.41	≫	1462.41	≈	1513.92	<	1604.87	1414.39	≪	1553.12	≈	1609.79
Bruttel and Kamecke (2012)	588.33	≈	561.63	≈	627.74	≫	516.71	538.17	<	611.91	≫	525.5
Dal Bó (2005)	751.82	≈	741.2	<	790.21	>	743.74	737.05	<	786.21	>	741.54
Dal Bó and Fréchette (2011)	6065.93	>	5646.38	≪	6634.92	≫	5110.1	5220.17	≪	6378.16	≫	5069.04
Dal Bó and Fréchette (2015)	9085.4	>	8951.57	≪	9835.77	≫	8264.26	8205.77	≪	9401.19	≫	7947.33
Dreber et al. (2008)	656.38	≈	648.55	≈	681.35	>	588.62	619.9	≈	662.24	>	596.78
Duffy and Ochs (2009)	2010.01	≈	1925.24	≈	1992.71	≫	1883.22	1883.52	≈	1914.83	>	1850.35
Fréchette and Yuksel (2017)	469.85	≈	433.18	<	474.93	>	427.79	438.55	<	478.2	≈	434.61
Fudenberg et al. (2012)	530.3	≈	528.36	≈	545.76	≈	529.88	514.87	≈	516.12	≈	515.97
Kagel and Schley (2013)	1866.19	≈	1751.81	≪	2365.94	≫	1678.7	1808.21	≪	2336.29	≫	1718.07
Sherstyuk et al. (2013)	1027.43	≈	1025.32	≪	1177.96	≫	1008.49	955.73	≪	1137.49	≫	958.99
Pooled	**25271.72**	≫	**24301.45**	≪	**27269.48**	≫	**23494.22**	**23009.84**	≪	**26479.73**	≫	**23143.38**

Note: Notation of treatments and meaning of relation signs are all as defined above, see Table A.9.

Table A.18: Best mixtures of pure strategies in relation to a Semi-Grim behavior strategy (ICL-BIC of the models, less is better and relation signs point toward better models)

	Best mixture of pure strategies									
	No Switching		Random Switching		Markov Switching	Best Switching		Semi-Grim		AD + SG
Specification										
# Models evaluated	5^{32}		5^{32}		5^{32}			1		1
# Pars estimated (by treatment)	16		16		82			3		5
# Parameters accounted for	3–5		3–5		12–35			3		5
First halves per session										
Aoyagi and Frechette (2009)	843.08	$\approx$	834.4	$\approx$	845.51	845.51	$\gg$	781.86	$\approx$	792.51
Blonski et al. (2011)	1069.58	$\approx$	1104.85	$\ll$	1221.28	1221.28	$\gg$	1069.28	$\approx$	1104.6
Bruttel and Kamecke (2012)	845.41	$\approx$	845.05	$>$	785.49	785.49	$\approx$	800.12	$\approx$	771.14
Dal Bó (2005)	651.88	$<$	689.58	$>$	652.36	652.36	$\approx$	629.17	$\approx$	618.39
Dal Bó and Fréchette (2011)	7164.32	$\ll$	7557.8	$\gg$	6422.83	6422.83	$<$	6597.93	$>$	6352.59
Dal Bó and Fréchette (2015)	8756.15	$\ll$	9253.62	$\gg$	8275.74	8275.74	$>$	8017.59	$\gg$	7830.12
Dreber et al. (2008)	863.26	$\approx$	864.49	$\gg$	752.16	752.16	$\approx$	782.37	$\approx$	764.44
Duffy and Ochs (2009)	1396.68	$<$	1467.36	$\gg$	1372.99	1372.99	$\approx$	1372.97	$\approx$	1361.15
Fréchette and Yuksel (2017)	313.03	$\approx$	337.5	$>$	301.74	301.74	$\approx$	299.62	$\approx$	289.54
Fudenberg et al. (2012)	451.47	$\approx$	435.83	$\approx$	435.86	435.86	$>$	381.01	$\approx$	377.96
Kagel and Schley (2013)	2685.4	$\ll$	3010.1	$\gg$	2439.06	2439.06	$\approx$	2561.76	$\gg$	2450.24
Sherstyuk et al. (2013)	1346.41	$<$	1481.65	$\gg$	1296.85	1296.85	$\approx$	1303.8	$\approx$	1234.52
Pooled	**26525.91**	$\ll$	**28023.06**	$\gg$	**25411.21**	**25411.21**	$\gg$	**24779.85**	$\gg$	**24202.51**
Second halves per session										
Aoyagi and Frechette (2009)	492.28	$\approx$	484.05	$\approx$	482.82	492.28	$\gg$	423.68	$\approx$	421.21
Blonski et al. (2011)	1462.41	$\approx$	1513.92	$<$	1604.87	1462.41	$\gg$	1346.79	$\approx$	1370.16
Bruttel and Kamecke (2012)	561.63	$\approx$	627.74	$\gg$	516.71	561.63	$\approx$	536.77	$\gg$	480.47
Dal Bó (2005)	741.2	$<$	790.21	$>$	743.74	741.2	$>$	699.05	$\approx$	677.24
Dal Bó and Fréchette (2011)	5646.38	$\ll$	6634.92	$\gg$	5110.1	5646.38	$\gg$	5128.69	$\gg$	4565.93
Dal Bó and Fréchette (2015)	8951.57	$\ll$	9835.77	$\gg$	8264.26	8951.57	$\gg$	7825.98	$\gg$	7306.25
Dreber et al. (2008)	648.55	$\approx$	681.35	$>$	588.62	648.55	$>$	589.84	$>$	544.66
Duffy and Ochs (2009)	1925.24	$\approx$	1992.71	$\gg$	1883.22	1925.24	$>$	1761.6	$\gg$	1656.55
Fréchette and Yuksel (2017)	433.18	$<$	474.93	$>$	427.79	433.18	$\approx$	423.34	$\approx$	422.61
Fudenberg et al. (2012)	528.36	$\approx$	545.76	$\approx$	529.88	528.36	$\gg$	452.6	$\approx$	433.74
Kagel and Schley (2013)	1751.81	$\ll$	2365.94	$\gg$	1678.7	1751.81	$\approx$	1775.62	$\gg$	1572.95
Sherstyuk et al. (2013)	1025.32	$\ll$	1177.96	$\gg$	1008.49	1025.32	$\approx$	951.34	$\gg$	834.74
Pooled	**24301.45**	$\ll$	**27269.48**	$\gg$	**23494.22**	**24301.45**	$\gg$	**22097.67**	$\gg$	**20541.83**

Note: This table extends Table A.13 by picking the best switching model per half-session, after picking the best-fitting mixture involving the pure forms of AD, Grim, TFT, AC and WSLS (as above) for each treatment independently, and examining its goodness-of-fit in relation to Semi-Grim and mixtures involving Semi-Grim. The model "AD+SG2" has the same number of degrees of freedom as the Semi-Grim model. In contrast to "Semi-Grim", SG2 has only two decrees of freedom including the noise term.

Table A.19: Table A.18 by treatments – Best mixtures of pure strategies in relation to a Semi-Grim behavior strategy

(a) First halves per session

	Best mixture of pure strategies										
	No Switching		Random Switching		Markov Switching	Best Switching		Semi-Grim		AD + SG
Specification										
# Models evaluated	5^{32}		5^{32}		5^{32}			1		1
# Pars estimated (by treatment)	16		16		82			3		5
# Parameters accounted for	3–5		3–5		12–35			3		5
AF09–34	843.08	≈	834.4	≈	845.51	845.51	≫	781.86	≈	792.51
BOS11–9	83.42	≈	83.96	≈	88.41	88.41	≈	86.56	≈	88.35
BOS11–14	97.73	≈	90	≈	92.94	92.94	≈	93.88	≈	98.01
BOS11–15	34.3	≈	32.69	≪	43.18	43.18	>	37.73	<	43.07
BOS11–16	167.3	≈	169.38	≈	170.57	170.57	≈	167.42	≈	157.13
BOS11–17	110.57	≈	118.71	≈	121.05	121.05	>	115.02	≈	119.79
BOS11–26	256.88	≈	262.33	≈	257.54	257.54	≈	244.5	≈	246.46
BOS11–27	102.11	≈	112.76	≈	111.44	111.44	>	92.83	≈	92.07
BOS11–30	56.81	≈	65.61	≈	64.33	64.33	>	55.74	<	61.12
BOS11–31	125.82	≈	135.1	≈	142.43	142.43	>	125.52	≈	128.49
BK12–28	845.41	≈	845.05	>	785.49	785.49	≈	800.12	≈	771.14
D05–18	235.84	≈	234.95	≈	235.63	235.63	≈	230.57	≈	238.35
D05–19	413.65	<	452.05	≫	408.22	408.22	≈	395.06	≈	375.07
DF11–6	810.5	<	925.1	>	770.36	770.36	≈	794.44	≈	748.9
DF11–7	1349.47	≈	1364.07	≫	1132.04	1132.04	<	1256.83	≈	1229.61
DF11–8	1496.25	≪	1712.65	≫	1279.8	1279.8	<	1389.06	≈	1286.68
DF11–22	1154.93	≈	1122.94	≈	1066.33	1066.33	>	965.96	≈	961.58
DF11–23	1142.96	≈	1217.02	≫	1020.09	1020.09	≈	1019.57	≈	972.17
DF11–24	1188.68	≈	1194.48	≫	1046.5	1046.5	<	1145.15	≈	1115.95
DF15–4	431.07	≈	467.36	>	395.89	395.89	≈	436.57	≈	422.43
DF15–5	1763.19	≪	2211.16	≫	1646.78	1646.78	<	1738.77	≫	1649.1
DF15–20	1569.49	≈	1543.46	≫	1439.66	1439.66	≈	1405.3	>	1366.09
DF15–21	2012.6	≪	2221.98	≫	1943.68	1943.68	>	1872.47	>	1827.37
DF15–33	2552.94	>	2400.56	≈	2336.73	2336.73	>	2186.26	≈	2178.12
DF15–35	403.53	≈	385.77	≈	396.36	396.36	>	349.06	≈	346.18
DRFN08–10	410.24	≈	390.77	>	334.73	334.73	<	367.86	≈	359.04
DRFN08–11	450.5	≈	470.91	≫	405.73	405.73	≈	411.01	≈	400.49
DO09–32	1396.68	<	1467.36	≫	1372.99	1372.99	≈	1372.97	≈	1361.15
FY17–25	313.03	≈	337.5	>	301.74	301.74	≈	299.62	≈	289.54
FRD12–29	451.47	≈	435.83	≈	435.86	435.86	>	381.01	≈	377.96
KS13–12	2685.4	≪	3010.1	≫	2439.06	2439.06	≈	2561.76	≫	2450.24
STS13–13	1346.41	<	1481.65	≫	1296.85	1296.85	≈	1303.8	≈	1234.52
Aoyagi and Frechette (2009)	843.08	≈	834.4	≈	845.51	845.51	≫	781.86	≈	792.51
Blonski et al. (2011)	1069.58	≈	1104.85	≪	1221.28	1221.28	≫	1069.28	≈	1104.6
Bruttel and Kamecke (2012)	845.41	≈	845.05	>	785.49	785.49	≈	800.12	≈	771.14
Dal Bó (2005)	651.88	<	689.58	>	652.36	652.36	≈	629.17	≈	618.39
Dal Bó and Fréchette (2011)	7164.32	≪	7557.8	≫	6422.83	6422.83	<	6597.93	>	6352.59
Dal Bó and Fréchette (2015)	8756.15	≪	9253.62	≫	8275.74	8275.74	>	8017.59	≫	7830.12
Dreber et al. (2008)	863.26	≈	864.49	≫	752.16	752.16	≈	782.37	≈	764.44
Duffy and Ochs (2009)	1396.68	<	1467.36	≫	1372.99	1372.99	≈	1372.97	≈	1361.15
Fréchette and Yuksel (2017)	313.03	≈	337.5	>	301.74	301.74	≈	299.62	≈	289.54
Fudenberg et al. (2012)	451.47	≈	435.83	≈	435.86	435.86	>	381.01	≈	377.96
Kagel and Schley (2013)	2685.4	≪	3010.1	≫	2439.06	2439.06	≈	2561.76	≫	2450.24
Sherstyuk et al. (2013)	1346.41	<	1481.65	≫	1296.85	1296.85	≈	1303.8	≈	1234.52
Pooled	**26525.91**	≪	**28023.06**	≫	**25411.21**	**25411.21**	≫	**24779.85**	≫	**24202.51**

(b) Second halves per session

	Best mixture of pure strategies										
	No Switching		Random Switching		Markov Switching	Best Switching		Semi-Grim		AD + SG
Specification										
# Models evaluated	5^{32}		5^{32}		5^{32}			1		1
# Pars estimated (by treatment)	16		16		82			3		5
# Parameters accounted for	3–5		3–5		12–35			3		5
AF09–34	492.28	≈	484.05	≈	482.82	492.28	≫	423.68	≈	421.21
BOS11–9	84.22	≈	96.42	≈	88.85	84.22	≈	75.1	≈	80.12
BOS11–14	40.82	≈	40.83	<	50.24	40.82	≈	35.58	≈	35.86
BOS11–15	15.52	≈	15.52	≪	29.01	15.52	≈	19.23	<	24.71
BOS11–16	157.48	≈	165.09	≈	157.84	157.48	≈	150.95	≈	138.89
BOS11–17	229.75	≈	225.64	≈	219.73	229.75	>	196.25	≈	201.03
BOS11–26	366.88	≈	365.76	≈	350.94	366.88	>	299.85	≈	309.63
BOS11–27	226.92	≈	255.26	≈	243.72	226.92	≈	235.88	≈	223.91
BOS11–30	146.49	≈	137.43	≈	145.96	146.49	≈	129.86	≈	132.45
BOS11–31	161.17	≈	174.2	≈	173.52	161.17	≈	154.02	≈	153.45
BK12–28	561.63	≈	627.74	≫	516.71	561.63	≈	536.77	≫	480.47
D05–18	350.59	≈	359.16	≈	351.93	350.59	≈	334.18	>	312.74
D05–19	388.49	<	428.21	≫	383.3	388.49	>	361.33	≈	359.54
DF11–6	633.6	≈	693.84	≫	557.16	633.6	>	526.15	≈	489.74
DF11–7	1427.15	<	1645.34	≫	1268.34	1427.15	≈	1316.79	≈	1250.02
DF11–8	1139.15	≪	1646.78	≫	960.35	1139.15	≈	1078.24	>	871.84
DF11–22	1196.64	≈	1160.77	≫	1018.52	1196.64	≫	930.3	>	858.03
DF11–23	723.5	≪	970.63	≫	737.29	723.5	≈	767.04	>	608.87
DF11–24	504.8	≈	496.02	≈	460.73	504.8	≈	483.25	≈	449.72
DF15–4	331.12	≈	402.51	≈	339.15	331.12	≈	320.02	≈	299.49
DF15–5	1666.6	≪	2234.36	≫	1438.87	1666.6	≈	1606.96	≫	1407.26
DF15–20	1572.51	≈	1548.84	≫	1339.13	1572.51	≫	1232.33	≫	1145.96
DF15–21	1664.01	≪	1914.7	≫	1504.63	1664.01	≈	1591.27	≫	1453.74
DF15–33	2913.27	≈	2919.03	≫	2735.52	2913.27	≫	2405.23	≈	2331.38
DF15–35	779.84	≈	792.29	≈	790.32	779.84	≫	641.02	≈	627.6
DRFN08–10	301.08	≈	289.13	≈	251.55	301.08	>	244.91	≈	234.76
DRFN08–11	345.37	≈	389.41	>	323.06	345.37	≈	341.42	>	305
DO09–32	1925.24	≈	1992.71	≫	1883.22	1925.24	>	1761.6	≫	1656.55
FY17–25	433.18	<	474.93	>	427.79	433.18	≈	423.34	≈	422.61
FRD12–29	528.36	≈	545.76	≈	529.88	528.36	≫	452.6	≈	433.74
KS13–12	1751.81	≪	2365.94	≫	1678.7	1751.81	≈	1775.62	≫	1572.95
STS13–13	1025.32	≪	1177.96	≫	1008.49	1025.32	≈	951.34	≫	834.74
Aoyagi and Frechette (2009)	492.28	≈	484.05	≈	482.82	492.28	≫	423.68	≈	421.21
Blonski et al. (2011)	1462.41	≈	1513.92	<	1604.87	1462.41	≫	1346.79	≈	1370.16
Bruttel and Kamecke (2012)	561.63	≈	627.74	≫	516.71	561.63	≈	536.77	≫	480.47
Dal Bó (2005)	741.2	<	790.21	>	743.74	741.2	>	699.05	≈	677.24
Dal Bó and Fréchette (2011)	5646.38	≪	6634.92	≫	5110.1	5646.38	≫	5128.69	≫	4565.93
Dal Bó and Fréchette (2015)	8951.57	≪	9835.77	≫	8264.26	8951.57	≫	7825.98	≫	7306.25
Dreber et al. (2008)	648.55	≈	681.35	>	588.62	648.55	>	589.84	>	544.66
Duffy and Ochs (2009)	1925.24	≈	1992.71	≫	1883.22	1925.24	>	1761.6	≫	1656.55
Fréchette and Yuksel (2017)	433.18	<	474.93	>	427.79	433.18	≈	423.34	≈	422.61
Fudenberg et al. (2012)	528.36	≈	545.76	≈	529.88	528.36	≫	452.6	≈	433.74
Kagel and Schley (2013)	1751.81	≪	2365.94	≫	1678.7	1751.81	≈	1775.62	≫	1572.95
Sherstyuk et al. (2013)	1025.32	≪	1177.96	≫	1008.49	1025.32	≈	951.34	≫	834.74
Pooled	**24301.45**	≪	**27269.48**	≫	**23494.22**	**24301.45**	≫	**22097.67**	≫	**20541.83**

Note: Notation of treatments and meaning of relation signs are all as defined above, see Table A.9.

Table A.20: Best mixtures of generalized strategies in relation to a Semi-Grim strategy (ICL-BIC of the models, less is better and relation signs point toward better models)

	Best mixture of generalized strategies									
	No Switching		Random Switching		Markov Switching	Best Switching		Semi-Grim		AD + SG
Specification										
# Models evaluated	8^{32}		8^{32}		8^{32}			1		1
# Pars estimated (by treatment)	64		64		196			3		5
# Parameters accounted for	6–10		6–10		15-35			3		5
First halves per session										
Aoyagi and Frechette (2009)	756.95	≈	763.11	≈	755.97	755.97	≈	781.86	≈	792.51
Blonski et al. (2011)	1134.67	≈	1173.15	≪	1272.13	1272.13	≫	1069.28	≈	1104.6
Bruttel and Kamecke (2012)	817.89	≈	835.6	>	787.63	787.63	≈	800.12	≈	771.14
Dal Bó (2005)	641.98	<	674.57	≈	653.11	653.11	≈	629.17	≈	618.39
Dal Bó and Fréchette (2011)	6921.58	≪	7467.72	≫	6465.99	6465.99	≈	6597.93	>	6352.59
Dal Bó and Fréchette (2015)	8446	≪	9183.55	≫	8168.2	8168.2	>	8017.59	≫	7830.12
Dreber et al. (2008)	787.71	<	865.64	≫	763.43	763.43	≈	782.37	≈	764.44
Duffy and Ochs (2009)	1395.4	<	1461.01	>	1394.31	1394.31	≈	1372.97	≈	1361.15
Fréchette and Yuksel (2017)	300.87	<	345.74	>	298.53	298.53	≈	299.62	≈	289.54
Fudenberg et al. (2012)	432.32	≈	432.38	≈	425.54	425.54	>	381.01	≈	377.96
Kagel and Schley (2013)	2709.95	≪	2993.4	≫	2539.99	2539.99	≈	2561.76	≫	2450.24
Sherstyuk et al. (2013)	1322.6	≪	1450	≫	1298.37	1298.37	≈	1303.8	≈	1234.52
Pooled	**25933.42**	≪	**27915.32**	≫	**25504.76**	**25504.76**	≫	**24779.85**	≫	**24202.51**
Second halves per session										
Aoyagi and Frechette (2009)	416.51	≈	437.8	≈	423.05	416.51	≈	423.68	≈	421.21
Blonski et al. (2011)	1414.39	≪	1553.12	≈	1609.79	1414.39	>	1346.79	≈	1370.16
Bruttel and Kamecke (2012)	538.17	<	611.91	≫	525.5	538.17	≈	536.77	≫	480.47
Dal Bó (2005)	737.05	<	786.21	>	741.54	737.05	>	699.05	≈	677.24
Dal Bó and Fréchette (2011)	5220.17	≪	6378.16	≫	5069.04	5220.17	≈	5128.69	≫	4565.93
Dal Bó and Fréchette (2015)	8205.77	≪	9401.19	≫	7947.33	8205.77	≫	7825.98	≫	7306.25
Dreber et al. (2008)	619.9	≈	662.24	>	596.78	619.9	≈	589.84	>	544.66
Duffy and Ochs (2009)	1883.52	≈	1914.83	>	1850.35	1883.52	>	1761.6	≫	1656.55
Fréchette and Yuksel (2017)	438.55	<	478.2	≈	434.61	438.55	≈	423.34	≈	422.61
Fudenberg et al. (2012)	514.87	≈	516.12	≈	515.97	514.87	≈	452.6	≈	433.74
Kagel and Schley (2013)	1808.21	≪	2336.29	≫	1718.07	1808.21	≈	1775.62	≫	1572.95
Sherstyuk et al. (2013)	955.73	≪	1137.49	≫	958.99	955.73	≈	951.34	≫	834.74
Pooled	**23009.84**	≪	**26479.73**	≫	**23143.38**	**23009.84**	≫	**22097.67**	≫	**20541.83**

Note: This table extends Table A.16 by picking the best switching model per half-session, after picking the best-fitting mixture involving the generalized forms of AD, Grim, TFT, AC and WSLS (as above) for each treatment independently, and examining its goodness-of-fit in relation to Semi-Grim and mixtures involving Semi-Grim.

Table A.21: Table A.20 by treatments – Best mixtures of generalized strategies in relation to a Semi-Grim strategy

(a) First halves per session

	Best mixture of generalized strategies									
	No Switching		Random Switching		Markov Switching	Best Switching		Semi-Grim		AD + SG
Specification										
# Models evaluated	8^{32}		8^{32}		8^{32}			1		1
# Pars estimated (by treatment)	64		64		196			3		5
# Parameters accounted for	6–10		6–10		15-35			3		5
AF09–34	756.95	≈	763.11	≈	755.97	755.97	≈	781.86	≈	792.51
BOS11–9	89.7	≈	87.81	≈	91.36	91.36	≈	86.56	≈	88.35
BOS11–14	102.27	≈	94.44	≈	96.5	96.5	≈	93.88	≈	98.01
BOS11–15	38.79	≈	37.18	≈	44.74	44.74	≈	37.73	<	43.07
BOS11–16	168.92	≈	176.43	≈	174.73	174.73	≈	167.42	≈	157.13
BOS11–17	115.07	≈	123.19	≈	123.74	123.74	>	115.02	≈	119.79
BOS11–26	257.82	≈	269.17	≈	256.37	256.37	≈	244.5	≈	246.46
BOS11–27	103.44	≈	114.9	≈	110.81	110.81	>	92.83	≈	92.07
BOS11–30	60.42	≈	68.55	≈	68.16	68.16	≫	55.74	<	61.12
BOS11–31	129.65	≈	137.48	≈	145.13	145.13	≈	125.52	≈	128.49
BK12–28	817.89	≈	835.6	>	787.63	787.63	≈	800.12	≈	771.14
D05–18	241.44	≈	230.66	≈	238.66	238.66	≈	230.57	≈	238.35
D05–19	396.28	≪	439.65	>	403.81	403.81	≈	395.06	≈	375.07
DF11–6	823.69	≈	909.31	>	772.55	772.55	≈	794.44	≈	748.9
DF11–7	1297.64	<	1370.65	≫	1181.36	1181.36	<	1256.83	≈	1229.61
DF11–8	1422.73	≪	1668.83	≫	1284.25	1284.25	<	1389.06	≈	1286.68
DF11–22	1080.23	≈	1110.68	≈	1056.77	1056.77	>	965.96	≈	961.58
DF11–23	1082.68	<	1185.69	≫	1027.3	1027.3	≈	1019.57	≈	972.17
DF11–24	1171.57	≈	1179.6	≫	1022.62	1022.62	≪	1145.15	≈	1115.95
DF15–4	439.54	≈	474.37	≈	412.27	412.27	≈	436.57	≈	422.43
DF15–5	1762.23	≪	2211.09	≫	1638.92	1638.92	≪	1738.77	≫	1649.1
DF15–20	1463.03	<	1547.14	≫	1433.87	1433.87	≈	1405.3	>	1366.09
DF15–21	1974.94	≪	2184.97	≫	1902.95	1902.95	≈	1872.47	>	1827.37
DF15–33	2379.17	≈	2350.87	≈	2296.41	2296.41	>	2186.26	≈	2178.12
DF15–35	384.6	≈	372.62	≈	382.07	382.07	>	349.06	≈	346.18
DRFN08–10	374.3	≈	391.56	>	339.73	339.73	≈	367.86	≈	359.04
DRFN08–11	408.63	<	468.48	≫	413.19	413.19	≈	411.01	≈	400.49
DO09–32	1395.4	<	1461.01	>	1394.31	1394.31	≈	1372.97	≈	1361.15
FY17–25	300.87	<	345.74	>	298.53	298.53	≈	299.62	≈	289.54
FRD12–29	432.32	≈	432.38	≈	425.54	425.54	>	381.01	≈	377.96
KS13–12	2709.95	≪	2993.4	≫	2539.99	2539.99	≈	2561.76	≫	2450.24
STS13–13	1322.6	≪	1450	≫	1298.37	1298.37	≈	1303.8	≈	1234.52
Aoyagi and Frechette (2009)	756.95	≈	763.11	≈	755.97	755.97	≈	781.86	≈	792.51
Blonski et al. (2011)	1134.67	≈	1173.15	≪	1272.13	1272.13	≫	1069.28	≈	1104.6
Bruttel and Kamecke (2012)	817.89	≈	835.6	>	787.63	787.63	≈	800.12	≈	771.14
Dal Bó (2005)	641.98	<	674.57	≈	653.11	653.11	≈	629.17	≈	618.39
Dal Bó and Fréchette (2011)	6921.58	≪	7467.72	≫	6465.99	6465.99	≈	6597.93	>	6352.59
Dal Bó and Fréchette (2015)	8446	≪	9183.55	≫	8168.2	8168.2	>	8017.59	≫	7830.12
Dreber et al. (2008)	787.71	<	865.64	≫	763.43	763.43	≈	782.37	≈	764.44
Duffy and Ochs (2009)	1395.4	<	1461.01	>	1394.31	1394.31	≈	1372.97	≈	1361.15
Fréchette and Yuksel (2017)	300.87	<	345.74	>	298.53	298.53	≈	299.62	≈	289.54
Fudenberg et al. (2012)	432.32	≈	432.38	≈	425.54	425.54	>	381.01	≈	377.96
Kagel and Schley (2013)	2709.95	≪	2993.4	≫	2539.99	2539.99	≈	2561.76	≫	2450.24
Sherstyuk et al. (2013)	1322.6	≪	1450	≫	1298.37	1298.37	≈	1303.8	≈	1234.52
Pooled	**25933.42**	≪	**27915.32**	≫	**25504.76**	**25504.76**	≫	**24779.85**	≫	**24202.51**

(b) Second halves per session

	Best mixture of generalized strategies									
	No Switching		Random Switching		Markov Switching	Best Switching		Semi-Grim		AD + SG
Specification										
# Models evaluated	8^{32}		8^{32}		8^{32}			1		1
# Pars estimated (by treatment)	64		64		196			3		5
# Parameters accounted for	6–10		6–10		15-35			3		5
AF09–34	416.51	≈	437.8	≈	423.05	416.51	≈	423.68	≈	421.21
BOS11–9	78.84	<	103.47	≈	83.98	78.84	≈	75.1	≈	80.12
BOS11–14	45.31	≈	42.43	≈	48.97	45.31	≈	35.58	≈	35.86
BOS11–15	20.01	≈	20.01	≪	33.5	20.01	≈	19.23	<	24.71
BOS11–16	148.98	≈	168.12	≈	158.84	148.98	≈	150.95	≈	138.89
BOS11–17	211.59	≈	225.1	≈	216.6	211.59	≈	196.25	≈	201.03
BOS11–26	327.16	≈	352.05	≈	338.09	327.16	≈	299.85	≈	309.63
BOS11–27	224.85	≈	254.56	≈	233.57	224.85	≈	235.88	≈	223.91
BOS11–30	139.46	≈	139.47	≈	146.9	139.46	≈	129.86	≈	132.45
BOS11–31	151.87	<	179.31	≈	171.15	151.87	≈	154.02	≈	153.45
BK12–28	538.17	<	611.91	≫	525.5	538.17	≈	536.77	≫	480.47
D05–18	340.33	≈	355.81	≈	346.45	340.33	≈	334.18	>	312.74
D05–19	392.47	<	426.15	>	384.46	392.47	>	361.33	≈	359.54
DF11–6	579.84	≈	628.84	≈	565.43	579.84	≈	526.15	≈	489.74
DF11–7	1359.89	≪	1582.11	≫	1299.86	1359.89	≈	1316.79	≈	1250.02
DF11–8	1028.93	≪	1600.86	≫	904.89	1028.93	≈	1078.24	>	871.84
DF11–22	1012.26	<	1102.07	≫	973.62	1012.26	≈	930.3	>	858.03
DF11–23	743.89	<	943.35	≫	739.29	743.89	≈	767.04	>	608.87
DF11–24	450.61	≈	477.85	≈	455.62	450.61	≈	483.25	≈	449.72
DF15–4	301.69	<	385.5	≈	307.03	301.69	≈	320.02	≈	299.49
DF15–5	1581.28	≪	2217.39	≫	1435.63	1581.28	≈	1606.96	≫	1407.26
DF15–20	1273.14	≪	1441.16	≫	1270.1	1273.14	≈	1232.33	≫	1145.96
DF15–21	1688.09	<	1878.92	≫	1544.66	1688.09	≈	1591.27	≫	1453.74
DF15–33	2582.61	<	2690.87	≫	2541.5	2582.61	>	2405.23	≈	2331.38
DF15–35	733.28	≈	742.93	≈	723.78	733.28	≫	641.02	≈	627.6
DRFN08–10	276.61	≈	285.26	≈	243.71	276.61	>	244.91	≈	234.76
DRFN08–11	339.09	≈	371.38	≈	339.95	339.09	≈	341.42	>	305
DO09–32	1883.52	≈	1914.83	>	1850.35	1883.52	>	1761.6	≫	1656.55
FY17–25	438.55	<	478.2	≈	434.61	438.55	≈	423.34	≈	422.61
FRD12–29	514.87	≈	516.12	≈	515.97	514.87	≈	452.6	≈	433.74
KS13–12	1808.21	≪	2336.29	≫	1718.07	1808.21	≈	1775.62	≫	1572.95
STS13–13	955.73	≪	1137.49	≫	958.99	955.73	≈	951.34	≫	834.74
Aoyagi and Frechette (2009)	416.51	≈	437.8	≈	423.05	416.51	≈	423.68	≈	421.21
Blonski et al. (2011)	1414.39	≪	1553.12	≈	1609.79	1414.39	>	1346.79	≈	1370.16
Bruttel and Kamecke (2012)	538.17	<	611.91	≫	525.5	538.17	≈	536.77	≫	480.47
Dal Bó (2005)	737.05	<	786.21	>	741.54	737.05	>	699.05	≈	677.24
Dal Bó and Fréchette (2011)	5220.17	≪	6378.16	≫	5069.04	5220.17	≈	5128.69	≫	4565.93
Dal Bó and Fréchette (2015)	8205.77	≪	9401.19	≫	7947.33	8205.77	≫	7825.98	≫	7306.25
Dreber et al. (2008)	619.9	≈	662.24	>	596.78	619.9	≈	589.84	>	544.66
Duffy and Ochs (2009)	1883.52	≈	1914.83	>	1850.35	1883.52	>	1761.6	≫	1656.55
Fréchette and Yuksel (2017)	438.55	<	478.2	≈	434.61	438.55	≈	423.34	≈	422.61
Fudenberg et al. (2012)	514.87	≈	516.12	≈	515.97	514.87	≈	452.6	≈	433.74
Kagel and Schley (2013)	1808.21	≪	2336.29	≫	1718.07	1808.21	≈	1775.62	≫	1572.95
Sherstyuk et al. (2013)	955.73	≪	1137.49	≫	958.99	955.73	≈	951.34	≫	834.74
Pooled	**23009.84**	≪	**26479.73**	≫	**23143.38**	**23009.84**	≫	**22097.67**	≫	**20541.83**

Note: Notation of treatments and meaning of relation signs are all as defined above, see Table A.9.

Table A.22: Best mixtures of pure or generalized strategies in relation to Semi-Grim (ICL-BIC of the models, less is better and relation signs point toward better models)

			Best mixture of pure or generalized strategies											Best Mixture
	Baseline		No		Random		Markov	Best						Best Switching
	Model		Switching		Switching		Switching	Switching		AD + SG		AD + 2SG		By Treatment
Specification														
# Models evaluated	1		13^{32}		13^{32}		13^{32}	3×13^{32}		1		1		$39^{32} \approx 10^{51}$
# Pars estimated (by treatment)	5		80		80		278	438		5		9		438
# Parameters accounted for	5		3–10		3–10		12-35	3–30		5		9		3–30
First halves per session														
Aoyagi and Frechette (2009)	886.44	≫	756.95	≈	763.11	≈	755.97	755.97	≈	781.86	≈	777.3	≈	755.97
Blonski et al. (2011)	1114.69	≫	1069.58	≈	1104.85	≪	1225.35	1225.35	≫	1069.28	<	1134.96	>	1069.39
Bruttel and Kamecke (2012)	845.41	≈	817.89	≈	835.6	>	785.49	785.49	≈	800.12	>	762.83	≈	785.49
Dal Bó (2005)	666.1	>	635.04	<	674.57	≈	648.75	648.75	≈	629.17	≈	600.26	<	631.2
Dal Bó and Fréchette (2011)	7423.23	≫	6904.79	≪	7456.12	≫	6388.49	6388.49	<	6597.93	≫	6304.97	≈	6388.49
Dal Bó and Fréchette (2015)	8880.62	≫	8434.93	≪	9166.72	≫	8158.31	8158.31	>	8017.59	≫	7810.7	≪	8138.61
Dreber et al. (2008)	871.32	≫	787.71	<	863.7	≫	752.16	752.16	≈	782.37	≈	763.52	≈	752.16
Duffy and Ochs (2009)	1448.71	≈	1395.4	<	1461.01	>	1372.99	1372.99	≈	1372.97	≈	1320.71	≈	1372.99
Fréchette and Yuksel (2017)	321.32	≈	300.87	<	337.5	>	298.53	298.53	≈	299.62	≈	284.11	≈	298.53
Fudenberg et al. (2012)	454.09	≈	432.32	≈	432.38	≈	425.54	425.54	>	381.01	≈	370.01	<	425.54
Kagel and Schley (2013)	2735.02	≈	2685.4	≪	2993.4	≫	2439.06	2439.06	≈	2561.76	≫	2421.27	≈	2439.06
Sherstyuk et al. (2013)	1389.33	≈	1322.6	≪	1450	≫	1296.85	1296.85	≈	1303.8	≫	1200.28	<	1296.85
Pooled	**27218.66**	≫	**25758.38**	≪	**27754.81**	≫	**25166.24**	**25166.24**	>	**24779.85**	≫	**24079.18**	≪	**24863.15**
Second halves per session														
Aoyagi and Frechette (2009)	534.29	≫	416.51	≈	437.8	≈	423.05	416.51	≈	423.68	≈	422.24	≈	416.51
Blonski et al. (2011)	1503.41	≫	1398.5	≪	1509.09	<	1593.01	1398.5	>	1346.79	≈	1385.91	≈	1394.16
Bruttel and Kamecke (2012)	588.33	>	538.17	<	611.91	≫	516.71	538.17	≈	536.77	>	478.23	≈	516.71
Dal Bó (2005)	751.82	≈	732.27	<	786.21	>	739.59	732.27	>	699.05	≈	679.04	<	729.48
Dal Bó and Fréchette (2011)	6065.93	≫	5195.88	≪	6378.16	≫	5007.24	5195.88	≈	5128.69	≫	4545.08	≪	4964.77
Dal Bó and Fréchette (2015)	9085.4	≫	8177.46	≪	9401.19	≫	7910.83	8177.46	≫	7825.98	≫	7310.27	≪	7893.79
Dreber et al. (2008)	656.38	≈	619.9	≈	662.24	>	581.94	619.9	≈	589.84	>	541.83	≈	581.94
Duffy and Ochs (2009)	2010.01	>	1883.52	≈	1914.83	>	1850.35	1883.52	>	1761.6	>	1602.93	≪	1850.35
Fréchette and Yuksel (2017)	469.85	≈	433.18	<	474.93	>	427.79	433.18	≈	423.34	≈	381.63	≪	427.79
Fudenberg et al. (2012)	530.3	≈	514.87	≈	516.12	≈	515.97	514.87	≈	452.6	>	414.24	<	514.87
Kagel and Schley (2013)	1866.19	≈	1751.81	≪	2336.29	≫	1678.7	1751.81	≈	1775.62	≫	1541.38	<	1678.7
Sherstyuk et al. (2013)	1027.43	>	955.73	≪	1137.49	≫	958.99	955.73	≈	951.34	≫	823.06	≪	955.73
Pooled	**25271.72**	≫	**22848.49**	≪	**26409.44**	≫	**22927.9**	**22848.49**	≫	**22097.67**	≫	**20454.13**	≪	**22422.07**

Note: This table extends Table A.16 by picking the best switching model per half-session, after picking the best-fitting mixture involving either the pure or generalized forms of AD, Grim, TFT, AC and WSLS (as above) for each treatment independently, and examining its goodness-of-fit in relation to Semi-Grim and mixtures involving Semi-Grim. The model "AD+SG2" has the same number of degrees of freedom as the Semi-Grim model.

Table A.23: Table A.22 by treatments – Best mixtures of pure or generalized strategies in relation to Semi-Grim

(a) First halves per session

			Best mixture of pure or generalized strategies											Best Mixture
	Baseline Model		No Switching		Random Switching		Markov Switching	Best Switching		AD + SG		AD + 2SG		Best Switching By Treatment
Specification														
# Models evaluated	1		13^{32}		13^{32}		13^{32}	3×13^{32}		1		1		$39^{32} \approx 10^{51}$
# Pars estimated (by treatment)	5		80		80		278	438		5		9		438
# Parameters accounted for	5		3–10		3–10		12-35	3–30		5		9		3–30
AF09–34	886.44	≫	756.95	≈	763.11	≈	755.97	755.97	≈	781.86	≈	777.3	≈	755.97
BOS11–9	85.17	≈	83.42	≈	83.96	≈	88.41	88.41	≈	86.56	≈	85.71	≈	83.42
BOS11–14	100.72	≈	97.73	≈	90	≈	92.94	92.94	≈	93.88	≈	95.87	≈	90
BOS11–15	37.29	≈	34.3	≈	32.69	≪	43.18	43.18	>	37.73	≪	53.61	≫	32.69
BOS11–16	176.55	≈	167.3	≈	169.38	≈	170.57	170.57	≈	167.42	≈	157.72	≈	167.3
BOS11–17	113.57	≈	110.57	≈	118.71	≈	121.05	121.05	>	115.02	<	122.41	>	110.57
BOS11–26	260.57	≈	256.88	≈	262.33	≈	256.37	256.37	≈	244.5	≈	249.78	≈	256.37
BOS11–27	103.61	≈	102.11	≈	112.76	≈	110.81	110.81	>	92.83	≈	93.42	≈	102.11
BOS11–30	59.81	>	56.81	≈	65.61	≈	64.33	64.33	>	55.74	≪	64.33	>	56.81
BOS11–31	127.32	≈	125.82	≈	135.1	≈	142.43	142.43	≈	125.52	≈	121.98	≈	125.82
BK12–28	845.41	≈	817.89	≈	835.6	>	785.49	785.49	≈	800.12	>	762.83	≈	785.49
D05–18	241.39	≈	235.84	≈	230.66	≈	235.63	235.63	≈	230.57	≈	229.01	≈	230.66
D05–19	421.17	>	396.28	≪	439.65	>	403.81	403.81	≈	395.06	>	364.87	<	396.28
DF11–6	880.04	≈	810.5	≈	909.31	>	770.36	770.36	≈	794.44	≈	752.56	≈	770.36
DF11–7	1423.93	>	1297.64	≈	1364.07	≫	1132.04	1132.04	<	1256.83	≈	1238	>	1132.04
DF11–8	1515.51	>	1422.73	≪	1668.83	≫	1279.8	1279.8	<	1389.06	≈	1289.21	≈	1279.8
DF11–22	1192.92	>	1080.23	≈	1110.68	≈	1056.77	1056.77	>	965.96	≈	944.2	≪	1056.77
DF11–23	1144.78	≈	1082.68	<	1185.69	≫	1020.09	1020.09	≈	1019.57	>	941.73	≈	1020.09
DF11–24	1239.14	>	1171.57	≈	1179.6	≫	1022.62	1022.62	≪	1145.15	≈	1090.82	≈	1022.62
DF15–4	460.23	>	431.07	≈	467.36	>	395.89	395.89	≈	436.57	≈	425	>	395.89
DF15–5	1808.3	>	1762.23	≪	2211.09	≫	1638.92	1638.92	≪	1738.77	≫	1639.52	≈	1638.92
DF15–20	1588.62	≫	1463.03	<	1543.46	≫	1433.87	1433.87	≈	1405.3	>	1364.37	≈	1433.87
DF15–21	2015.1	>	1974.94	≪	2184.97	≫	1902.95	1902.95	≈	1872.47	>	1811.11	<	1902.95
DF15–33	2573.89	≫	2379.17	≈	2350.87	≈	2296.41	2296.41	>	2186.26	≈	2174.56	≪	2296.41
DF15–35	405.32	≈	384.6	≈	372.62	≈	382.07	382.07	>	349.06	≈	343.65	<	372.62
DRFN08–10	413.58	>	374.3	≈	390.77	>	334.73	334.73	<	367.86	≈	358.63	≈	334.73
DRFN08–11	454.24	>	408.63	<	468.48	≫	405.73	405.73	≈	411.01	≈	398.59	≈	405.73
DO09–32	1448.71	≈	1395.4	<	1461.01	>	1372.99	1372.99	≈	1372.97	≈	1320.71	≈	1372.99
FY17–25	321.32	≈	300.87	<	337.5	>	298.53	298.53	≈	299.62	≈	284.11	≈	298.53
FRD12–29	454.09	≈	432.32	≈	432.38	≈	425.54	425.54	>	381.01	≈	370.01	<	425.54
KS13–12	2735.02	≈	2685.4	≪	2993.4	≫	2439.06	2439.06	≈	2561.76	≫	2421.27	≈	2439.06
STS13–13	1389.33	≈	1322.6	≪	1450	≫	1296.85	1296.85	≈	1303.8	≫	1200.28	<	1296.85
Aoyagi and Frechette (2009)	886.44	≫	756.95	≈	763.11	≈	755.97	755.97	≈	781.86	≈	777.3	≈	755.97
Blonski et al. (2011)	1114.69	≫	1069.58	≈	1104.85	≪	1225.35	1225.35	≫	1069.28	<	1134.96	>	1069.39
Bruttel and Kamecke (2012)	845.41	≈	817.89	≈	835.6	>	785.49	785.49	≈	800.12	>	762.83	≈	785.49
Dal Bó (2005)	666.1	>	635.04	<	674.57	≈	648.75	648.75	≈	629.17	≈	600.26	<	631.2
Dal Bó and Fréchette (2011)	7423.23	≫	6904.79	≪	7456.12	≫	6388.49	6388.49	<	6597.93	≫	6304.97	≈	6388.49
Dal Bó and Fréchette (2015)	8880.62	≫	8434.93	≪	9166.72	≫	8158.31	8158.31	>	8017.59	≫	7810.7	≪	8138.61
Dreber et al. (2008)	871.32	≫	787.71	<	863.7	≫	752.16	752.16	≈	782.37	≈	763.52	≈	752.16
Duffy and Ochs (2009)	1448.71	≈	1395.4	<	1461.01	>	1372.99	1372.99	≈	1372.97	≈	1320.71	≈	1372.99
Fréchette and Yuksel (2017)	321.32	≈	300.87	<	337.5	>	298.53	298.53	≈	299.62	≈	284.11	≈	298.53
Fudenberg et al. (2012)	454.09	≈	432.32	≈	432.38	≈	425.54	425.54	>	381.01	≈	370.01	<	425.54
Kagel and Schley (2013)	2735.02	≈	2685.4	≪	2993.4	≫	2439.06	2439.06	≈	2561.76	≫	2421.27	≈	2439.06
Sherstyuk et al. (2013)	1389.33	≈	1322.6	≪	1450	≫	1296.85	1296.85	≈	1303.8	≫	1200.28	<	1296.85
Pooled	**27218.66**	≫	**25758.38**	≪	**27754.81**	≫	**25166.24**	**25166.24**	>	**24779.85**	≫	**24079.18**	≪	**24863.15**

(b) Second halves per session

			Best mixture of pure or generalized strategies											Best Mixture
	Baseline Model		No Switching		Random Switching		Markov Switching	Best Switching		AD + SG		AD + 2SG		Best Switching By Treatment
Specification														
# Models evaluated	1		13^{32}		13^{32}		13^{32}	3×13^{32}		1		1		$39^{32} \approx 10^{51}$
# Pars estimated (by treatment)	5		80		80		278	438		5		9		438
# Parameters accounted for	5		3–10		3–10		12-35	3–30		5		9		3–30
AF09–34	534.29	≫	416.51	≈	437.8	≈	423.05	416.51	≈	423.68	≈	422.24	≈	416.51
BOS11–9	87.22	≈	78.84	≈	96.42	≈	83.98	78.84	≈	75.1	≈	76.06	≈	78.84
BOS11–14	43.82	≈	40.82	≈	40.83	≈	48.97	40.82	≈	35.58	≈	38.21	≈	40.82
BOS11–15	18.52	≈	15.52	≈	15.52	≪	29.01	15.52	≈	19.23	≪	30.15	≫	15.52
BOS11–16	160.48	≈	148.98	≈	165.09	≈	157.84	148.98	≈	150.95	≈	149.71	≈	148.98
BOS11–17	232.75	>	211.59	≈	225.1	≈	216.6	211.59	≈	196.25	≈	198.59	≈	211.59
BOS11–26	369.98	≫	327.16	≈	352.05	≈	338.09	327.16	≈	299.85	≈	295.25	<	327.16
BOS11–27	228.41	≈	224.85	≈	254.56	≈	233.57	224.85	≈	235.88	≈	224.21	≈	224.85
BOS11–30	149.49	≈	139.46	≈	137.43	≈	145.96	139.46	≈	129.86	≈	133.81	≈	137.43
BOS11–31	162.67	≈	151.87	≈	174.2	≈	171.15	151.87	≈	154.02	≈	149.77	≈	151.87
BK12–28	588.33	>	538.17	<	611.91	≫	516.71	538.17	≈	536.77	>	478.23	≈	516.71
D05–18	355.62	≈	340.33	≈	355.81	≈	346.45	340.33	≈	334.18	≈	315.38	<	340.33
D05–19	392.65	≈	388.49	<	426.15	>	383.3	388.49	>	361.33	≈	357.27	<	383.3
DF11–6	751.56	>	579.84	≈	628.84	≈	557.16	579.84	≈	526.15	≈	509.84	≈	557.16
DF11–7	1571.76	≫	1359.89	≪	1582.11	≫	1268.34	1359.89	≈	1316.79	>	1246.93	≈	1268.34
DF11–8	1142.1	>	1028.93	≪	1600.86	≫	904.89	1028.93	≈	1078.24	>	872.45	≈	904.89
DF11–22	1198.53	>	1012.26	<	1102.07	≫	973.62	1012.26	≈	930.3	>	860.39	<	973.62
DF11–23	842.37	≈	723.5	<	943.35	>	737.29	723.5	≈	767.04	>	582.24	<	723.5
DF11–24	532.68	≫	450.61	≈	477.85	≈	455.62	450.61	≈	483.25	>	424.76	≈	450.61
DF15–4	345.97	>	301.69	<	385.5	≈	307.03	301.69	≈	320.02	≈	306.89	≈	301.69
DF15–5	1686.18	>	1581.28	≪	2217.39	≫	1435.63	1581.28	≈	1606.96	≫	1409.52	≈	1435.63
DF15–20	1572.51	≫	1273.14	≪	1441.16	≫	1270.1	1273.14	≈	1232.33	≫	1141.29	<	1270.1
DF15–21	1754.13	≈	1664.01	≪	1878.92	≫	1504.63	1664.01	≈	1591.27	≫	1422.87	≈	1504.63
DF15–33	2915.83	≫	2582.61	<	2690.87	≫	2541.5	2582.61	>	2405.23	≈	2349.48	≪	2541.5
DF15–35	781.64	>	733.28	≈	742.93	≈	723.78	733.28	≫	641.02	≈	627.73	<	723.78
DRFN08–10	304.41	≈	276.61	≈	285.26	≈	243.71	276.61	>	244.91	≈	236.44	≈	243.71
DRFN08–11	348.47	≈	339.09	≈	371.38	≈	323.06	339.09	≈	341.42	≫	299.09	≈	323.06
DO09–32	2010.01	>	1883.52	≈	1914.83	>	1850.35	1883.52	>	1761.6	>	1602.93	≪	1850.35
FY17–25	469.85	≈	433.18	<	474.93	>	427.79	433.18	≈	423.34	≈	381.63	≪	427.79
FRD12–29	530.3	≈	514.87	≈	516.12	≈	515.97	514.87	≈	452.6	>	414.24	<	514.87
KS13–12	1866.19	≈	1751.81	≪	2336.29	≫	1678.7	1751.81	≈	1775.62	≫	1541.38	<	1678.7
STS13–13	1027.43	>	955.73	≪	1137.49	≫	958.99	955.73	≈	951.34	≫	823.06	≪	955.73
Aoyagi and Frechette (2009)	534.29	≫	416.51	≈	437.8	≈	423.05	416.51	≈	423.68	≈	422.24	≈	416.51
Blonski et al. (2011)	1503.41	≫	1398.5	≪	1509.09	<	1593.01	1398.5	>	1346.79	≈	1385.91	≈	1394.16
Bruttel and Kamecke (2012)	588.33	>	538.17	<	611.91	≫	516.71	538.17	≈	536.77	>	478.23	≈	516.71
Dal Bó (2005)	751.82	≈	732.27	<	786.21	>	739.59	732.27	>	699.05	≈	679.04	<	729.48
Dal Bó and Fréchette (2011)	6065.93	≫	5195.88	≪	6378.16	≫	5007.24	5195.88	≈	5128.69	≫	4545.08	≪	4964.77
Dal Bó and Fréchette (2015)	9085.4	≫	8177.46	≪	9401.19	≫	7910.83	8177.46	≫	7825.98	≫	7310.27	≪	7893.79
Dreber et al. (2008)	656.38	≈	619.9	≈	662.24	>	581.94	619.9	≈	589.84	>	541.83	≈	581.94
Duffy and Ochs (2009)	2010.01	>	1883.52	≈	1914.83	>	1850.35	1883.52	>	1761.6	>	1602.93	≪	1850.35
Fréchette and Yuksel (2017)	469.85	≈	433.18	<	474.93	>	427.79	433.18	≈	423.34	≈	381.63	≪	427.79
Fudenberg et al. (2012)	530.3	≈	514.87	≈	516.12	≈	515.97	514.87	≈	452.6	>	414.24	<	514.87
Kagel and Schley (2013)	1866.19	≈	1751.81	≪	2336.29	≫	1678.7	1751.81	≈	1775.62	≫	1541.38	<	1678.7
Sherstyuk et al. (2013)	1027.43	>	955.73	≪	1137.49	≫	958.99	955.73	≈	951.34	≫	823.06	≪	955.73
Pooled	**25271.72**	≫	**22848.49**	≪	**26409.44**	≫	**22927.9**	**22848.49**	≫	**22097.67**	≫	**20454.13**	≪	**22422.07**

Note: Notation of treatments and meaning of relation signs are all as defined above, see Table A.9.

Table A.24: Table A.3 by treatments – Memory-1 or Memory-2, and semi-grim, pure or generalized pure?

(a) First halves per session

	Memory-2 Generalizations of Semi-Grim + AD								Best Mixtures of Generalized Pure Strategies						Best Pure
	M2"General"		M2"TFT"		M2"Grim"		AD+SG		M1+M2"TFT"		M1+M2"Grim"		M1		M1 & M2
Specification															
# Models evaluated	1		1		1		1		22^{32}		22^{32}		13^{32}		5^{32}
# Pars estimated (by treatment)	12		6		6		5		160		160		80		32
# Parameters accounted for	12		6		6		5		6–15		6–15		6–10		3–8
AF09–34	756.04	≈	764.13	≈	749.99	≈	781.86	≈	756.95	≈	756.95	≈	756.95	≪	884.86
BOS11–9	91.44	≈	87.24	≈	90.13	≈	86.56	≈	83.42	≈	83.42	≈	83.42	≈	85.2
BOS11–14	103.75	≈	98.34	≈	97.69	≈	93.88	≈	97.73	≈	97.73	≈	97.73	≈	97.73
BOS11–15	50.59	≫	41.48	≈	41.64	>	37.73	≈	34.3	≈	34.3	≈	34.3	≈	34.3
BOS11–16	175.94	>	168.96	≈	168.84	≈	167.42	≈	167.3	≈	167.3	≈	167.3	≈	174.26
BOS11–17	128.36	≫	118.65	≈	119.18	≈	115.02	≈	110.57	≈	110.57	≈	110.57	≈	110.57
BOS11–26	253.27	≈	244.2	≈	242.92	≈	244.5	≈	256.88	≈	256.88	≈	256.88	≈	256.88
BOS11–27	100.21	>	94.88	≈	93.66	≈	92.83	≈	100.97	≈	100.97	≈	102.11	≈	100.97
BOS11–30	69.22	≫	60.24	≈	60.24	≫	55.74	≈	56.77	≈	56.77	≈	56.81	≈	56.77
BOS11–31	131.77	≈	127.07	≈	126.46	≈	125.52	≈	125.82	≈	125.82	≈	125.82	≈	156.95
BK12–28	807.47	≈	802.89	≈	804.16	≈	800.12	≈	817.89	≈	817.89	≈	817.89	≈	839.97
D05–18	241.79	≈	235.57	≈	236.43	≈	230.57	≈	235.84	≈	235.84	≈	235.84	≈	235.84
D05–19	408.97	≈	400.1	≈	400.16	≈	395.06	≈	396.28	≈	396.28	≈	396.28	≈	415.08
DF11–6	806.97	≈	797.22	≈	798.57	≈	794.44	≈	810.5	≈	810.5	≈	810.5	<	877.78
DF11–7	1252.93	≈	1248.87	≈	1249.66	≈	1256.83	≈	1297.64	≈	1297.64	≈	1297.64	<	1424.78
DF11–8	1403.92	≈	1393.05	≈	1393.09	≈	1389.06	≈	1422.73	≈	1422.73	≈	1422.73	<	1501.88
DF11–22	973.99	≈	965.39	≈	969.46	≈	965.96	≪	1080.23	≈	1080.23	≈	1080.23	≪	1188.65
DF11–23	1026.82	≈	1024.62	≈	1022.57	≈	1019.57	≈	1082.68	≈	1082.68	≈	1082.68	≈	1148.16
DF11–24	1131.28	≈	1144.21	≈	1128.27	≈	1145.15	≈	1171.57	≈	1171.57	≈	1171.57	<	1224.49
DF15–4	442.4	≈	439.96	≈	437.41	≈	436.57	≈	431.07	≈	431.07	≈	431.07	≈	456.32
DF15–5	1752.09	≈	1739.69	≈	1739.11	≈	1738.77	≈	1751.2	≈	1756.46	≈	1762.23	≈	1817.09
DF15–20	1408.72	≈	1403.6	≈	1408.86	≈	1405.3	≈	1463.03	≈	1463.03	≈	1463.03	<	1585.91
DF15–21	1871.42	≈	1871.98	≈	1864.48	≈	1872.47	<	1971.78	≈	1974.94	≈	1974.94	≈	2022.58
DF15–33	2154.98	≈	2176.37	≈	2184.09	≈	2186.26	≪	2379.17	≈	2379.17	≈	2379.17	≪	2575.64
DF15–35	357.11	≈	350.57	≈	350.98	≈	349.06	<	384.6	≈	384.6	≈	384.6	≈	411.07
DRFN08–10	375.03	≈	366.4	≈	367.62	≈	367.86	≈	374.3	≈	374.3	≈	374.3	≈	410.24
DRFN08–11	420.9	≈	413.48	≈	412.38	≈	411.01	≈	408.63	≈	408.63	≈	408.63	≈	451.13
DO09–32	1361.84	≈	1377.17	≈	1369.86	≈	1372.97	≈	1395.4	≈	1395.4	≈	1395.4	≈	1426.34
FY17–25	305.9	≈	299.72	≈	296.93	≈	299.62	≈	300.87	≈	300.87	≈	300.87	≈	317.35
FRD12–29	387.8	≈	379.84	≈	378.07	≈	381.01	<	432.32	≈	432.32	≈	432.32	≈	463.4
KS13–12	2542.02	≈	2556.45	≈	2552.09	≈	2561.76	≈	2679.23	≈	2685.4	≈	2685.4	≈	2730.66
STS13–13	1311.64	≈	1307.45	≈	1303.94	≈	1303.8	≈	1322.6	≈	1322.6	≈	1322.6	<	1398.69
Aoyagi and Frechette (2009)	756.04	≈	764.13	≈	749.99	≈	781.86	≈	756.95	≈	756.95	≈	756.95	≪	884.86
Blonski et al. (2011)	1244.76	≫	1121.17	≈	1120.87	≫	1069.28	≈	1069.56	≈	1069.56	≈	1069.58	≈	1105.98
Bruttel and Kamecke (2012)	807.47	≈	802.89	≈	804.16	≈	800.12	≈	817.89	≈	817.89	≈	817.89	≈	839.97
Dal Bó (2005)	660.68	>	641.34	≈	642.26	≈	629.17	≈	635.04	≈	635.04	≈	635.04	≈	653.05
Dal Bó and Fréchette (2011)	6671.28	≈	6616.44	≈	6604.7	≈	6597.93	≪	6904.79	≈	6904.79	≈	6904.79	≪	7391.89
Dal Bó and Fréchette (2015)	8068.37	≈	8028.83	≈	8031.59	≈	8017.59	≪	8423.8	≈	8431.51	≈	8434.93	≪	8893.78
Dreber et al. (2008)	805.74	>	785.48	≈	785.6	≈	782.37	≈	787.71	≈	787.71	≈	787.71	<	863.47
Duffy and Ochs (2009)	1361.84	≈	1377.17	≈	1369.86	≈	1372.97	≈	1395.4	≈	1395.4	≈	1395.4	≈	1426.34
Fréchette and Yuksel (2017)	305.9	≈	299.72	≈	296.93	≈	299.62	≈	300.87	≈	300.87	≈	300.87	≈	317.35
Fudenberg et al. (2012)	387.8	≈	379.84	≈	378.07	≈	381.01	<	432.32	≈	432.32	≈	432.32	≈	463.4
Kagel and Schley (2013)	2542.02	≈	2556.45	≈	2552.09	≈	2561.76	≈	2679.23	≈	2685.4	≈	2685.4	≈	2730.66
Sherstyuk et al. (2013)	1311.64	≈	1307.45	≈	1303.94	≈	1303.8	≈	1322.6	≈	1322.6	≈	1322.6	<	1398.69
Pooled	**25434.21**	≫	**24972.71**	≈	**24931.86**	≈	**24779.85**	≪	**25750.84**	≈	**25757.44**	≈	**25758.38**	≪	**27115.39**

(b) Second halves per session

	Memory-2 Generalizations of Semi-Grim + AD								Best Mixtures of Generalized Pure Strategies						Best Pure
	M2"General"		M2"TFT"		M2"Grim"		AD+SG		M1+M2"TFT"		M1+M2"Grim"		M1		M1 & M2
Specification															
# Models evaluated	1		1		1		1		22^{32}		22^{32}		13^{32}		5^{32}
# Pars estimated (by treatment)	12		6		6		5		160		160		80		32
# Parameters accounted for	12		6		6		5		6–15		6–15		6–10		3–8
AF09–34	415.47	≈	421.18	>	409.19	≈	423.68	≈	416.51	≈	416.51	≈	416.51	≪	540.47
BOS11–9	88.57	>	79.59	≈	79.59	≈	75.1	≈	78.84	≈	78.84	≈	78.84	≈	84.22
BOS11–14	58.78	≫	40.08	≈	39.03	≈	35.58	≈	40.82	≈	40.82	≈	40.82	≈	40.82
BOS11–15	33.32	≫	19.62	≈	19.63	>	19.23	≈	15.52	≈	15.52	≈	15.52	≈	15.52
BOS11–16	158.81	≈	153.59	≈	150.12	≈	150.95	≈	148.98	≈	148.98	≈	148.98	≈	157.48
BOS11–17	205.77	≈	197.54	≈	199.15	≈	196.25	≈	211.59	≈	211.59	≈	211.59	≈	228.36
BOS11–26	309.39	≈	304.57	≈	304.15	≈	299.85	≈	327.16	≈	327.16	≈	327.16	<	374.79
BOS11–27	227.82	≈	231.03	≈	234.28	≈	235.88	≈	224.85	≈	224.85	≈	224.85	≈	281.24
BOS11–30	138.28	>	133.27	≈	131.54	≈	129.86	≈	139.46	≈	139.46	≈	139.46	≈	146.49
BOS11–31	157.58	≈	156.52	≈	155.81	≈	154.02	≈	151.87	≈	151.87	≈	151.87	≈	196.99
BK12–28	536.19	≈	532.08	≈	529.47	≈	536.77	≈	538.17	≈	538.17	≈	538.17	≈	567.99
D05–18	350.65	>	338.4	≈	337.77	≈	334.18	≈	340.33	≈	340.33	≈	340.33	≈	350.59
D05–19	366.67	≈	366.81	≈	364.88	≈	361.33	≈	380.66	≈	386.44	≈	388.49	≈	388.49
DF11–6	532.38	≈	524.97	≈	526.02	≈	526.15	≈	579.84	≈	579.84	≈	579.84	<	747.77
DF11–7	1316.59	≈	1310.02	≈	1309.99	≈	1316.79	≈	1359.89	≈	1359.89	≈	1359.89	≪	1566.58
DF11–8	1092.7	≈	1082.36	≈	1082.77	≈	1078.24	≈	1028.93	≈	1028.93	≈	1028.93	<	1153.72
DF11–22	928.2	≈	926.45	≈	928.99	≈	930.3	≈	1012.26	≈	1012.26	≈	1012.26	≈	1152.14
DF11–23	776.48	≈	771.57	≈	770.87	≈	767.04	≈	723.5	≈	723.5	≈	723.5	≈	782.51
DF11–24	479.3	≈	479.38	≈	471.25	≈	483.25	≈	450.61	≈	450.61	≈	450.61	<	530.97
DF15–4	329.82	≈	322.21	≈	323.22	≈	320.02	≈	301.69	≈	301.69	≈	301.69	<	342.05
DF15–5	1610.1	≈	1602.79	≈	1599.28	≈	1606.96	≈	1581.28	≈	1581.28	≈	1581.28	<	1712.9
DF15–20	1222.77	≈	1231.06	≈	1229.59	≈	1232.33	≈	1273.14	≈	1273.14	≈	1273.14	≪	1582.66
DF15–21	1575.91	≈	1587.09	≈	1571.12	≈	1591.27	≈	1664.01	≈	1664.01	≈	1664.01	<	1754.9
DF15–33	2378.58	≈	2399.8	≈	2401.15	≈	2405.23	<	2582.61	≈	2582.61	≈	2582.61	≪	2935.81
DF15–35	642.04	≈	639.91	≈	637.62	≈	641.02	<	722.6	≈	733.28	≈	733.28	≈	789.09
DRFN08–10	232.84	≈	233.55	≈	223.78	<	244.91	<	276.61	≈	276.61	≈	276.61	≈	301.08
DRFN08–11	354.52	≈	341.48	≈	340.95	≈	341.42	≈	336.45	≈	336.84	≈	339.09	≈	345.37
DO09–32	1706.1	≈	1753.41	≈	1719.86	≈	1761.6	≈	1857.06	≈	1876.72	≈	1883.52	≈	2003.41
FY17–25	422.32	≈	424.41	≈	419.44	≈	423.34	≈	433.18	≈	433.18	≈	433.18	<	464.23
FRD12–29	452.64	≈	450.08	≈	447.25	≈	452.6	<	484.5	≈	477.91	≈	514.87	≈	534.47
KS13–12	1782.43	≈	1777.83	≈	1773.55	≈	1775.62	≈	1751.81	≈	1751.81	≈	1751.81	≈	1830.26
STS13–13	959.21	≈	952.56	≈	949.46	≈	951.34	≈	955.73	≈	955.73	≈	955.73	≈	1023.43
Aoyagi and Frechette (2009)	415.47	≈	421.18	>	409.19	≈	423.68	≈	416.51	≈	416.51	≈	416.51	≪	540.47
Blonski et al. (2011)	1518.54	≫	1395.94	≈	1393.41	≫	1346.79	≈	1398.5	≈	1398.5	≈	1398.5	<	1564.48
Bruttel and Kamecke (2012)	536.19	≈	532.08	≈	529.47	≈	536.77	≈	538.17	≈	538.17	≈	538.17	≈	567.99
Dal Bó (2005)	727.25	≈	710.88	≈	708.32	≈	699.05	≈	726.04	≈	731.81	≈	732.27	≈	741.2
Dal Bó and Fréchette (2011)	5201.05	≈	5137.82	≈	5132.96	≈	5128.69	≈	5195.88	≈	5195.88	≈	5195.88	≪	5960.78
Dal Bó and Fréchette (2015)	7840.87	≈	7829.51	≈	7808.63	≈	7825.98	≪	8172.63	≈	8177.46	≈	8177.46	≪	9143.98
Dreber et al. (2008)	597.17	≈	580.63	≈	570.33	≈	589.84	≈	618.5	≈	618.89	≈	619.9	≈	648.55
Duffy and Ochs (2009)	1706.1	≈	1753.41	≈	1719.86	≈	1761.6	≈	1857.06	≈	1876.72	≈	1883.52	≈	2003.41
Fréchette and Yuksel (2017)	422.32	≈	424.41	≈	419.44	≈	423.34	≈	433.18	≈	433.18	≈	433.18	<	464.23
Fudenberg et al. (2012)	452.64	≈	450.08	≈	447.25	≈	452.6	<	484.5	≈	477.91	≈	514.87	≈	534.47
Kagel and Schley (2013)	1782.43	≈	1777.83	≈	1773.55	≈	1775.62	≈	1751.81	≈	1751.81	≈	1751.81	≈	1830.26
Sherstyuk et al. (2013)	959.21	≈	952.56	≈	949.46	≈	951.34	≈	955.73	≈	955.73	≈	955.73	≈	1023.43
Pooled	**22669.91**	≫	**22258.14**	≈	**22153.69**	≈	**22097.67**	≪	**22811.34**	≈	**22828.13**	≈	**22848.49**	≪	**25177.57**

Note: Notation of treatments and meaning of relation signs are all as defined above, see Table A.9.

Table A.25: **Continuation strategies: Memory-1 or Memory-2, and semi-grim, pure or generalized pure?** Strategy mixtures are estimated treatment-by-treatment. The resulting ICL-BICs are pooled within experiments and overall (less is better, relation signs point to better models)

	Memory-2 Generalizations of Semi-Grim + AD								Best Mixtures of Generalized Pure Strategies						Best Pure
	M2"General"		M2"TFT"		M2"Grim"		AD+SG		M1+M2"TFT"		M1+M2"Grim"		M1		M1 & M2
Specification															
# Models evaluated	1		1		1		1		22^{32}		22^{32}		13^{32}		5^{32}
# Pars estimated (by treatment)	12		6		6		5		160		160		80		32
# Parameters accounted for	12		6		6		5		6–15		6–15		6–10		3–8
First halves per session															
Aoyagi and Frechette (2009)	692.5	≈	690.85	≈	686.2	≈	694.72	>	649.38	≈	646.7	≈	645.31	≪	791.38
Blonski et al. (2011)	714	≫	601.67	≈	601.95	≫	549.45	≪	760.28	≈	768.65	≫	713.8	≈	703.06
Bruttel and Kamecke (2012)	572.14	≈	566.75	≈	567.58	≈	567.86	≈	569.25	≈	576.94	≈	585.42	≈	588.54
Dal Bó (2005)	385.61	>	367.94	≈	366.48	≈	358.51	≪	404.24	≈	402.79	≈	407.86	≈	389.05
Dal Bó and Fréchette (2011)	3596.64	≈	3542.28	≈	3538.64	≈	3533.99	≈	3481.93	≈	3517.82	≈	3536.73	≪	3835.73
Dal Bó and Fréchette (2015)	5017.27	≈	4974.8	≈	4988.94	≈	4991.74	≪	5193.81	≈	5218.03	≈	5259.64	≪	5538.35
Dreber et al. (2008)	464.84	>	444.11	≈	444.71	≈	437.17	≈	474.89	≈	483.06	≈	478.09	≈	462.72
Duffy and Ochs (2009)	1060.26	≈	1063.66	≈	1074.9	≈	1090.22	≈	1039.24	≈	1045.68	≈	1047.59	≈	1102.63
Fréchette and Yuksel (2017)	174.64	≈	167.06	≈	164.75	≈	161.45	≪	182.7	≈	188.04	≈	188.5	≈	181.98
Fudenberg et al. (2012)	301.76	≈	293.52	≈	294.4	≈	291.43	<	319.76	≈	322.89	≈	319.45	<	366.77
Kagel and Schley (2013)	1746.26	≈	1749.95	≈	1753.68	≈	1782.82	>	1651.6	≈	1679.19	<	1761.98	≈	1805.96
Sherstyuk et al. (2013)	917.07	≈	907.95	≈	913.52	≈	912.8	≈	857.56	≈	870.11	≈	865.67	<	941.92
Pooled	**16080.69**	≫	**15589.39**	≈	**15614.59**	>	**15481.59**	≪	**15948.02**	<	**16109.87**	≈	**16077.95**	≪	**16858.76**
Second halves per session															
Aoyagi and Frechette (2009)	396.32	≈	391.42	>	387.48	≈	389.24	≈	368.08	≈	365.6	≈	363.58	≪	484.41
Blonski et al. (2011)	1012.48	≫	919.29	≈	922.48	≫	867.87	<	1007.71	≈	1021.03	>	992.44	≈	1055.98
Bruttel and Kamecke (2012)	333.51	≈	337.12	≈	329.73	≈	347.4	≈	318.55	≈	328.38	≈	344.88	≈	316.37
Dal Bó (2005)	449.03	≈	434.38	≈	433.82	≈	424.44	<	451.25	<	471.53	≈	475.11	≈	463.53
Dal Bó and Fréchette (2011)	2854.52	≈	2801.46	≈	2800.71	≈	2817.31	>	2619.87	≈	2643.97	<	2737.11	<	2885.4
Dal Bó and Fréchette (2015)	5006.3	≈	5013.49	≈	5012.99	≈	5043.81	≈	5034.8	≈	5099.68	≈	5164.78	≪	5575.88
Dreber et al. (2008)	272.94	≈	258.88	≈	253.47	≈	264.94	≈	287.55	≈	288.95	≈	295.06	≈	287.58
Duffy and Ochs (2009)	1375.43	≈	1367.68	≈	1389.92	≈	1403.03	≈	1339.22	≈	1359.29	≈	1381.01	≪	1617.76
Fréchette and Yuksel (2017)	308.21	≈	304.2	≈	306.93	≈	313.5	≈	311.03	≈	311.99	≈	309.63	≪	356.11
Fudenberg et al. (2012)	384.37	≈	382.32	≈	378.59	≈	380.75	≈	367.2	≈	364.46	≈	373.44	<	447.18
Kagel and Schley (2013)	1204.38	≈	1202.61	≈	1197.19	≈	1211.37	>	1088.27	≈	1122.98	≈	1170.12	≈	1169.32
Sherstyuk et al. (2013)	598.79	≈	590.65	≈	591.38	≈	586.72	>	503.98	≈	517.77	≈	527.09	≈	583.8
Pooled	**14633.97**	≫	**14222.35**	≈	**14223.53**	≈	**14159.8**	≈	**14059.75**	<	**14267.75**	≈	**14387.48**	≪	**15400.68**

Note: Results treatment-by-treatment are in the appendix. The main body contains ICL-BICs aggregated at paper level. Relation signs and p-values are exactly as above, see Table 1.3. "M2" ("M1") denotes strategies, whose actions may depend on actions in $t-2$ and $t-1$ ($t-1$ only). The supplements "General", "TFT", "Grim" indicate whether parameters of behavior strategies may depend on: all four possible histories in $t-2$ (M2 "General"), whether the opponent cooperated in $t-2$ (M2 "TFT"), or whether there was joint cooperation in $t-2$ (M2 "Grim"). Pure M2 strategies do not have such free parameters. Columns 1-3 contain one memory-2 version of semi-grim each. Column 4 is memory-1 semi-grim. Columns 5-7 are memory-2 and memory-1 versions of generalized prototypical strategies. The last column contains the best fitting combinations of a set of pure memory-1 and memory-2 strategies from the literature (TFT, Grim, AD, Grim2, TF2T, T2, 2TFT, 2PTFT) for definitions see Table A.7 in the Appendix.

Table A.26: Is there a single "semi grim" type? Mixture models involving SG

	Best Mixture Best Switching		SG + AD		1.5×SG+AD		2×SG+AD		3×SG+AD		3×P5+AD		2×P5+AD		P5+AD
Specification															
# Models evaluated	$39^{32} \approx 10^{51}$		1		1		1		1		1		1		1
# Pars estimated (by treatment)	438		5		7		9		13		19		17		11
# Parameters accounted for	3-30		5		7		9		13		19		17		11
First halves per session															
Aoyagi and Frechette (2009)	755.97	≈	781.86	≈	792.51	≈	777.3	≈	782.13	>	741.95	≈	744.86	≈	744.06
Blonski et al. (2011)	1069.39	≈	1069.28	≈	1104.6	≈	1134.96	≪	1232.97	≪	1332.48	≫	1205.47	≫	1106.01
Bruttel and Kamecke (2012)	785.49	≈	800.12	≈	771.14	≈	762.83	≈	748.06	≈	751.86	≈	759.45	≈	803.58
Dal Bó (2005)	631.2	≈	629.17	≈	618.39	≈	600.26	≪	626.56	≈	639.8	>	609.1	≈	620.38
Dal Bó and Fréchette (2011)	6388.49	<	6597.93	>	6352.59	≈	6304.97	≈	6198.12	≈	6216.22	<	6295.32	≪	6553.25
Dal Bó and Fréchette (2015)	8138.61	≈	8017.59	≫	7830.12	≈	7810.7	≈	7828.38	≈	7829.74	≈	7775.7	≪	7969.32
Dreber et al. (2008)	752.16	≈	782.37	≈	764.44	≈	763.52	≈	766.77	≈	765.81	≈	767.32	≈	783.45
Duffy and Ochs (2009)	1372.99	≈	1372.97	≈	1361.15	≈	1320.71	≈	1297.84	≈	1291.42	<	1345.16	≈	1361.86
Fréchette and Yuksel (2017)	298.53	≈	299.62	≈	289.54	≈	284.11	≈	289.88	≈	294.05	≈	285.33	≈	291.69
Fudenberg et al. (2012)	425.54	>	381.01	≈	377.96	≈	370.01	≈	380.86	≈	381.34	≈	372.32	≈	377.33
Kagel and Schley (2013)	2439.06	≈	2561.76	≫	2450.24	≈	2421.27	≈	2385.02	≈	2354.05	≈	2398.74	≪	2551.68
Sherstyuk et al. (2013)	1296.85	≈	1303.8	≈	1234.52	≈	1200.28	≈	1184.82	≈	1177.24	≈	1186.92	≪	1286.14
Pooled	**24863.15**	≈	**24779.85**	≫	**24202.51**	≈	**24079.18**	≈	**24195.57**	<	**24468.99**	>	**24219.87**	≪	**24704.09**
Second halves per session															
Aoyagi and Frechette (2009)	416.51	≈	423.68	≈	421.21	≈	422.24	≈	423.63	>	404.95	≈	408.59	≈	409.04
Blonski et al. (2011)	1394.16	≈	1346.79	≈	1370.16	≈	1385.91	<	1442.85	≪	1555.48	≫	1453.1	≫	1379.87
Bruttel and Kamecke (2012)	516.71	≈	536.77	≫	480.47	≈	478.23	≈	470.25	≈	443.83	≈	471.73	<	528.54
Dal Bó (2005)	729.48	>	699.05	≈	677.24	≈	679.04	<	697.21	≈	707.25	≈	687.86	≈	696.41
Dal Bó and Fréchette (2011)	4964.77	≈	5128.69	≫	4565.93	≈	4545.08	≈	4426.48	≈	4461.98	≈	4493.1	≪	5045.34
Dal Bó and Fréchette (2015)	7893.79	≈	7825.98	≫	7306.25	≈	7310.27	>	7170.25	≈	7089.56	≈	7151.84	≪	7683.76
Dreber et al. (2008)	581.94	≈	589.84	>	544.66	≈	541.83	≈	539.47	≈	519.28	≈	518.82	<	562.99
Duffy and Ochs (2009)	1850.35	≈	1761.6	≫	1656.55	≈	1602.93	>	1518.65	≈	1509.7	<	1598.04	≪	1715.88
Fréchette and Yuksel (2017)	427.79	≈	423.34	≈	422.61	≈	381.63	≈	375.03	≈	384.11	≈	382.16	<	409.93
Fudenberg et al. (2012)	514.87	≈	452.6	≈	433.74	≈	414.24	≈	405.22	≈	410.69	≈	421.81	≈	448.37
Kagel and Schley (2013)	1678.7	≈	1775.62	≫	1572.95	≈	1541.38	>	1488.49	≈	1477.87	≈	1527.47	≪	1748.01
Sherstyuk et al. (2013)	955.73	≈	951.34	≫	834.74	≈	823.06	≈	799.39	≈	801.53	≈	815.26	≪	935.01
Pooled	**22422.07**	≈	**22097.67**	≫	**20541.83**	≈	**20454.13**	>	**20231.09**	<	**20459.26**	≈	**20403.95**	≪	**21818.45**

Note: This table verifies a number of possible mixtures involving Semi-Grim types as a robustness check for the sufficiency of focussing on the mixtures examined above. E.g. "3× SG refers to a model containing three different versions of memory-1 semi-grim with allowing for heterogeneity of randomization parameters across subjects.

Table A.27: Table A.26 by treatments – Is there a single “semi grim” type? Mixture models involving SG

(a) First halves per session

	Best Mixture Best Switching		SG + AD		1.5×SG+AD		2×SG+AD		3×SG+AD		3×P5+AD		2×P5+AD		P5+AD
Specification															
# Models evaluated	$39^{32} \approx 10^{51}$		1		1		1		1		1		1		1
# Pars estimated (by treatment)	438		5		7		9		13		19		17		11
# Parameters accounted for	3-30		5		7		9		13		19		17		11
AF09–34	755.97	≈	781.86	≈	792.51	≈	777.3	≈	782.13	>	741.95	≈	744.86	≈	744.06
BOS11–9	83.42	≈	86.56	≈	88.35	≈	85.71	<	92	<	97.71	≈	91.58	≈	89.57
BOS11–14	90	≈	93.88	≈	98.01	≈	95.87	≪	105.42	<	113.81	≫	99.92	≈	96.86
BOS11–15	32.69	≈	37.73	<	43.07	≪	53.61	≪	61.19	≪	72.34	≫	60.83	≫	42.63
BOS11–16	167.3	≈	167.42	≈	157.13	≈	157.72	≈	162.97	≈	171.76	≈	165.4	≈	169.7
BOS11–17	110.57	≈	115.02	≈	119.79	≈	122.41	≈	129.42	≈	123.86	≈	124.68	>	112.95
BOS11–26	256.37	≈	244.5	≈	246.46	≈	249.78	≈	248.26	≈	247.15	≈	245.48	≈	245.83
BOS11–27	102.11	≈	92.83	≈	92.07	≈	93.42	<	103.66	≈	106.06	≫	93.17	≈	91.86
BOS11–30	56.81	≈	55.74	<	61.12	≈	64.33	<	73.55	≪	82.55	≫	70.18	≫	58.74
BOS11–31	125.82	≈	125.52	≈	128.49	≈	121.98	≈	126.3	≈	126.95	≈	124.03	≈	127.75
BK12–28	785.49	≈	800.12	≈	771.14	≈	762.83	≈	748.06	≈	751.86	≈	759.45	≈	803.58
D05–18	230.66	≈	230.57	≈	238.35	≈	229.01	<	241.65	≈	249.85	≈	238.41	≈	233.85
D05–19	396.28	≈	395.06	≈	375.07	≈	364.87	≈	375.69	≈	376.48	≈	361.48	<	381.57
DF11–6	770.36	≈	794.44	≈	748.9	≈	752.56	≈	730.86	≈	734.21	≈	753.19	≈	793.66
DF11–7	1132.04	<	1256.83	≈	1229.61	≈	1238	≈	1219.19	≈	1214.51	≈	1243.2	≈	1256.83
DF11–8	1279.8	<	1389.06	≈	1286.68	≈	1289.21	≈	1255.59	≈	1249.19	<	1279.81	≪	1379.72
DF11–22	1056.77	>	965.96	≈	961.58	≈	944.2	≈	934.1	≈	934.68	≈	945.32	≈	963.43
DF11–23	1020.09	≈	1019.57	≈	972.17	≈	941.73	≈	921.62	≈	919.31	≈	937.03	≈	1003.42
DF11–24	1022.62	≪	1145.15	≈	1115.95	≈	1090.82	≈	1066.75	≈	1062.01	≈	1066.78	≈	1118.5
DF15–4	395.89	≈	436.57	≈	422.43	≈	425	≈	433.05	≈	423.74	≈	421.84	≈	426.78
DF15–5	1638.92	≪	1738.77	≫	1649.1	≈	1639.52	≈	1632.23	≈	1637.48	≈	1637.39	≪	1735.05
DF15–20	1433.87	≈	1405.3	>	1366.09	≈	1364.37	≈	1365.64	≈	1341.25	≈	1352.57	≈	1392.99
DF15–21	1902.95	≈	1872.47	>	1827.37	≈	1811.11	≈	1806.23	≈	1811.27	≈	1792.58	≈	1852.64
DF15–33	2296.41	>	2186.26	≈	2178.12	≈	2174.56	≈	2165.14	≈	2158.49	≈	2161.68	≈	2179.74
DF15–35	372.62	≈	349.06	≈	346.18	≈	343.65	≈	350.27	≈	346.71	≈	333.83	≈	341.3
DRFN08–10	334.73	<	367.86	≈	359.04	≈	358.63	≈	358.23	≈	357.95	≈	359.19	≈	367.27
DRFN08–11	405.73	≈	411.01	≈	400.49	≈	398.59	≈	399.43	≈	394.56	≈	399.03	≈	411.28
DO09–32	1372.99	≈	1372.97	≈	1361.15	≈	1320.71	≈	1297.84	≈	1291.42	<	1345.16	≈	1361.86
FY17–25	298.53	≈	299.62	≈	289.54	≈	284.11	≈	289.88	≈	294.05	≈	285.33	≈	291.69
FRD12–29	425.54	>	381.01	≈	377.96	≈	370.01	≈	380.86	≈	381.34	≈	372.32	≈	377.33
KS13–12	2439.06	≈	2561.76	≫	2450.24	≈	2421.27	≈	2385.02	≈	2354.05	≈	2398.74	≪	2551.68
STS13–13	1296.85	≈	1303.8	≈	1234.52	≈	1200.28	≈	1184.82	≈	1177.24	≈	1186.92	≪	1286.14
Aoyagi and Frechette (2009)	755.97	≈	781.86	≈	792.51	≈	777.3	≈	782.13	>	741.95	≈	744.86	≈	744.06
Blonski et al. (2011)	1069.39	≈	1069.28	≈	1104.6	≈	1134.96	≪	1232.97	≪	1332.48	≫	1205.47	≫	1106.01
Bruttel and Kamecke (2012)	785.49	≈	800.12	≈	771.14	≈	762.83	≈	748.06	≈	751.86	≈	759.45	≈	803.58
Dal Bó (2005)	631.2	≈	629.17	≈	618.39	≈	600.26	≪	626.56	≈	639.8	>	609.1	≈	620.38
Dal Bó and Fréchette (2011)	6388.49	<	6597.93	>	6352.59	≈	6304.97	≈	6198.12	≈	6216.22	<	6295.32	≪	6553.25
Dal Bó and Fréchette (2015)	8138.61	≈	8017.59	≫	7830.12	≈	7810.7	≈	7828.38	≈	7829.74	≈	7775.7	≪	7969.32
Dreber et al. (2008)	752.16	≈	782.37	≈	764.44	≈	763.52	≈	766.77	≈	765.81	≈	767.32	≈	783.45
Duffy and Ochs (2009)	1372.99	≈	1372.97	≈	1361.15	≈	1320.71	≈	1297.84	≈	1291.42	<	1345.16	≈	1361.86
Fréchette and Yuksel (2017)	298.53	≈	299.62	≈	289.54	≈	284.11	≈	289.88	≈	294.05	≈	285.33	≈	291.69
Fudenberg et al. (2012)	425.54	>	381.01	≈	377.96	≈	370.01	≈	380.86	≈	381.34	≈	372.32	≈	377.33
Kagel and Schley (2013)	2439.06	≈	2561.76	≫	2450.24	≈	2421.27	≈	2385.02	≈	2354.05	≈	2398.74	≪	2551.68
Sherstyuk et al. (2013)	1296.85	≈	1303.8	≈	1234.52	≈	1200.28	≈	1184.82	≈	1177.24	≈	1186.92	≪	1286.14
Pooled	**24863.15**	≈	**24779.85**	≫	**24202.51**	≈	**24079.18**	≈	**24195.57**	<	**24468.99**	>	**24219.87**	≪	**24704.09**

(b) Second halves per session

	Best Mixture Best Switching		SG + AD		1.5×SG+AD		2×SG+AD		3×SG+AD		3×P5+AD		2×P5+AD		P5+AD
Specification															
# Models evaluated	$39^{32} \approx 10^{51}$		1		1		1		1		1		1		1
# Pars estimated (by treatment)	438		5		7		9		13		19		17		11
# Parameters accounted for	3-30		5		7		9		13		19		17		11
AF09–34	416.51	≈	423.68	≈	421.21	≈	422.24	≈	423.63	>	404.95	≈	408.59	≈	409.04
BOS11–9	78.84	≈	75.1	≈	80.12	≈	76.06	<	81.99	≈	86.75	>	77.82	≈	78.45
BOS11–14	40.82	≈	35.58	≈	35.86	≪	38.21	≪	44.97	≪	61.2	≫	51.58	≈	43.6
BOS11–15	15.52	≈	19.23	<	24.71	≪	30.15	≪	37.6	≪	53.63	≫	36.89	≫	18.77
BOS11–16	148.98	≈	150.95	≈	138.89	≈	149.71	≈	144.32	≈	145.7	≈	143.01	≈	151.37
BOS11–17	211.59	≈	196.25	≈	201.03	≈	198.59	≈	205.53	≈	205.55	≈	199.44	≈	196.67
BOS11–26	327.16	≈	299.85	≈	309.63	≈	295.25	≈	301.95	≈	305.72	≈	300.57	≈	301.47
BOS11–27	224.85	≈	235.88	≈	223.91	≈	224.21	≈	212.63	≈	212.04	≈	222.13	≈	234.53
BOS11–30	137.43	≈	129.86	≈	132.45	≈	133.81	≈	137.88	≈	146.11	≫	134.06	≈	130.39
BOS11–31	151.87	≈	154.02	≈	153.45	≈	149.77	≈	145.78	≈	148.5	≈	157.41	≈	154.5
BK12–28	516.71	≈	536.77	≫	480.47	≈	478.23	≈	470.25	≈	443.83	≈	471.73	<	528.54
D05–18	340.33	≈	334.18	>	312.74	≈	315.38	≈	323.23	≈	323.92	≈	314.03	≈	330.79
D05–19	383.3	≈	361.33	≈	359.54	≈	357.27	≈	364.76	≈	369.86	≈	364.62	≈	360.66
DF11–6	557.16	≈	526.15	≈	489.74	≈	509.84	≈	495.28	≈	492.63	≈	484.7	≈	516.27
DF11–7	1268.34	≈	1316.79	≈	1250.02	≈	1246.93	≈	1197.33	≈	1212.7	≈	1235.02	≈	1305.98
DF11–8	904.89	≪	1078.24	>	871.84	≈	872.45	≈	834.02	<	852.42	<	869.39	≪	1065.6
DF11–22	973.62	≈	930.3	>	858.03	≈	860.39	≈	848.36	≈	832.44	≈	844.82	<	918.07
DF11–23	723.5	≈	767.04	>	608.87	≈	582.24	≈	556.55	≈	545.64	≈	564.18	<	741.18
DF11–24	450.61	≈	483.25	≈	449.72	≈	424.76	≈	424.94	≈	423.85	≈	424.99	≈	460.55
DF15–4	301.69	≈	320.02	≈	299.49	≈	306.89	≈	301.34	≈	299.43	≈	295.28	≈	318.1
DF15–5	1435.63	≪	1606.96	≫	1407.26	≈	1409.52	≈	1395.3	≈	1409.68	≈	1407.43	≪	1596.73
DF15–20	1270.1	≈	1232.33	≫	1145.96	≈	1141.29	≈	1113.17	≈	1107.65	≈	1121.22	<	1215.9
DF15–21	1504.63	≈	1591.27	≫	1453.74	≈	1422.87	≈	1390.81	≈	1367.29	≈	1403.53	≪	1559.69
DF15–33	2541.5	>	2405.23	≈	2331.38	≈	2349.48	>	2265.94	>	2184.74	<	2237.97	<	2318.99
DF15–35	723.78	>	641.02	≈	627.6	≈	627.73	≈	627.87	≈	609.97	≈	610.6	≈	633.52
DRFN08–10	243.71	≈	244.91	≈	234.76	≈	236.44	≈	234.24	≈	218.82	≈	218.68	≈	225.25
DRFN08–11	323.06	≈	341.42	>	305	≈	299.09	≈	296.13	≈	287.15	≈	291.03	≈	332.84
DO09–32	1850.35	≈	1761.6	≫	1656.55	≈	1602.93	>	1518.65	≈	1509.7	<	1598.04	≪	1715.88
FY17–25	427.79	≈	423.34	≈	422.61	≈	381.63	≈	375.03	≈	384.11	≈	382.16	<	409.93
FRD12–29	514.87	≈	452.6	≈	433.74	≈	414.24	≈	405.22	≈	410.69	≈	421.81	≈	448.37
KS13–12	1678.7	≈	1775.62	≫	1572.95	≈	1541.38	>	1488.49	≈	1477.87	≈	1527.47	≪	1748.01
STS13–13	955.73	≈	951.34	≫	834.74	≈	823.06	≈	799.39	≈	801.53	≈	815.26	≪	935.01
Aoyagi and Frechette (2009)	416.51	≈	423.68	≈	421.21	≈	422.24	≈	423.63	>	404.95	≈	408.59	≈	409.04
Blonski et al. (2011)	1394.16	≈	1346.79	≈	1370.16	≈	1385.91	<	1442.85	≪	1555.48	≫	1453.1	≫	1379.87
Bruttel and Kamecke (2012)	516.71	≈	536.77	≫	480.47	≈	478.23	≈	470.25	≈	443.83	≈	471.73	<	528.54
Dal Bó (2005)	729.48	>	699.05	≈	677.24	≈	679.04	<	697.21	≈	707.25	≈	687.86	≈	696.41
Dal Bó and Fréchette (2011)	4964.77	≈	5128.69	≫	4565.93	≈	4545.08	≈	4426.48	≈	4461.98	≈	4493.1	≪	5045.34
Dal Bó and Fréchette (2015)	7893.79	≈	7825.98	≫	7306.25	≈	7310.27	>	7170.25	≈	7089.56	≈	7151.84	≪	7683.76
Dreber et al. (2008)	581.94	≈	589.84	>	544.66	≈	541.83	≈	539.47	≈	519.28	≈	518.82	<	562.99
Duffy and Ochs (2009)	1850.35	≈	1761.6	≫	1656.55	≈	1602.93	>	1518.65	≈	1509.7	<	1598.04	≪	1715.88
Fréchette and Yuksel (2017)	427.79	≈	423.34	≈	422.61	≈	381.63	≈	375.03	≈	384.11	≈	382.16	<	409.93
Fudenberg et al. (2012)	514.87	≈	452.6	≈	433.74	≈	414.24	≈	405.22	≈	410.69	≈	421.81	≈	448.37
Kagel and Schley (2013)	1678.7	≈	1775.62	≫	1572.95	≈	1541.38	>	1488.49	≈	1477.87	≈	1527.47	≪	1748.01
Sherstyuk et al. (2013)	955.73	≈	951.34	≫	834.74	≈	823.06	≈	799.39	≈	801.53	≈	815.26	≪	935.01
Pooled	**22422.07**	≈	**22097.67**	≫	**20541.83**	≈	**20454.13**	>	**20231.09**	<	**20459.26**	≈	**20403.95**	≪	**21818.45**

Note: Notation of treatments and meaning of relation signs are all as defined above, see Table A.9.

Table A.28: Strategies as a function of behavior in $t-2$ (TFT scheme)

Experiment	Cooperation after $\emptyset,(c,c),(d,c)$ in $t-2$							Cooperation after $(c,d),(d,d)$ in $t-2$						
	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$
First halves per session														
Aoyagi and Frechette (2009)	0.93	$\gg$	0.439	$\approx$	0.388	$\approx$	0.434	0.789	$\gg$	0.463	$\approx$	0.44	$>$	0.291
Blonski et al. (2011)	0.901	$\gg$	0.27	$\approx$	0.146	$\gg$	0.053	0.667	$\approx$	0.296	$\approx$	0.321	$\gg$	0.027
Bruttel and Kamecke (2012)	0.908	$\gg$	0.312	$\approx$	0.218	$\approx$	0.151	0.944	$\gg$	0.247	$\approx$	0.247	$\gg$	0.063
Dal Bó (2005)	0.93	$\gg$	0.232	$\approx$	0.31	$>$	0.126	0.833	$>$	0.147	$\approx$	0.413	$\gg$	0.071
Dal Bó and Fréchette (2011)	0.955	$\gg$	0.352	$\approx$	0.298	$\gg$	0.086	0.885	$\gg$	0.291	$\approx$	0.41	$\gg$	0.048
Dal Bó and Fréchette (2015)	0.944	$\gg$	0.301	$\approx$	0.277	$\gg$	0.098	0.847	$\gg$	0.288	$\approx$	0.44	$\gg$	0.044
Dreber et al. (2008)	0.902	$\gg$	0.213	$\approx$	0.189	$\gg$	0.061	1	$>$	0.233	$\approx$	0.302	$\gg$	0.025
Duffy and Ochs (2009)	0.927	$\gg$	0.316	$\approx$	0.304	$\approx$	0.232	0.691	$\gg$	0.277	$\approx$	0.361	$\gg$	0.08
Fréchette and Yuksel (2017)	0.943	$\gg$	0.153	$\approx$	0.241	$\approx$	0.1	1	$\approx$		$\approx$	0.4	$\approx$	0.086
Fudenberg et al. (2012)	0.984	$\gg$	0.394	$\approx$	0.347	$\gg$	0.05	0.895	$\gg$	0.41	$\approx$	0.579	$\gg$	0.069
Kagel and Schley (2013)	0.94	$\gg$	0.29	$\approx$	0.25	$\gg$	0.125	0.787	$\gg$	0.196	$\approx$	0.402	$\gg$	0.032
Sherstyuk et al. (2013)	0.951	$\gg$	0.329	$\approx$	0.341	$>$	0.186	0.844	$\gg$	0.328	$\approx$	0.424	$\gg$	0.09
Pooled	0.944	$\gg$	0.312	$>$	0.279	$\gg$	0.106	0.826	$\gg$	0.287	$\approx$	0.41	$\gg$	0.05
Second halves per session														
Aoyagi and Frechette (2009)	0.961	$\gg$	0.408	$\approx$	0.567	$\approx$	0.447	0.867	$\gg$	0.381	$\approx$	0.451	$\approx$	0.328
Blonski et al. (2011)	0.922	$\gg$	0.224	$\approx$	0.195	$\gg$	0.029	0.944	$\gg$	0.402	$\approx$	0.324	$\gg$	0.018
Bruttel and Kamecke (2012)	0.948	$\gg$	0.239	$\approx$	0.214	$\approx$	0.118	0.923	$>$	0.167	$\approx$	0.5	$\gg$	0.018
Dal Bó (2005)	0.919	$\gg$	0.264	$\approx$	0.39	$\gg$	0.113	0.938	$\gg$	0.175	$\approx$	0.383	$\gg$	0.047
Dal Bó and Fréchette (2011)	0.979	$\gg$	0.391	$\approx$	0.29	$\gg$	0.075	0.975	$\gg$	0.334	$\approx$	0.547	$\gg$	0.022
Dal Bó and Fréchette (2015)	0.977	$\gg$	0.304	$\approx$	0.328	$\gg$	0.064	0.927	$\gg$	0.343	$\approx$	0.532	$\gg$	0.028
Dreber et al. (2008)	0.917	$\gg$	0.111	$<$	0.311	$\gg$	0.005	0.909	$>$	0.5	$\approx$	0.629	$\gg$	0.01
Duffy and Ochs (2009)	0.98	$\gg$	0.408	$\approx$	0.371	$>$	0.232	0.849	$\gg$	0.316	$\approx$	0.415	$\gg$	0.058
Fréchette and Yuksel (2017)	0.973	$\gg$	0.213	$\approx$	0.286	$\approx$	0.214	0.818	$\approx$	0.286	$\approx$	0.575	$\gg$	0.038
Fudenberg et al. (2012)	0.974	$\gg$	0.5	$\approx$	0.41	$\gg$	0.111	0.84	$>$	0.463	$\approx$	0.417	$\gg$	0.075
Kagel and Schley (2013)	0.967	$\gg$	0.281	$\approx$	0.263	$\gg$	0.061	0.872	$\gg$	0.188	$\approx$	0.527	$\gg$	0.018
Sherstyuk et al. (2013)	0.973	$\gg$	0.503	$\approx$	0.417	$\gg$	0.12	0.968	$\gg$	0.431	$\approx$	0.5	$\gg$	0.062
Pooled	0.973	$\gg$	0.325	$\approx$	0.315	$\gg$	0.076	0.917	$\gg$	0.332	$\approx$	0.499	$\gg$	0.028

Note: Relation signs, bootstrap procedure, and derived p-values are exactly as above, see Table 1.2, with the obvious adaptation that the Holm-Bonferroni correction now applies to all eight tests per data set.

Table A.29: Strategies as a function of behavior in $t-2$ (Grim scheme)

Experiment	Cooperation after $\emptyset,(c,c)$ in $t-2$							Cooperation after $(c,d),(d,c),(d,d)$ in $t-2$						
	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$
First halves per session														
Aoyagi and Frechette (2009)	0.939	$\gg$	0.39	$\approx$	0.439	$\approx$	0.556	0.782	$\gg$	0.485	$\approx$	0.39	$>$	0.32
Blonski et al. (2011)	0.903	$\gg$	0.248	$\approx$	0.174	$\gg$	0.045	0.714	$>$	0.318	$\approx$	0.216	$>$	0.031
Bruttel and Kamecke (2012)	0.919	$\gg$	0.296	$\approx$	0.245	$\approx$	0.179	0.833	$\gg$	0.278	$\approx$	0.213	$\gg$	0.071
Dal Bó (2005)	0.926	$\gg$	0.184	$\approx$	0.31	$\approx$	0.143	0.889	$\gg$	0.254	$\approx$	0.39	$\gg$	0.074
Dal Bó and Fréchette (2011)	0.961	$\gg$	0.342	$\approx$	0.307	$\gg$	0.081	0.849	$\gg$	0.324	$\approx$	0.364	$\gg$	0.054
Dal Bó and Fréchette (2015)	0.95	$\gg$	0.265	$\approx$	0.301	$\gg$	0.081	0.843	$\gg$	0.328	$\approx$	0.369	$\gg$	0.052
Dreber et al. (2008)	0.901	$\gg$	0.154	$\approx$	0.217	$\gg$	0.062	1	$\gg$	0.359	$\approx$	0.203	$\gg$	0.031
Duffy and Ochs (2009)	0.932	$\gg$	0.218	$\approx$	0.301	$\approx$	0.208	0.748	$\gg$	0.361	$\approx$	0.35	$\gg$	0.102
Fréchette and Yuksel (2017)	0.942	$\gg$	0.132	$\approx$	0.245	$\gg$	0	1	$\approx$	0.182	$\approx$	0.364	$\approx$	0.111
Fudenberg et al. (2012)	0.985	$\gg$	0.429	$\approx$	0.408	$\gg$	0	0.921	$\gg$	0.377	$\approx$	0.443	$\gg$	0.068
Kagel and Schley (2013)	0.947	$\gg$	0.236	$\approx$	0.288	$\gg$	0.133	0.763	$\gg$	0.298	$\approx$	0.305	$\gg$	0.042
Sherstyuk et al. (2013)	0.953	$\gg$	0.312	$\approx$	0.395	$\gg$	0.172	0.875	$\gg$	0.343	$\approx$	0.349	$\gg$	0.107
Pooled	0.949	$\gg$	0.278	$\approx$	0.3	$\gg$	0.091	0.825	$\gg$	0.333	$\approx$	0.346	$\gg$	0.059
Second halves per session														
Aoyagi and Frechette (2009)	0.965	$\gg$	0.438	$\approx$	0.625	$\approx$	0.333	0.846	$\gg$	0.371	$<$	0.443	$\approx$	0.378
Blonski et al. (2011)	0.922	$\gg$	0.157	$\approx$	0.232	$\gg$	0.027	0.941	$\gg$	0.425	$\approx$	0.23	$\gg$	0.019
Bruttel and Kamecke (2012)	0.946	$\gg$	0.156	$\approx$	0.233	$\approx$	0.173	0.958	$\gg$	0.327	$\approx$	0.4	$\gg$	0.019
Dal Bó (2005)	0.918	$\gg$	0.178	$<$	0.4	$>$	0.131	0.937	$\gg$	0.32	$\approx$	0.373	$\gg$	0.052
Dal Bó and Fréchette (2011)	0.981	$\gg$	0.373	$\approx$	0.323	$\gg$	0.077	0.95	$\gg$	0.38	$\approx$	0.416	$\gg$	0.025
Dal Bó and Fréchette (2015)	0.98	$\gg$	0.264	$<$	0.366	$\gg$	0.058	0.904	$\gg$	0.369	$\approx$	0.44	$\gg$	0.031
Dreber et al. (2008)	0.913	$\gg$	0.029	$\ll$	0.314	$\gg$	0.007	0.955	$\gg$	0.417	$\approx$	0.611	$\gg$	0.009
Duffy and Ochs (2009)	0.981	$\gg$	0.362	$\approx$	0.433	$\approx$	0.226	0.889	$\gg$	0.369	$\approx$	0.368	$\gg$	0.077
Fréchette and Yuksel (2017)	0.976	$\gg$	0.173	$\approx$	0.308	$\approx$	0.222	0.75	$>$	0.294	$\approx$	0.49	$\gg$	0.06
Fudenberg et al. (2012)	0.976	$\gg$	0.473	$\approx$	0.509	$\approx$	0.2	0.854	$\gg$	0.5	$\approx$	0.328	$\gg$	0.077
Kagel and Schley (2013)	0.969	$\gg$	0.218	$\approx$	0.293	$>$	0.098	0.868	$\gg$	0.332	$\approx$	0.394	$\gg$	0.02
Sherstyuk et al. (2013)	0.974	$\gg$	0.465	$\approx$	0.486	$\gg$	0.107	0.952	$\gg$	0.505	$\approx$	0.369	$\gg$	0.072
Pooled	0.975	$\gg$	0.282	$\ll$	0.351	$\gg$	0.07	0.908	$\gg$	0.378	$\approx$	0.404	$\gg$	0.033

Note: Relation signs, bootstrap procedure, and derived p-values are exactly as above, see Table 1.2, with the obvious adaptation that the Holm-Bonferroni correction now applies to all eight tests per data set.

Table A.30: Table A.29 by treatments – Strategies as a function of behavior in $t-2$ (Grim scheme)

(a) First halves per session

Treatment	Equality	Cooperation after $(d,c),(c,d),(d,d)$ in $t-2$							Cooperation after ../tex-r1/ext-grim-tab2.tex in $t-2$						
	p-value	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$
Aoyagi and Frechette (2009)															
AF09–34	0	0.939	$\gg$	0.39	$\approx$	0.439	$\approx$	0.556	0.782	$\gg$	0.485	$\approx$	0.39	$>$	0.32
Blonski et al. (2011)															
BOS11–9	0.23	-		0.182		0.182		0.031							
BOS11–14	0.16	-		0.188		0.062		0.029							
BOS11–15	0.04	-		0.167		0		0.005							
BOS11–16	0	0.934	$\gg$	0.136	$\approx$	0.136	$\approx$	0.056	0.667	$\approx$	0.333	$\approx$	0.333	$>$	0.076
BOS11–17	1	0.5	$\approx$	0.231	$\approx$	0.462	$\approx$	0.115	NA	$\approx$	0.25	$\approx$	0.5	$\approx$	0.167
BOS11–26	0.005	0.857	$>$	0.258	$\approx$	0.097	$\approx$	0.07	0.5	$\approx$	0.2	$\approx$	0.35	$\gg$	0.02
BOS11–27	0.18	0.875	$\approx$	0.556	$\approx$	0.333	$\approx$	0.091	1	$\approx$	0.1	$\approx$	0.1	$\approx$	0.044
BOS11–30	0.275	-		0		0		0.058							
BOS11–31	0	0.983	$\gg$	0.385	$\approx$	0.231	$\approx$	0.091	0.5	$\approx$	0.577	$\approx$	0.115	$\approx$	0.015
BOS11–All	0	0.903	$\gg$	0.248	$\approx$	0.174	$\gg$	0.045	0.714	$>$	0.318	$\approx$	0.216	$>$	0.031
Bruttel and Kamecke (2012)															
BK12–28	0	0.919	$\gg$	0.296	$\approx$	0.245	$\approx$	0.179	0.833	$\gg$	0.278	$\approx$	0.213	$\gg$	0.071
Dal Bó (2005)															
D05–18	0	0.821	$\gg$	0.208	$\approx$	0.25	$\approx$	0.091	0.75	$\approx$	0.273	$\approx$	0.364	$\approx$	0.118
D05–19	0	0.954	$\gg$	0.175	$\approx$	0.333	$\approx$	0.158	1	$\gg$	0.243	$\approx$	0.405	$\gg$	0.044
D05–All	0	0.926	$\gg$	0.184	$\approx$	0.31	$\approx$	0.143	0.889	$\gg$	0.254	$\approx$	0.39	$\gg$	0.074
Dal Bó and Fréchette (2011)															
DF11–6	0.059	0.667	$\approx$	0.294	$\approx$	0.235	$\gg$	0.038	0.917	$\gg$	0.375	$\approx$	0.35	$\gg$	0.034
DF11–7	0.002	0.632	$>$	0.254	$\approx$	0.254	$\gg$	0.089	0.786	$>$	0.391	$\approx$	0.266	$\gg$	0.029
DF11–8	0	0.979	$\gg$	0.446	$\approx$	0.28	$\gg$	0.105	0.923	$\gg$	0.361	$\approx$	0.222	$\gg$	0.06
DF11–22	0	0.922	$\gg$	0.34	$\approx$	0.381	$\gg$	0.06	0.833	$\gg$	0.279	$\approx$	0.338	$\gg$	0.048
DF11–23	0	0.976	$\gg$	0.448	$\approx$	0.321	$\gg$	0.16	0.859	$\gg$	0.325	$\approx$	0.462	$\gg$	0.054
DF11–24	0	0.967	$\gg$	0.228	$\approx$	0.366	$>$	0.135	0.813	$\gg$	0.308	$\approx$	0.436	$\gg$	0.107
DF11–All	0	0.961	$\gg$	0.342	$\approx$	0.307	$\gg$	0.081	0.849	$\gg$	0.324	$\approx$	0.364	$\gg$	0.054
Dal Bó and Fréchette (2015)															
DF15–4	0.017	0.571	$>$	0.073	$\approx$	0.268	$>$	0.018	0.5	$\approx$	0.429	$\approx$	0.5	$\gg$	0.044
DF15–5	0	0.92	$\gg$	0.223	$\approx$	0.219	$\gg$	0.076	0.95	$\gg$	0.369	$\approx$	0.323	$\gg$	0.086
DF15–20	0	0.933	$\gg$	0.222	$\approx$	0.335	$\gg$	0.073	0.825	$\gg$	0.225	$\approx$	0.337	$\gg$	0.046
DF15–21	0	0.959	$\gg$	0.325	$\approx$	0.329	$\gg$	0.129	0.873	$\gg$	0.455	$>$	0.411	$\gg$	0.077
DF15–33	0	0.953	$\gg$	0.313	$\approx$	0.322	$\gg$	0.111	0.802	$\gg$	0.288	$\approx$	0.356	$\gg$	0.047
DF15–35	0	0.98	$\gg$	0.276	$\approx$	0.448	$\approx$	0.214	0.882	$\gg$	0.356	$\approx$	0.422	$\gg$	0.042
DF15–All	0	0.95	$\gg$	0.265	$\approx$	0.301	$\gg$	0.081	0.843	$\gg$	0.328	$\approx$	0.369	$\gg$	0.052
Dreber et al. (2008)															
DRFN08–10	0	0.885	$\gg$	0.143	$\approx$	0.13	$>$	0.031	1	$>$	0.333	$\approx$	0.167	$>$	0.018
DRFN08–11	0	0.914	$\gg$	0.167	$\approx$	0.318	$>$	0.091	1	$>$	0.375	$\approx$	0.225	$\gg$	0.043
DRFN08–All	0	0.901	$\gg$	0.154	$\approx$	0.217	$\gg$	0.062	1	$\gg$	0.359	$\approx$	0.203	$\gg$	0.031
Duffy and Ochs (2009)															
DO09–32	0	0.932	$\gg$	0.218	$\approx$	0.301	$\approx$	0.208	0.748	$\gg$	0.361	$\approx$	0.35	$\gg$	0.102
Fréchette and Yuksel (2017)															
FY17–25	0	0.942	$\gg$	0.132	$\approx$	0.245	$\gg$	0	1	$\approx$	0.182	$\approx$	0.364	$\approx$	0.111
Fudenberg et al. (2012)															
FRD12–29	0	0.985	$\gg$	0.429	$\approx$	0.408	$\gg$	0	0.921	$\gg$	0.377	$\approx$	0.443	$\gg$	0.068
Kagel and Schley (2013)															
KS13–12	0	0.947	$\gg$	0.236	$\approx$	0.288	$\gg$	0.133	0.763	$\gg$	0.298	$\approx$	0.305	$\gg$	0.042
Sherstyuk et al. (2013)															
STS13–13	0	0.953	$\gg$	0.312	$\approx$	0.395	$\gg$	0.172	0.875	$\gg$	0.343	$\approx$	0.349	$\gg$	0.107
Pooled	0	0.949	$\gg$	0.278	$\approx$	0.3	$\gg$	0.091	0.825	$\gg$	0.333	$\approx$	0.346	$\gg$	0.059

(b) Second halves per session

Treatment	Equality	Cooperation after $(d,c),(c,d),(d,d)$ in $t-2$							Cooperation after ../tex-r1/ext-grim-tab3.tex in $t-2$						
	p-value	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$	$\hat{\sigma}_{cc}$		$\hat{\sigma}_{cd}$		$\hat{\sigma}_{dc}$		$\hat{\sigma}_{dd}$
Aoyagi and Frechette (2009)															
AF09–34	0	0.965	$\gg$	0.438	$\approx$	0.625	$\approx$	0.333	0.846	$\gg$	0.371	$\approx$	0.443	$\approx$	0.378
Blonski et al. (2011)															
BOS11–9	0.006	0.917	$>$	0	$\approx$	0.154	$\approx$	0.021	NA	$\approx$	0.333	$\approx$	0.333	$\approx$	0
BOS11–14	0.025	-		0.2		0.4		0.013							
BOS11–15	0	-		0		0		0.002							
BOS11–16	0	0.855	$\gg$	0.12	$\approx$	0.24	$>$	0	0.5	$\approx$	0.6	$\approx$	0.2	$\approx$	0.03
BOS11–17	0	0.912	$\gg$	0.161	$\approx$	0.194	$\approx$	0.048	1	$\approx$	0.208	$\approx$	0.333	$\gg$	0.024
BOS11–26	0	0.955	$\gg$	0.171	$\approx$	0.195	$\gg$	0.022	1	$>$	0.316	$\approx$	0.211	$\gg$	0.033
BOS11–27	0.01	0.867	$>$	0.31	$\approx$	0.414	$>$	0.109	0.9	$\gg$	0.518	$\approx$	0.268	$>$	0.014
BOS11–30	0.099	0.75	$\approx$	0.083	$\approx$	0.083	$\approx$	0	1	$\approx$	0.333	$\approx$	0.25	$\approx$	0.022
BOS11–31	0.004	1	$>$	0.143	$\approx$	0.286	$\approx$	0.062	1	$>$	0.613	$\approx$	0.097	$>$	0.018
BOS11–All	0	0.922	$\gg$	0.157	$\approx$	0.232	$\gg$	0.027	0.941	$\gg$	0.425	$\approx$	0.23	$\gg$	0.019
Bruttel and Kamecke (2012)															
BK12–28	0	0.946	$\gg$	0.156	$\approx$	0.233	$\approx$	0.173	0.958	$\gg$	0.327	$\approx$	0.4	$\gg$	0.019
Dal Bó (2005)															
D05–18	0	0.85	$\gg$	0.227	$<$	0.523	$\approx$	0.194	0.9	$\gg$	0.325	$\approx$	0.425	$\gg$	0.076
D05–19	0	0.949	$\gg$	0.13	$\approx$	0.283	$\approx$	0.083	1	$\gg$	0.314	$\approx$	0.314	$\gg$	0.04
D05–All	0	0.918	$\gg$	0.178	$<$	0.4	$>$	0.131	0.937	$\gg$	0.32	$\approx$	0.373	$\gg$	0.052
Dal Bó and Fréchette (2011)															
DF11–6	0.006	1	$>$	0.267	$\approx$	0.378	$\gg$	0.031	1	$\gg$	0.442	$\approx$	0.581	$\gg$	0.012
DF11–7	0	0.903	$\gg$	0.36	$\approx$	0.346	$\gg$	0.12	0.95	$\gg$	0.4	$\approx$	0.389	$\gg$	0.042
DF11–8	0	1	$\gg$	0.395	$>$	0.163	$\gg$	0.047	1	$\gg$	0.453	$\approx$	0.266	$\gg$	0.02
DF11–22	0	0.971	$\gg$	0.462	$\approx$	0.387	$\gg$	0.056	0.903	$\gg$	0.265	$\approx$	0.426	$\gg$	0.018
DF11–23	0	0.974	$\gg$	0.387	$\approx$	0.6	$\approx$	0.314	0.98	$\gg$	0.425	$\approx$	0.397	$\gg$	0.036
DF11–24	0	0.984	$\gg$	0.192	$\approx$	0.25	$\approx$	1	0.9	$>$	0.471	$\approx$	0.559	$\gg$	0.073
DF11–All	0	0.981	$\gg$	0.373	$\approx$	0.323	$\gg$	0.077	0.95	$\gg$	0.38	$\approx$	0.416	$\gg$	0.025
Dal Bó and Fréchette (2015)															
DF15–4	0.034	0.75	$>$	0.059	$\approx$	0.176	$\approx$	0.007	1	$\approx$	0.091	$\approx$	0.545	$>$	0.024
DF15–5	0	0.981	$\gg$	0.226	$\approx$	0.218	$\gg$	0.031	0.846	$\gg$	0.411	$\approx$	0.274	$\gg$	0.041
DF15–20	0	0.958	$\gg$	0.348	$\approx$	0.402	$\gg$	0.069	0.889	$\gg$	0.255	$\approx$	0.333	$\gg$	0.02
DF15–21	0	0.981	$\gg$	0.234	$\approx$	0.288	$>$	0.133	0.929	$\gg$	0.424	$\approx$	0.348	$\gg$	0.058
DF15–33	0	0.981	$\gg$	0.273	$\ll$	0.517	$\gg$	0.077	0.911	$\gg$	0.34	$<$	0.557	$\gg$	0.028
DF15–35	0	0.986	$\gg$	0.362	$\approx$	0.569	$\approx$	0.375	0.887	$\gg$	0.533	$\approx$	0.358	$\gg$	0.032
DF15–All	0	0.98	$\gg$	0.264	$<$	0.366	$\gg$	0.058	0.904	$\gg$	0.369	$\approx$	0.44	$\gg$	0.031
Dreber et al. (2008)															
DRFN08–10	0	0.667	$\gg$	0.02	$\approx$	0.18	$\approx$	0	1	$\approx$	0.75	$\approx$	0.875	$\gg$	0.002
DRFN08–11	0	0.943	$\gg$	0.036	$\ll$	0.436	$>$	0.031	0.929	$\gg$	0.321	$\approx$	0.536	$\gg$	0.028
DRFN08–All	0	0.913	$\gg$	0.029	$\ll$	0.314	$\gg$	0.007	0.955	$\gg$	0.417	$\approx$	0.611	$\gg$	0.009
Duffy and Ochs (2009)															
DO09–32	0	0.981	$\gg$	0.362	$\approx$	0.433	$\approx$	0.226	0.889	$\gg$	0.369	$\approx$	0.368	$\gg$	0.077
Fréchette and Yuksel (2017)															
FY17–25	0	0.976	$\gg$	0.173	$\approx$	0.308	$\approx$	0.222	0.75	$>$	0.294	$\approx$	0.49	$\gg$	0.06
Fudenberg et al. (2012)															
FRD12–29	0	0.976	$\gg$	0.473	$\approx$	0.509	$\approx$	0.2	0.854	$\gg$	0.5	$\approx$	0.328	$\gg$	0.077
Kagel and Schley (2013)															
KS13–12	0	0.969	$\gg$	0.218	$\approx$	0.293	$>$	0.098	0.868	$\gg$	0.332	$\approx$	0.394	$\gg$	0.02
Sherstyuk et al. (2013)															
STS13–13	0	0.974	$\gg$	0.465	$\approx$	0.486	$\gg$	0.107	0.952	$\gg$	0.505	$\approx$	0.369	$\gg$	0.072
Pooled	0	0.975	$\gg$	0.282	$\ll$	0.351	$\gg$	0.07	0.908	$\gg$	0.378	$\approx$	0.404	$\gg$	0.033

Table A.31: 1- and 2-memory SG behavior strategies versus best mixtures (by treatment) of 1- and 2-memory pure strategies (No switching) (ICL-BIC of the models, less is better and relation signs point toward better models)

	SG+ SG M2"General"		SG M2"General"		Semi-Grim		Best Pure		Pure M1+G2,T2		Pure M1
Specification											
# Models evaluated	1		1		1		5		1		1
# Pars estimated (by treatment)	7		3		3		32		5		3
# Parameters accounted for	7		3		3		3-8		5		3
First halves per session											
Aoyagi and Frechette (2009)	855.34	$\approx$	847.81	$\approx$	835.89	$\approx$	891.63	$\approx$	891.63	$\approx$	897.8
Blonski et al. (2011)	2337.47	$\gg$	2188.04	$\gg$	1089.36	$\ll$	1241.55	$\ll$	1367.4	$\gg$	1239.58
Bruttel and Kamecke (2012)	1025.99	$\approx$	1021.23	$\gg$	817.24	$\approx$	861.15	$\approx$	861.15	$\approx$	862.58
Dal Bó (2005)	968.96	$\gg$	907.92	$\gg$	653.33	$\approx$	678.73	$\ll$	713.82	$>$	678.73
Dal Bó and Fréchette (2011)	14795.82	$\approx$	14789.67	$\gg$	7282.65	$<$	7668.25	$\approx$	7725.56	$\approx$	7670.28
Dal Bó and Fréchette (2015)	13772.1	$\gg$	13479.92	$\gg$	8887.67	$\approx$	9096.12	$\ll$	9276.23	$\gg$	9116.67
Dreber et al. (2008)	1176.51	$\approx$	1165.17	$\gg$	838.33	$\approx$	875.56	$<$	905.5	$>$	875.56
Duffy and Ochs (2009)	1670.22	$\approx$	1650.03	$\gg$	1437.86	$\approx$	1449.33	$\approx$	1459.86	$\approx$	1449.33
Fréchette and Yuksel (2017)	393.16	$\approx$	372.41	$\approx$	335.07	$\approx$	319.92	$\ll$	344.74	$\gg$	319.92
Fudenberg et al. (2012)	466.79	$\approx$	452.21	$\gg$	398.38	$\ll$	474.56	$\approx$	474.56	$\approx$	479.33
Kagel and Schley (2013)	3526.46	$\approx$	3570.33	$\gg$	2912.53	$>$	2739.66	$\approx$	2760.67	$\approx$	2739.66
Sherstyuk et al. (2013)	1685.47	$\approx$	1691.71	$\gg$	1413	$\approx$	1421.45	$\approx$	1421.45	$\approx$	1428.6
Pooled	**42929.62**	$\gg$	**42318.82**	$\gg$	**27010.74**	$\ll$	**27851.71**	$\ll$	**28384.93**	$\gg$	**27867.48**
Second halves per session											
Aoyagi and Frechette (2009)	515.26	$>$	500.7	$\approx$	494.93	$\approx$	548.36	$\approx$	548.36	$\approx$	553.46
Blonski et al. (2011)	3075.21	$\gg$	2951.31	$\gg$	1441.28	$\ll$	1757.39	$\ll$	1863.15	$\gg$	1757.39
Bruttel and Kamecke (2012)	833.83	$\approx$	838.57	$\gg$	595.23	$\approx$	583.12	$\approx$	583.12	$\approx$	594.04
Dal Bó (2005)	1041.04	$\gg$	975.62	$\gg$	748.55	$\approx$	747.84	$\ll$	785.02	$\gg$	747.84
Dal Bó and Fréchette (2011)	13878.91	$\approx$	13949.42	$\gg$	6160.5	$\approx$	6250.91	$\approx$	6306.7	$\approx$	6430.56
Dal Bó and Fréchette (2015)	14391.56	$\approx$	14280.59	$\gg$	9015.88	$<$	9477.45	$\approx$	9544.21	$\approx$	9552.41
Dreber et al. (2008)	1118.6	$\approx$	1106.62	$\gg$	665.13	$\approx$	664.79	$\ll$	690.58	$\approx$	664.79
Duffy and Ochs (2009)	2016.24	$\approx$	1993.56	$\gg$	1794.26	$\ll$	2016.45	$\approx$	2016.45	$\approx$	2042.07
Fréchette and Yuksel (2017)	561.78	$>$	528.38	$\approx$	481.62	$\approx$	474.69	$\ll$	502.3	$>$	474.69
Fudenberg et al. (2012)	532.03	$\approx$	530.32	$>$	485.43	$<$	551	$\approx$	551	$\approx$	571.98
Kagel and Schley (2013)	2648.79	$\approx$	2676.25	$\gg$	2261.67	$\gg$	1919.9	$\approx$	1919.9	$\approx$	1971.47
Sherstyuk et al. (2013)	1248.54	$\approx$	1293.11	$>$	1087.07	$\approx$	1029.75	$\approx$	1029.75	$<$	1127.23
Pooled	**42117.12**	$>$	**41806.84**	$\gg$	**25340.99**	$<$	**26159.81**	$\ll$	**26522.89**	$\approx$	**26597.37**

Note: Relation signs, bootstrap procedure, and derived p-values are exactly as above, see Table 1.2. Pure M1 refers to TFT, Grim, and AD. G2 denotes Grim2. For definitions of the strategies see Table A.7.

Table A.32: Table A.31 by treatments – 1- and 2-memory SG behavior strategies versus best mixtures (by treatment) of 1- and 2-memory pure strategies (No switching)

(a) First halves per session

	SG+ SG M2“General”		SG M2“General”		Semi-Grim		Best Pure		Pure M1+G2,T2		Pure M1
Specification											
# Models evaluated	1		1		1		5		1		1
# Pars estimated (by treatment)	7		3		3		32		5		3
# Parameters accounted for	7		3		3		3-8		5		3
AF09–34	855.34	≈	847.81	≈	835.89	≈	891.63	≈	891.63	≈	897.8
BOS11–9	228.81	≫	213.06	≫	82.26	≈	99.25	≪	112.53	≫	99.25
BOS11–14	260.4	≈	249.04	≫	87.7	≪	114.56	≪	127.38	≫	114.56
BOS11–15	273.29	>	256.51	≫	31.07	≪	72.06	≪	85.01	≫	72.06
BOS11–16	225	>	210.23	>	170.96	≈	176.25	<	188.95	>	176.25
BOS11–17	165.97	≫	148.89	>	119.9	≈	123.55	≪	139.81	≫	123.55
BOS11–26	509.26	>	483.9	≫	254.14	≈	275.47	≪	293.71	>	275.47
BOS11–27	227.67	>	217.47	≫	108.51	≈	116.34	≈	116.34	≈	116.68
BOS11–30	173.13	≫	156.27	≫	63.02	≈	64.25	≪	77.67	≫	64.25
BOS11–31	203.85	≈	202.6	>	141.75	≈	167.46	≈	175.92	>	167.46
BK12–28	1025.99	≈	1021.23	≫	817.24	≈	861.15	≈	861.15	≈	862.58
D05–18	305.64	≫	281.91	≫	224.25	≈	240.35	≪	263.72	≫	240.35
D05–19	658.37	≫	622.47	≫	426.95	≈	436.26	≈	446.55	≈	436.26
DF11–6	3212.26	≈	3201.72	≫	894.35	≈	929.98	≈	939.5	≈	929.98
DF11–7	3939.04	≈	3932.55	≫	1369.26	<	1498.06	≈	1530.47	≈	1498.06
DF11–8	3028.46	≈	3058.62	≫	1648.75	≈	1568.94	≈	1568.94	≈	1571.62
DF11–22	1830.58	≈	1822.78	≫	1042.26	≪	1226.5	≈	1236.62	≈	1226.5
DF11–23	1453.39	≈	1461.14	≫	1117.42	≈	1176.02	≈	1176.02	≈	1181.42
DF11–24	1294.39	≈	1285.94	>	1194.45	≈	1246.18	≈	1247.07	≈	1246.54
DF15–4	1783.05	≈	1749.99	≫	477.13	≈	494.11	≪	523.98	≫	494.11
DF15–5	3031.87	>	2953.98	≫	2194.38	≫	1845.7	≈	1889.41	≈	1845.7
DF15–20	2763.46	≈	2713.19	≫	1481.46	<	1642.7	≈	1670.78	>	1642.7
DF15–21	2460.51	≈	2433.58	≫	2111.65	≈	2058.02	≈	2058.02	≈	2079.98
DF15–33	3248.44	>	3172.27	≫	2256.38	≪	2613.59	<	2676.03	>	2613.59
DF15–35	443.95	≈	427.76	≫	349.17	<	423.09	≈	428.84	≈	423.09
DRFN08–10	569.36	≈	559.43	≫	382.91	≈	415.65	<	432.45	≈	415.65
DRFN08–11	602.25	≈	602.24	>	453.32	≈	457.81	≈	469.55	≈	457.81
DO09–32	1670.22	≈	1650.03	≫	1437.86	≈	1449.33	≈	1459.86	≈	1449.33
FY17–25	393.16	≈	372.41	≈	335.07	≈	319.92	≪	344.74	≫	319.92
FRD12–29	466.79	≈	452.21	≫	398.38	≪	474.56	≈	474.56	≈	479.33
KS13–12	3526.46	≈	3570.33	≫	2912.53	>	2739.66	≈	2760.67	≈	2739.66
STS13–13	1685.47	≈	1691.71	≫	1413	≈	1421.45	≈	1421.45	≈	1428.6
Aoyagi and Frechette (2009)	855.34	≈	847.81	≈	835.89	≈	891.63	≈	891.63	≈	897.8
Blonski et al. (2011)	2337.47	≫	2188.04	≫	1089.36	≪	1241.55	≪	1367.4	≫	1239.58
Bruttel and Kamecke (2012)	1025.99	≈	1021.23	≫	817.24	≈	861.15	≈	861.15	≈	862.58
Dal Bó (2005)	968.96	≫	907.92	≫	653.33	≈	678.73	≪	713.82	>	678.73
Dal Bó and Fréchette (2011)	14795.82	≈	14789.67	≫	7282.65	<	7668.25	≈	7725.56	≈	7670.28
Dal Bó and Fréchette (2015)	13772.1	≫	13479.92	≫	8887.67	≈	9096.12	≪	9276.23	≫	9116.67
Dreber et al. (2008)	1176.51	≈	1165.17	≫	838.33	≈	875.56	<	905.5	>	875.56
Duffy and Ochs (2009)	1670.22	≈	1650.03	≫	1437.86	≈	1449.33	≈	1459.86	≈	1449.33
Fréchette and Yuksel (2017)	393.16	≈	372.41	≈	335.07	≈	319.92	≪	344.74	≫	319.92
Fudenberg et al. (2012)	466.79	≈	452.21	≫	398.38	≪	474.56	≈	474.56	≈	479.33
Kagel and Schley (2013)	3526.46	≈	3570.33	≫	2912.53	>	2739.66	≈	2760.67	≈	2739.66
Sherstyuk et al. (2013)	1685.47	≈	1691.71	≫	1413	≈	1421.45	≈	1421.45	≈	1428.6
Pooled	**42929.62**	≫	**42318.82**	≫	**27010.74**	≪	**27851.71**	≪	**28384.93**	≫	**27867.48**

(b) Second halves per session

	SG+ SG M2“General”		SG M2“General”		Semi-Grim		Best Pure		Pure M1+G2,T2		Pure M1
Specification											
# Models evaluated	1		1		1		5		1		1
# Pars estimated (by treatment)	7		3		3		32		5		3
# Parameters accounted for	7		3		3		3-8		5		3
AF09–34	515.26	>	500.7	≈	494.93	≈	548.36	≈	548.36	≈	553.46
BOS11–9	262.26	≈	252.38	≫	92.34	≈	100.69	≪	111.7	≫	100.69
BOS11–14	316.89	>	301.99	≫	35.25	≪	74.75	≪	86.28	≫	74.75
BOS11–15	357.64	>	340.78	≫	11.86	≪	93.99	≪	106.45	≫	93.99
BOS11–16	206.46	>	194.41	≈	162.19	≈	166.7	<	179.74	>	166.7
BOS11–17	327	≈	313.44	≫	212.8	≈	232.04	≈	237.43	≈	232.04
BOS11–26	635.75	≈	617.18	≫	333.39	<	391.24	≈	404.11	>	391.24
BOS11–27	388.11	≈	384.8	>	262.85	≈	292.85	≈	296.91	≈	292.85
BOS11–30	246.9	>	231.15	≫	131.11	<	161.56	≈	173.63	≫	161.56
BOS11–31	264.1	≈	265.11	>	169.45	<	213.53	≈	216.82	≈	213.53
BK12–28	833.83	≈	838.57	≫	595.23	≈	583.12	≈	583.12	≈	594.04
D05–18	450.68	≫	424.87	≫	336.26	≈	353.97	≈	364.98	≈	353.97
D05–19	585.4	≫	547.21	≫	410.17	≈	391.74	≪	416.49	≫	391.74
DF11–6	3524.22	≈	3504.27	≫	610.65	<	807.87	≈	830.4	≈	807.87
DF11–7	4029.73	≈	4054.52	≫	1566.15	≈	1638.56	≈	1655.2	≈	1638.56
DF11–8	2783	≈	2835.26	≫	1570.36	≫	1172.76	≈	1172.76	<	1228.26
DF11–22	1884.84	≈	1904.65	≫	1031.86	≈	1173.61	≈	1173.61	≈	1229.35
DF11–23	1003.64	≈	1024.22	>	885.87	≈	792.63	≈	792.63	≈	866.55
DF11–24	615.76	≈	599.58	>	479.46	≪	643.83	≈	655.18	≈	643.83
DF15–4	1896.41	≈	1863.03	≫	384.53	≈	417.63	≪	441.51	≫	417.63
DF15–5	3236.45	≈	3202.05	≫	2172.99	≫	1735.14	≈	1764.47	≈	1735.14
DF15–20	2796.05	≈	2784.9	≫	1393.96	<	1646.2	≈	1646.2	≈	1663.73
DF15–21	2061.25	≈	2051.69	≫	1826.53	≈	1832.26	≈	1840.23	≈	1832.26
DF15–33	3542.83	≈	3534.1	≫	2550.95	≪	3002.88	≈	3002.88	≈	3026.08
DF15–35	817.74	≈	815.66	≫	669.42	≪	819.77	≈	819.77	≈	860.08
DRFN08–10	664.97	≈	653.29	≫	288.29	≈	315.7	<	330.73	≈	315.7
DRFN08–11	448.73	≈	449.83	≈	374.74	≈	346.99	≈	356.35	≈	346.99
DO09–32	2016.24	≈	1993.56	≫	1794.26	≪	2016.45	≈	2016.45	≈	2042.07
FY17–25	561.78	>	528.38	≈	481.62	≈	474.69	≪	502.3	>	474.69
FRD12–29	532.03	≈	530.32	>	485.43	<	551	≈	551	≈	571.98
KS13–12	2648.79	≈	2676.25	≫	2261.67	≫	1919.9	≈	1919.9	≈	1971.47
STS13–13	1248.54	≈	1293.11	>	1087.07	≈	1029.75	≈	1029.75	<	1127.23
Aoyagi and Frechette (2009)	515.26	>	500.7	≈	494.93	≈	548.36	≈	548.36	≈	553.46
Blonski et al. (2011)	3075.21	≫	2951.31	≫	1441.28	≪	1757.39	≪	1863.15	≫	1757.39
Bruttel and Kamecke (2012)	833.83	≈	838.57	≫	595.23	≈	583.12	≈	583.12	≈	594.04
Dal Bó (2005)	1041.04	≫	975.62	≫	748.55	≈	747.84	≪	785.02	≫	747.84
Dal Bó and Fréchette (2011)	13878.91	≈	13949.42	≫	6160.5	≈	6250.91	≈	6306.7	≈	6430.56
Dal Bó and Fréchette (2015)	14391.56	≈	14280.59	≫	9015.88	<	9477.45	≈	9544.21	≈	9552.41
Dreber et al. (2008)	1118.6	≈	1106.62	≫	665.13	≈	664.79	≪	690.58	≈	664.79
Duffy and Ochs (2009)	2016.24	≈	1993.56	≫	1794.26	≪	2016.45	≈	2016.45	≈	2042.07
Fréchette and Yuksel (2017)	561.78	>	528.38	≈	481.62	≈	474.69	≪	502.3	>	474.69
Fudenberg et al. (2012)	532.03	≈	530.32	>	485.43	<	551	≈	551	≈	571.98
Kagel and Schley (2013)	2648.79	≈	2676.25	≫	2261.67	≫	1919.9	≈	1919.9	≈	1971.47
Sherstyuk et al. (2013)	1248.54	≈	1293.11	>	1087.07	≈	1029.75	≈	1029.75	<	1127.23
Pooled	**42117.12**	>	**41806.84**	≫	**25340.99**	<	**26159.81**	≪	**26522.89**	≈	**26597.37**

Note: Notation of treatments and meaning of relation signs are all as defined above, see Table A.9.

Table A.33: 1- and 2-memory SG behavior strategies versus best mixtures (by treatment) of 1- and 2-memory pure strategies (Random switching) (ICL-BIC of the models, less is better and relation signs point toward better models)

	SG+SG M2"General"		SG M2"General"		Semi-Grim		Best Pure		Pure 1+G2,T2		Pure 1
Specification											
# Models evaluated	1		1		1		5		1		1
# Pars estimated (by treatment)	7		3		3		32		5		3
# Parameters accounted for	7		3		3		3-8		5		3
First halves per session											
Aoyagi and Frechette (2009)	846.9	$\approx$	846.43	$\approx$	835.89	$\approx$	862.48	$\approx$	862.48	$\approx$	891.2
Blonski et al. (2011)	1938.36	$\gg$	1807.07	$\gg$	1089.36	$<$	1141.74	$<$	1168.97	$\approx$	1147.53
Bruttel and Kamecke (2012)	986.56	$\approx$	969.46	$\gg$	817.24	$\approx$	837.88	$\approx$	837.88	$\approx$	857.62
Dal Bó (2005)	810.96	$\approx$	798.82	$\gg$	653.33	$\ll$	690.17	$\approx$	693.14	$\approx$	692.19
Dal Bó and Fréchette (2011)	9041.66	$>$	8900.69	$\gg$	7282.65	$\ll$	7638.05	$\approx$	7645.17	$<$	7825.68
Dal Bó and Fréchette (2015)	11458.55	$\gg$	11208.45	$\gg$	8887.67	$\ll$	9301.85	$\approx$	9306.74	$<$	9460.02
Dreber et al. (2008)	1104.74	$\approx$	1080.21	$\gg$	838.33	$\approx$	871.6	$\approx$	871.39	$\approx$	879
Duffy and Ochs (2009)	1613.97	$\approx$	1588.23	$\gg$	1437.86	$\approx$	1488.29	$\approx$	1488.29	$\approx$	1507.66
Fréchette and Yuksel (2017)	400.09	$\gg$	363.06	$>$	335.07	$<$	349.53	$\approx$	354.74	$\approx$	352.99
Fudenberg et al. (2012)	442.4	$\approx$	440.73	$>$	398.38	$<$	445.18	$\approx$	445.18	$\approx$	466.32
Kagel and Schley (2013)	3481.07	$\approx$	3490.59	$\gg$	2912.53	$\approx$	2979.94	$\approx$	2979.94	$\approx$	3059.61
Sherstyuk et al. (2013)	1626.21	$\approx$	1601.7	$\gg$	1413	$<$	1483.72	$\approx$	1483.75	$\approx$	1503.01
Pooled	**34006.81**	$\gg$	**33277.82**	$\gg$	**27010.74**	$\ll$	**28272.53**	$\approx$	**28320.03**	$\ll$	**28752.26**
Second halves per session											
Aoyagi and Frechette (2009)	498.98	$\approx$	498.38	$\approx$	494.93	$\approx$	521.74	$\approx$	531.13	$\approx$	537.76
Blonski et al. (2011)	2648.18	$\gg$	2535.71	$\gg$	1441.28	$\ll$	1609.58	$\approx$	1637.46	$>$	1613.11
Bruttel and Kamecke (2012)	802.05	$\approx$	798.92	$\gg$	595.23	$\approx$	620.35	$\approx$	620.35	$\approx$	632.85
Dal Bó (2005)	915.79	$\approx$	904.46	$\gg$	748.55	$\ll$	793.71	$\approx$	796.01	$\approx$	807.66
Dal Bó and Fréchette (2011)	8212.23	$\approx$	8185.18	$\gg$	6160.5	$\ll$	6655.07	$\approx$	6655.57	$\ll$	6955.42
Dal Bó and Fréchette (2015)	12150.58	$>$	12016.88	$\gg$	9015.88	$\ll$	9880.99	$\approx$	9886.61	$\ll$	10178.06
Dreber et al. (2008)	1002.39	$\approx$	994.93	$\gg$	665.13	$\approx$	694.37	$\approx$	699.01	$\approx$	694.37
Duffy and Ochs (2009)	1970.43	$\approx$	1973.39	$\gg$	1794.26	$\ll$	2010.69	$\approx$	2010.69	$\approx$	2083.26
Fréchette and Yuksel (2017)	560.37	$>$	526.45	$\approx$	481.62	$\approx$	500.54	$\approx$	503.62	$\approx$	500.54
Fudenberg et al. (2012)	514.64	$\approx$	510.99	$\approx$	485.43	$\ll$	546.56	$\approx$	548.09	$<$	591.31
Kagel and Schley (2013)	2680.42	$\approx$	2675.61	$\gg$	2261.67	$\approx$	2312.35	$\approx$	2312.35	$<$	2399.2
Sherstyuk et al. (2013)	1256.5	$\approx$	1261.23	$\gg$	1087.07	$<$	1167.39	$\approx$	1167.39	$<$	1245.55
Pooled	**33467.87**	$\gg$	**33064.51**	$\gg$	**25340.99**	$\ll$	**27480.48**	$\approx$	**27550.66**	$\ll$	**28348.53**

Note: Relation signs, bootstrap procedure, and derived p-values are exactly as above, see Table 1.2. Pure M1 refers to TFT, Grim, and AD. G2 denotes Grim2. For definitions of the strategies see Table A.7.

Table A.34: Table A.33 by treatments – 1- and 2-memory SG behavior strategies versus best mixtures (by treatment) of 1- and 2-memory pure strategies (Random switching)

(a) First halves per session

	SG+SG M2"General"		SG M2"General"		Semi-Grim		Best Pure		Pure 1+G2,T2		Pure 1
Specification											
# Models evaluated	1		1		1		5		1		1
# Pars estimated (by treatment)	7		3		3		32		5		3
# Parameters accounted for	7		3		3		3-8		5		3
AF09–34	846.9	≈	846.43	≈	835.89	≈	862.48	≈	862.48	≈	891.2
BOS11–9	168.61	≫	153.78	≫	82.26	≈	83.96	≈	86.52	≈	83.96
BOS11–14	210.98	≈	207.95	≫	87.7	≈	90.01	≈	92.44	≈	90.01
BOS11–15	221.49	≫	204.63	≫	31.07	≈	32.69	≈	33.3	≈	32.69
BOS11–16	212.6	>	199.27	>	170.96	≈	176.09	≈	177.8	≈	176.09
BOS11–17	142.08	≫	125.22	≈	119.9	≈	118.75	≈	121.83	≈	118.75
BOS11–26	458.54	≫	427.81	≫	254.14	≈	259.54	≈	259.54	≈	267.51
BOS11–27	167.95	≈	164.96	>	108.51	≈	109.62	≈	109.62	≈	113.56
BOS11–30	90.04	≫	73.18	>	63.02	≈	65.48	≈	68.48	≈	65.48
BOS11–31	195.97	≈	200.2	>	141.75	≈	169.35	≈	169.35	≈	169.44
BK12–28	986.56	≈	969.46	≫	817.24	≈	837.88	≈	837.88	≈	857.62
D05–18	262.83	≈	256.79	>	224.25	<	238.03	≈	240.12	≈	238.03
D05–19	543.17	≈	538.48	≫	426.95	<	449.48	≈	449.48	≈	452.03
DF11–6	1030.71	≈	998.16	≫	894.35	<	951.32	≈	951.32	≈	965.47
DF11–7	1482.77	≈	1460.6	>	1369.26	≈	1396.1	≈	1396.1	≈	1405.07
DF11–8	2145.02	≈	2117.53	≫	1648.75	<	1707.55	≈	1707.55	≈	1768.61
DF11–22	1643.66	≈	1622.27	≫	1042.26	≪	1139.78	≈	1140.58	≈	1162.24
DF11–23	1388.55	≈	1392.28	≫	1117.42	≈	1185.74	≈	1185.74	≈	1246
DF11–24	1313.25	≈	1282.93	>	1194.45	≈	1227.04	≈	1236.96	≈	1262.13
DF15–4	550.04	≫	511.86	≈	477.13	≈	475.23	≈	477.75	≈	475.23
DF15–5	2545.46	≫	2459.44	≫	2194.38	≈	2214.8	≈	2214.8	≈	2235.3
DF15–20	2434.72	≫	2354.53	≫	1481.46	<	1548.72	≈	1548.72	≈	1572.04
DF15–21	2359.09	≈	2351.69	≫	2111.65	≪	2225.46	≈	2225.46	<	2291.78
DF15–33	3090.18	≈	3078.85	≫	2256.38	≪	2420.93	≈	2421.39	<	2469.21
DF15–35	438.24	≈	422.92	≫	349.17	<	389.46	≈	389.46	≈	398.96
DRFN08–10	538.54	≈	517.1	≫	382.91	≈	395.82	≈	395.82	≈	398.11
DRFN08–11	561.29	≈	559.61	>	453.32	≈	471.86	≈	472.06	≈	478.79
DO09–32	1613.97	≈	1588.23	≫	1437.86	≈	1488.29	≈	1488.29	≈	1507.66
FY17–25	400.09	≫	363.06	>	335.07	<	349.53	≈	354.74	≈	352.99
FRD12–29	442.4	≈	440.73	>	398.38	<	445.18	≈	445.18	≈	466.32
KS13–12	3481.07	≈	3490.59	≫	2912.53	≈	2979.94	≈	2979.94	≈	3059.61
STS13–13	1626.21	≈	1601.7	≫	1413	<	1483.72	≈	1483.75	≈	1503.01
Aoyagi and Frechette (2009)	846.9	≈	846.43	≈	835.89	≈	862.48	≈	862.48	≈	891.2
Blonski et al. (2011)	1938.36	≫	1807.07	≫	1089.36	<	1141.74	<	1168.97	≈	1147.53
Bruttel and Kamecke (2012)	986.56	≈	969.46	≫	817.24	≈	837.88	≈	837.88	≈	857.62
Dal Bó (2005)	810.96	≈	798.82	≫	653.33	≪	690.17	≈	693.14	≈	692.19
Dal Bó and Fréchette (2011)	9041.66	>	8900.69	≫	7282.65	≪	7638.05	≈	7645.17	<	7825.68
Dal Bó and Fréchette (2015)	11458.55	≫	11208.45	≫	8887.67	≪	9301.85	≈	9306.74	<	9460.02
Dreber et al. (2008)	1104.74	≈	1080.21	≫	838.33	≈	871.6	≈	871.39	≈	879
Duffy and Ochs (2009)	1613.97	≈	1588.23	≫	1437.86	≈	1488.29	≈	1488.29	≈	1507.66
Fréchette and Yuksel (2017)	400.09	≫	363.06	>	335.07	<	349.53	≈	354.74	≈	352.99
Fudenberg et al. (2012)	442.4	≈	440.73	>	398.38	<	445.18	≈	445.18	≈	466.32
Kagel and Schley (2013)	3481.07	≈	3490.59	≫	2912.53	≈	2979.94	≈	2979.94	≈	3059.61
Sherstyuk et al. (2013)	1626.21	≈	1601.7	≫	1413	<	1483.72	≈	1483.75	≈	1503.01
Pooled	**34006.81**	≫	**33277.82**	≫	**27010.74**	≪	**28272.53**	≈	**28320.03**	≪	**28752.26**

(b) Second halves per session

	SG+SG M2"General"		SG M2"General"		Semi-Grim		Best Pure		Pure 1+G2,T2		Pure 1
Specification											
# Models evaluated	1		1		1		5		1		1
# Pars estimated (by treatment)	7		3		3		32		5		3
# Parameters accounted for	7		3		3		3-8		5		3
AF09–34	498.98	≈	498.38	≈	494.93	≈	521.74	≈	531.13	≈	537.76
BOS11–9	213.11	≫	196.77	≫	92.34	≈	96.65	≈	99.64	≈	96.65
BOS11–14	59.94	≫	43.82	≈	35.25	<	40.83	<	43.83	≈	40.83
BOS11–15	334.66	>	317.8	≫	11.86	≈	15.52	≪	18.52	≫	15.52
BOS11–16	196.1	≫	180.84	≈	162.19	≈	166.4	≈	168.97	≈	166.4
BOS11–17	322.09	≈	307.49	≫	212.8	≈	224.02	≈	224.02	≈	227.57
BOS11–26	577.71	≈	570.16	≫	333.39	<	375.4	≈	375.72	≈	375.4
BOS11–27	375.08	≈	375.07	>	262.85	≈	304.34	≈	304.34	≈	308.69
BOS11–30	231.84	≈	228.65	≫	131.11	≈	141.22	≈	144.11	≈	141.22
BOS11–31	267.55	≈	265.05	>	169.45	≈	208.24	≈	208.24	≈	210.78
BK12–28	802.05	≈	798.92	≫	595.23	≈	620.35	≈	620.35	≈	632.85
D05–18	390.84	≈	385.35	>	336.26	<	360.28	≈	361.7	≈	360.28
D05–19	519.98	≈	515.56	≫	410.17	<	430.77	≈	430.77	<	445.25
DF11–6	855.84	≈	852.06	≫	610.65	<	719.86	≈	719.86	≈	737.29
DF11–7	1807.16	≈	1803.16	≫	1566.15	≪	1683.6	≈	1683.6	≈	1710.18
DF11–8	2192.09	≈	2193.11	≫	1570.36	<	1641.29	≈	1641.29	<	1736.37
DF11–22	1811.46	≈	1810.44	≫	1031.86	<	1120.33	≈	1120.33	<	1218.47
DF11–23	1024.7	≈	1020.39	>	885.87	≈	946.29	≈	948.73	≈	1000.66
DF11–24	483.28	≈	479.09	≈	479.46	<	514.84	≈	514.84	≈	536.29
DF15–4	475.49	≫	438.92	>	384.53	≈	403.13	≈	405.76	≈	403.13
DF15–5	2818.99	≫	2728.87	≫	2172.99	<	2253.42	≈	2253.42	≈	2284.97
DF15–20	2476.53	≈	2470	≫	1393.96	<	1532.28	≈	1532.28	≈	1606.34
DF15–21	2052.8	≈	2046.05	≫	1826.53	≪	1939.3	≈	1940.01	<	1995.85
DF15–33	3515.78	≈	3532.97	≫	2550.95	≪	2910.55	≈	2911.64	<	3012.62
DF15–35	770.16	≈	770.91	>	669.42	≪	814.34	≈	814.34	≈	857.65
DRFN08–10	565.43	≈	561.61	≫	288.29	≈	300.31	≈	301.48	≈	300.31
DRFN08–11	432.06	≈	429.82	>	374.74	≈	391.96	≈	394.02	≈	391.96
DO09–32	1970.43	≈	1973.39	≫	1794.26	≪	2010.69	≈	2010.69	≈	2083.26
FY17–25	560.37	>	526.45	≈	481.62	≈	500.54	≈	503.62	≈	500.54
FRD12–29	514.64	≈	510.99	≈	485.43	≪	546.56	≈	548.09	<	591.31
KS13–12	2680.42	≈	2675.61	≫	2261.67	≈	2312.35	≈	2312.35	<	2399.2
STS13–13	1256.5	≈	1261.23	≫	1087.07	<	1167.39	≈	1167.39	<	1245.55
Aoyagi and Frechette (2009)	498.98	≈	498.38	≈	494.93	≈	521.74	≈	531.13	≈	537.76
Blonski et al. (2011)	2648.18	≫	2535.71	≫	1441.28	≪	1609.58	≈	1637.46	>	1613.11
Bruttel and Kamecke (2012)	802.05	≈	798.92	≫	595.23	≈	620.35	≈	620.35	≈	632.85
Dal Bó (2005)	915.79	≈	904.46	≫	748.55	≪	793.71	≈	796.01	≈	807.66
Dal Bó and Fréchette (2011)	8212.23	≈	8185.18	≫	6160.5	≪	6655.07	≈	6655.57	≪	6955.42
Dal Bó and Fréchette (2015)	12150.58	>	12016.88	≫	9015.88	≪	9880.99	≈	9886.61	≪	10178.06
Dreber et al. (2008)	1002.39	≈	994.93	≫	665.13	≈	694.37	≈	699.01	≈	694.37
Duffy and Ochs (2009)	1970.43	≈	1973.39	≫	1794.26	≪	2010.69	≈	2010.69	≈	2083.26
Fréchette and Yuksel (2017)	560.37	>	526.45	≈	481.62	≈	500.54	≈	503.62	≈	500.54
Fudenberg et al. (2012)	514.64	≈	510.99	≈	485.43	≪	546.56	≈	548.09	<	591.31
Kagel and Schley (2013)	2680.42	≈	2675.61	≫	2261.67	≈	2312.35	≈	2312.35	<	2399.2
Sherstyuk et al. (2013)	1256.5	≈	1261.23	≫	1087.07	<	1167.39	≈	1167.39	<	1245.55
Pooled	**33467.87**	≫	**33064.51**	≫	**25340.99**	≪	**27480.48**	≈	**27550.66**	≪	**28348.53**

Note: Notation of treatments and meaning of relation signs are all as defined above, see Table A.9.

Table A.35: 1-memory or 2-memory Semi-Grim strategies, complexity of memory, mixtures of 1-memory and 2-memory SG (no switching) (ICL-BIC of the models, less is better and relation signs point toward better models)

	SG M2"General"		SG M2"Semi-Grim"		SG M2"Grim"		Semi-Grim		SG M1 + M2"Grim"		SG M1 + M2"General"
Specification											
# Models evaluated	1		1		1		1		1		1
# Pars estimated (by treatment)	5		4		3		3		5		7
# Parameters accounted for	5		4		3		3		5		7
First halves per session											
Aoyagi and Frechette (2009)	865.91	$\approx$	864.19	$\approx$	843.09	$\approx$	835.89	$<$	906.78	$\gg$	848.86
Blonski et al. (2011)	1421.49	$>$	1397.85	$>$	1375.08	$\gg$	1089.36	$\ll$	1555.38	$<$	1591.37
Bruttel and Kamecke (2012)	969.35	$\approx$	967.88	$\approx$	966.75	$\gg$	817.24	$\ll$	968.22	$\approx$	968.68
Dal Bó (2005)	798.82	$\approx$	794.23	$\approx$	791.74	$\gg$	653.33	$\ll$	939.56	$>$	849.06
Dal Bó and Fréchette (2011)	8512.04	$\approx$	8495.44	$\approx$	8479.3	$\gg$	7282.65	$\ll$	8625.51	$\approx$	8659.2
Dal Bó and Fréchette (2015)	11283.53	$\approx$	11282.42	$\approx$	11280.81	$\gg$	8887.67	$\ll$	11725.16	$\approx$	11671.5
Dreber et al. (2008)	1177.21	$\approx$	1173.36	$\approx$	1170.29	$\gg$	838.33	$\ll$	1199.59	$\approx$	1202.45
Duffy and Ochs (2009)	1588.23	$\approx$	1587.59	$\approx$	1586.14	$\gg$	1437.86	$\ll$	1610.06	$\approx$	1629.09
Fréchette and Yuksel (2017)	362.68	$\approx$	360.88	$\approx$	359.65	$\approx$	335.07	$<$	365.5	$\approx$	369.6
Fudenberg et al. (2012)	440.73	$\approx$	442.18	$\approx$	440.31	$>$	398.38	$\ll$	452.14	$\approx$	455.2
Kagel and Schley (2013)	3490.59	$\approx$	3488.45	$\approx$	3478.42	$\gg$	2912.53	$\ll$	3438.64	$\approx$	3435.84
Sherstyuk et al. (2013)	1601.7	$\approx$	1602.31	$\approx$	1600.41	$\gg$	1413	$\ll$	1596.66	$\approx$	1598.4
Pooled	**32694.65**	$\approx$	**32602.68**	$\approx$	**32481.42**	$\gg$	**27010.74**	$\ll$	**33565.57**	$\approx$	**33534.58**
Second halves per session											
Aoyagi and Frechette (2009)	498.38	$\approx$	496.59	$\approx$	495.48	$\approx$	494.93	$\approx$	501.5	$\approx$	503.4
Blonski et al. (2011)	2277.26	$>$	2253.69	$>$	2230.87	$\gg$	1441.28	$\ll$	2411.7	$\approx$	2458.66
Bruttel and Kamecke (2012)	1013.73	$\approx$	1011.93	$\approx$	1010.14	$\gg$	595.23	$\ll$	1038.68	$\approx$	1040.33
Dal Bó (2005)	904.41	$\approx$	900.53	$\approx$	902.58	$\gg$	748.55	$\ll$	969.26	$\approx$	951.14
Dal Bó and Fréchette (2011)	8322.63	$\approx$	8300.39	$\approx$	8283.81	$\gg$	6160.5	$\ll$	8428.76	$\approx$	8461.64
Dal Bó and Fréchette (2015)	14925.81	$\approx$	14915.3	$\approx$	14901.44	$\gg$	9015.88	$\ll$	15226.83	$\approx$	15283.12
Dreber et al. (2008)	827.1	$\approx$	824.75	$\approx$	820.93	$\gg$	665.13	$\ll$	843.61	$\approx$	848.54
Duffy and Ochs (2009)	1973.39	$\approx$	1971.08	$\approx$	1968.89	$\gg$	1794.26	$\ll$	1988.35	$\approx$	1988.91
Fréchette and Yuksel (2017)	526.45	$\approx$	527.58	$\approx$	525.79	$\approx$	481.62	$<$	546.95	$<$	559.74
Fudenberg et al. (2012)	510.99	$\approx$	509.24	$\approx$	507.45	$\approx$	485.43	$\approx$	507.15	$\approx$	509.35
Kagel and Schley (2013)	2675.61	$\approx$	2674.59	$\approx$	2673.64	$\gg$	2261.67	$\ll$	2637.36	$\approx$	2623.98
Sherstyuk et al. (2013)	1261.23	$\approx$	1260.86	$\approx$	1259.78	$\gg$	1087.07	$<$	1219.58	$\approx$	1228.3
Pooled	**35899.35**	$\approx$	**35792.43**	$\approx$	**35690.23**	$\gg$	**25340.99**	$\ll$	**36502.1**	$\approx$	**36712.43**

Note: Relation signs, bootstrap procedure, and derived p-values are exactly as above.

Table A.36: Table A.35 by treatments – 1-memory or 2-memory Semi-Grim strategies, complexity of memory, mixtures of 1-memory and 2-memory SG (no switching)

(a) First halves per session

	SG M2“General”		SG M2“Semi-Grim”		SG M2“Grim”		Semi-Grim		SG M1 + M2“Grim”		SG M1 + M2“General”
Specification											
# Models evaluated	1		1		1		1		1		1
# Pars estimated (by treatment)	5		4		3		3		5		7
# Parameters accounted for	5		4		3		3		5		7
AF09–34	865.91	≈	864.19	≈	843.09	≈	835.89	<	906.78	≫	848.86
BOS11–9	95.12	≈	93.62	≈	92.12	>	82.26	≪	108.85	≈	111.63
BOS11–14	99.31	≈	97.81	≈	96.32	≈	87.7	≪	112.69	≈	114.94
BOS11–15	37.29	≈	35.79	≈	34.3	≈	31.07	≪	50.93	<	53.92
BOS11–16	199.22	≈	197.93	≈	197.5	>	170.96	<	211.68	≈	203.65
BOS11–17	125.22	≈	123.72	≈	122.22	≈	119.9	≪	139.08	≈	142.08
BOS11–26	335.64	≈	333.79	≈	331.95	>	254.14	≪	363.18	≈	366.9
BOS11–27	135.45	≈	133.95	≈	132.45	>	108.51	≪	149.17	≈	152.18
BOS11–30	73.18	≈	71.68	≈	70.18	≈	63.02	≪	87.04	≈	90.04
BOS11–31	270.99	≈	269.49	≈	267.99	≫	141.75	≪	282.68	≈	285.92
BK12–28	969.35	≈	967.88	≈	966.75	≫	817.24	≪	968.22	≈	968.68
D05–18	256.79	≈	254.92	≈	253.12	>	224.25	≪	301.43	≈	288.42
D05–19	538.48	≈	536.47	≈	536.5	≫	426.95	≪	634.58	>	555.67
DF11–6	998.16	≈	996.27	≈	994.37	≫	894.35	≪	1027.52	≈	1032.2
DF11–7	1460.6	≈	1458.64	≈	1456.69	>	1369.26	≪	1494.99	≈	1499
DF11–8	1990.14	≈	1988.22	≈	1986.31	≫	1648.75	≪	2021.5	≈	2025.23
DF11–22	1367.84	≈	1365.95	≈	1364.06	≫	1042.26	≪	1398.28	≈	1401.94
DF11–23	1385.44	≈	1383.73	≈	1381.92	≫	1117.42	≪	1379.96	≈	1386.38
DF11–24	1282.93	≈	1281.09	≈	1279.8	>	1194.45	<	1276.35	≈	1276.77
DF15–4	511.86	≈	509.91	≈	507.95	≈	477.13	≪	546.28	≈	549.97
DF15–5	2459.45	≈	2458.01	≈	2456.99	≫	2194.38	≪	2557.48	≈	2547.91
DF15–20	1939.87	≈	1937.5	≈	1935.13	≫	1481.46	≪	2018.71	≈	2021.82
DF15–21	2351.69	≈	2365.28	≈	2379.17	≫	2111.65	≪	2462.49	≫	2387.65
DF15–33	3568.57	≈	3566.01	≈	3563.45	≫	2256.38	≪	3682.71	≈	3689.45
DF15–35	422.92	≈	422.38	≈	420.63	≫	349.17	≪	428.33	≈	433.87
DRFN08–10	614.11	≈	612.45	≈	610.78	≫	382.91	≪	633.52	≈	635.7
DRFN08–11	559.59	≈	558.11	≈	557.41	>	453.32	<	562.57	≈	561.85
DO09–32	1588.23	≈	1587.59	≈	1586.14	≫	1437.86	≪	1610.06	≈	1629.09
FY17–25	362.68	≈	360.88	≈	359.65	≈	335.07	<	365.5	≈	369.6
FRD12–29	440.73	≈	442.18	≈	440.31	>	398.38	≪	452.14	≈	455.2
KS13–12	3490.59	≈	3488.45	≈	3478.42	≫	2912.53	≪	3438.64	≈	3435.84
STS13–13	1601.7	≈	1602.31	≈	1600.41	≫	1413	≪	1596.66	≈	1598.4
Aoyagi and Frechette (2009)	865.91	≈	864.19	≈	843.09	≈	835.89	<	906.78	≫	848.86
Blonski et al. (2011)	1421.49	>	1397.85	>	1375.08	≫	1089.36	≪	1555.38	<	1591.37
Bruttel and Kamecke (2012)	969.35	≈	967.88	≈	966.75	≫	817.24	≪	968.22	≈	968.68
Dal Bó (2005)	798.82	≈	794.23	≈	791.74	≫	653.33	≪	939.56	>	849.06
Dal Bó and Fréchette (2011)	8512.04	≈	8495.44	≈	8479.3	≫	7282.65	≪	8625.51	≈	8659.2
Dal Bó and Fréchette (2015)	11283.53	≈	11282.42	≈	11280.81	≫	8887.67	≪	11725.16	≈	11671.5
Dreber et al. (2008)	1177.21	≈	1173.36	≈	1170.29	≫	838.33	≪	1199.59	≈	1202.45
Duffy and Ochs (2009)	1588.23	≈	1587.59	≈	1586.14	≫	1437.86	≪	1610.06	≈	1629.09
Fréchette and Yuksel (2017)	362.68	≈	360.88	≈	359.65	≈	335.07	<	365.5	≈	369.6
Fudenberg et al. (2012)	440.73	≈	442.18	≈	440.31	>	398.38	≪	452.14	≈	455.2
Kagel and Schley (2013)	3490.59	≈	3488.45	≈	3478.42	≫	2912.53	≪	3438.64	≈	3435.84
Sherstyuk et al. (2013)	1601.7	≈	1602.31	≈	1600.41	≫	1413	≪	1596.66	≈	1598.4
Pooled	**32694.65**	≈	**32602.68**	≈	**32481.42**	≫	**27010.74**	≪	**33565.57**	≈	**33534.58**

(b) Second halves per session

	SG M2“General”		SG M2“Semi-Grim”		SG M2“Grim”		Semi-Grim		SG M1 + M2“Grim”		SG M1 + M2“General”
Specification											
# Models evaluated	1		1		1		1		1		1
# Pars estimated (by treatment)	5		4		3		3		5		7
# Parameters accounted for	5		4		3		3		5		7
AF09–34	498.38	≈	496.59	≈	495.48	≈	494.93	≈	501.5	≈	503.4
BOS11–9	132.55	≈	131.06	≈	129.56	>	92.34	≪	144.91	≈	147.93
BOS11–14	43.82	≈	42.32	≈	40.82	≈	35.25	≪	57.68	<	60.61
BOS11–15	14.95	>	13.45	>	11.95	≈	11.86	≪	28.81	<	31.81
BOS11–16	180.41	≈	179.18	≈	178.71	≈	162.19	<	193.95	≈	196.03
BOS11–17	366.29	≈	364.79	≈	363.3	≫	212.8	≪	380.12	≈	383.08
BOS11–26	521.64	≈	519.8	≈	517.95	≫	333.39	≪	549.32	≈	552.16
BOS11–27	390.6	≈	389.1	≈	387.61	>	262.85	<	403.67	≈	407.41
BOS11–30	178.29	≈	176.8	≈	175.3	>	131.11	<	192.09	≈	194.6
BOS11–31	398.63	≈	397.13	≈	395.63	≫	169.45	≪	411.07	≈	414.92
BK12–28	1013.73	≈	1011.93	≈	1010.14	≫	595.23	≪	1038.68	≈	1040.33
D05–18	385.3	≈	383.77	≈	382.42	>	336.26	≪	409.23	≈	410.57
D05–19	515.56	≈	513.92	≈	518.04	≫	410.17	≪	556.49	>	535.61
DF11–6	852.06	≈	850.17	≈	848.28	≫	610.65	≪	882.56	≈	886.33
DF11–7	1803.16	≈	1801.21	≈	1799.25	≫	1566.15	≪	1837.54	≈	1841.44
DF11–8	2239.88	≈	2237.97	≈	2236.05	≫	1570.36	≪	2271.07	≈	2274.87
DF11–22	1895.06	≈	1893.17	≈	1891.28	≫	1031.86	≪	1924.73	≈	1927.87
DF11–23	1026.45	≈	1018.73	≈	1017.07	>	885.87	<	998.41	≈	999.98
DF11–24	479.09	≈	477.61	≈	475.73	≈	479.46	≈	487.52	≈	493.46
DF15–4	438.92	≈	436.97	≈	435.01	>	384.53	≪	473.58	≈	477.38
DF15–5	2723.35	≈	2723.7	≈	2723.94	≫	2172.99	≪	2795.2	≈	2819.55
DF15–20	2389.9	≈	2387.53	≈	2385.16	≫	1393.96	≪	2468.89	≈	2473.66
DF15–21	2046.05	≈	2044.63	≈	2042.29	≫	1826.53	≪	2052.9	≈	2051.25
DF15–33	6527.52	≈	6524.96	≈	6522.39	≫	2550.95	≪	6637.01	≈	6648.75
DF15–35	770.91	≈	774.19	≈	775.14	≫	669.42	<	770.1	≈	771.71
DRFN08–10	393.77	≈	392.11	≈	390.44	≫	288.29	≪	411.68	≈	415.01
DRFN08–11	429.82	≈	429.84	≈	428.39	>	374.74	≈	428.43	≈	428.63
DO09–32	1973.39	≈	1971.08	≈	1968.89	≫	1794.26	≪	1988.35	≈	1988.91
FY17–25	526.45	≈	527.58	≈	525.79	≈	481.62	<	546.95	<	559.74
FRD12–29	510.99	≈	509.24	≈	507.45	≈	485.43	≈	507.15	≈	509.35
KS13–12	2675.61	≈	2674.59	≈	2673.64	≫	2261.67	≪	2637.36	≈	2623.98
STS13–13	1261.23	≈	1260.86	≈	1259.78	≫	1087.07	<	1219.58	≈	1228.3
Aoyagi and Frechette (2009)	498.38	≈	496.59	≈	495.48	≈	494.93	≈	501.5	≈	503.4
Blonski et al. (2011)	2277.26	>	2253.69	>	2230.87	≫	1441.28	≪	2411.7	≈	2458.66
Bruttel and Kamecke (2012)	1013.73	≈	1011.93	≈	1010.14	≫	595.23	≪	1038.68	≈	1040.33
Dal Bó (2005)	904.41	≈	900.53	≈	902.58	≫	748.55	≪	969.26	≈	951.14
Dal Bó and Fréchette (2011)	8322.63	≈	8300.39	≈	8283.81	≫	6160.5	≪	8428.76	≈	8461.64
Dal Bó and Fréchette (2015)	14925.81	≈	14915.3	≈	14901.44	≫	9015.88	≪	15226.83	≈	15283.12
Dreber et al. (2008)	827.1	≈	824.75	≈	820.93	≫	665.13	≪	843.61	≈	848.54
Duffy and Ochs (2009)	1973.39	≈	1971.08	≈	1968.89	≫	1794.26	≪	1988.35	≈	1988.91
Fréchette and Yuksel (2017)	526.45	≈	527.58	≈	525.79	≈	481.62	<	546.95	<	559.74
Fudenberg et al. (2012)	510.99	≈	509.24	≈	507.45	≈	485.43	≈	507.15	≈	509.35
Kagel and Schley (2013)	2675.61	≈	2674.59	≈	2673.64	≫	2261.67	≪	2637.36	≈	2623.98
Sherstyuk et al. (2013)	1261.23	≈	1260.86	≈	1259.78	≫	1087.07	<	1219.58	≈	1228.3
Pooled	**35899.35**	≈	**35792.43**	≈	**35690.23**	≫	**25340.99**	≪	**36502.1**	≈	**36712.43**

Note: Notation of treatments and meaning of relation signs are all as defined above, see Table A.9.

Table A.37: Mixtures of 1- and 2-memory pure and generalized strategies (no switching)
(ICL-BIC of the models, less is better and relation signs point toward better models)

	Gen M2		Gen M1		Best Pure M2		Pure M1		+ G2, TFT2, T2		+ 2TFT
Specification											
# Models evaluated	1		1		5		1		1		1
# Pars estimated (by treatment)	9		6		32		3		6		7
# Parameters accounted for	9		6		3–8		3		6		7
First halves per session											
Aoyagi and Frechette (2009)	764.25	≈	757.68	≪	884.86	≈	892.99	≈	890.72	≈	892.49
Blonski et al. (2011)	1167.82	≈	1208.25	>	1105.96	≈	1105.89	≪	1169.27	<	1195.88
Bruttel and Kamecke (2012)	827.89	≈	853.09	≈	839.97	≈	851.01	≈	841.77	≈	843.55
Dal Bó (2005)	667.03	≈	655.4	≈	653.05	≈	653.05	≈	667.82	≈	672.66
Dal Bó and Fréchette (2011)	7378.08	≈	7433.78	≈	7391.89	≈	7453.78	≈	7410.56	≈	7426.49
Dal Bó and Fréchette (2015)	8826.62	≈	8852.04	≈	8893.78	≈	8946.72	≈	8929.45	≈	8959.61
Dreber et al. (2008)	888.62	≈	876.1	≈	863.47	≈	863.47	≈	875.14	≈	879.91
Duffy and Ochs (2009)	1414.26	≈	1407.43	≈	1426.34	≈	1446.74	≈	1429.36	≈	1440.65
Fréchette and Yuksel (2017)	322.84	≈	324.71	≈	317.35	≈	317.35	<	330.66	≈	334.41
Fudenberg et al. (2012)	433.05	≈	432.32	≈	463.4	≈	469.22	≈	465.31	≈	467.27
Kagel and Schley (2013)	2710.64	≈	2739.15	≈	2730.66	≈	2737.32	≈	2733.03	≈	2737.72
Sherstyuk et al. (2013)	1386.14	≈	1369.48	≈	1398.69	≈	1416.84	≈	1400.69	≈	1403.5
Pooled	**27115.51**	≈	**27128.29**	≈	**27115.38**	≈	**27263.8**	≈	**27362.62**	≈	**27509.48**
Second halves per session											
Aoyagi and Frechette (2009)	417.68	≈	416.51	≪	540.47	≈	543.34	≈	546.38	≈	544.96
Blonski et al. (2011)	1601.27	≈	1588.79	≈	1564.48	≈	1567.21	≈	1614.81	≈	1640.42
Bruttel and Kamecke (2012)	575.98	≈	592.59	≈	567.99	≈	587.38	≈	569.78	≈	571.6
Dal Bó (2005)	739.07	<	756.94	≈	741.2	≈	741.2	≈	756.26	≈	761.39
Dal Bó and Fréchette (2011)	5926.01	<	6059.85	≈	5960.78	≪	6189.93	>	5983.61	≈	5994.24
Dal Bó and Fréchette (2015)	8955.93	<	9139.62	≈	9143.98	<	9333.86	>	9170.84	≈	9204.77
Dreber et al. (2008)	645.2	≈	656.58	≈	648.55	≈	648.55	<	660.03	≈	663.65
Duffy and Ochs (2009)	1888.67	≈	1914.18	≈	2003.41	≈	2034.56	≈	2005.7	≈	2009.16
Fréchette and Yuksel (2017)	444.26	≈	438.55	<	464.23	≈	464.23	≈	472.21	≈	474.13
Fudenberg et al. (2012)	477.91	≈	514.87	≈	534.47	≈	562.1	≈	536.37	≈	537.09
Kagel and Schley (2013)	1806.93	≪	1923.93	>	1830.26	<	1924.38	>	1832.61	≈	1835.1
Sherstyuk et al. (2013)	1029.88	<	1249.12	≫	1023.43	<	1109.62	>	1025.44	≈	1027.45
Pooled	**24837.07**	≪	**25470.38**	≈	**25177.57**	≪	**25815.79**	≫	**25392.89**	≈	**25519.27**

Note: Relation signs, bootstrap procedure, and derived p-values are exactly as above, see Table 1.2. Pure M1 refers to TFT, Grim, and AD. G2 denotes Grim2. For definitions of pure strategies see Table A.7. Gen M1 refers to generalized versions of TFT, Grim, and AD with memory-1. "+ G2, TFT2, T2" adds those strategies to the set of "Pure M1". "+2TFT" adds this strategy on top of the former.

Table A.38: Table A.37 by treatments – Mixtures of 1- and 2-memory pure and generalized strategies (no switching)

(a) First halves per session

	Gen M2		Gen M1		Best Pure M2		Pure M1		+ G2, TFT2, T2		+ 2TFT
Specification											
# Models evaluated	1		1		5		1		1		1
# Pars estimated (by treatment)	9		6		32		3		6		7
# Parameters accounted for	9		6		3–8		3		6		7
AF09–34	764.25	≈	757.68	≪	884.86	≈	892.99	≈	890.72	≈	892.49
BOS11–9	86.93	≈	89.7	≈	85.2	≈	85.2	≈	89.33	≈	90.83
BOS11–14	103.76	≈	102.27	≈	97.73	≈	97.73	≈	102.22	≈	103.88
BOS11–15	41.19	≈	38.79	>	34.3	≈	34.3	≪	38.79	≈	40.29
BOS11–16	173.13	≈	169.08	≈	174.24	≈	174.24	≈	178.7	≈	180.69
BOS11–17	119.24	≈	115.07	≈	110.57	≈	110.57	≈	115.16	≈	116.89
BOS11–26	259.69	≈	262.42	≈	256.88	≈	256.88	≈	259.48	≈	261.42
BOS11–27	102.01	≈	107.7	≈	100.97	≈	103.2	≈	102.47	≈	103.97
BOS11–30	65.81	≫	60.42	>	56.77	≈	56.77	<	61.29	≈	64.59
BOS11–31	125.92	≪	202.72	≈	156.95	≈	156.95	≈	161.73	≈	163.21
BK12–28	827.89	≈	853.09	≈	839.97	≈	851.01	≈	841.77	≈	843.55
D05–18	246.67	≈	241.44	≈	235.84	≈	235.84	≈	242.03	≈	243.88
D05–19	413.98	≈	409.7	≈	415.08	≈	415.08	≈	421.53	≈	423.82
DF11–6	883.72	≈	881.9	≈	877.78	≈	885.43	≈	879.67	≈	881.56
DF11–7	1436.53	≈	1432.97	≈	1424.78	≈	1424.78	≈	1430.65	≈	1432.61
DF11–8	1503.83	≈	1543.89	≈	1501.88	≈	1538.15	≈	1502.59	≈	1504.5
DF11–22	1178.2	≈	1185.37	≈	1188.65	≈	1189.26	≈	1190.54	≈	1191.58
DF11–23	1137.85	≈	1155.41	≈	1148.16	≈	1166.13	≈	1150.31	≈	1152.13
DF11–24	1189.48	≈	1201.92	≈	1224.49	≈	1233.88	≈	1224.49	≈	1226.42
DF15–4	468.06	≈	462.19	≈	456.32	≈	456.32	≈	462.19	≈	464.14
DF15–5	1756.46	≈	1762.23	≈	1817.09	≈	1818.32	≈	1819.54	≈	1821.88
DF15–20	1586.29	≈	1594.81	≈	1585.91	≈	1592.93	≈	1588.28	≈	1594.48
DF15–21	2002.93	≈	2003.37	≈	2022.58	≈	2069.89	≈	2025.12	≈	2029.73
DF15–33	2558.85	≈	2563.96	≈	2575.64	≈	2575.64	≈	2585.4	≈	2592.83
DF15–35	401.54	≈	430.5	≈	411.07	≈	416.14	≈	413.93	≈	415.7
DRFN08–10	424.56	≈	416.07	≈	410.24	≈	410.24	≈	415.24	≈	416.93
DRFN08–11	457.75	≈	455.83	≈	451.13	≈	451.13	≈	455.7	≈	458.08
DO09–32	1414.26	≈	1407.43	≈	1426.34	≈	1446.74	≈	1429.36	≈	1440.65
FY17–25	322.84	≈	324.71	≈	317.35	≈	317.35	<	330.66	≈	334.41
FRD12–29	433.05	≈	432.32	≈	463.4	≈	469.22	≈	465.31	≈	467.27
KS13–12	2710.64	≈	2739.15	≈	2730.66	≈	2737.32	≈	2733.03	≈	2737.72
STS13–13	1386.14	≈	1369.48	≈	1398.69	≈	1416.84	≈	1400.69	≈	1403.5
Aoyagi and Frechette (2009)	764.25	≈	757.68	≪	884.86	≈	892.99	≈	890.72	≈	892.49
Blonski et al. (2011)	1167.82	≈	1208.25	>	1105.96	≈	1105.89	≪	1169.27	<	1195.88
Bruttel and Kamecke (2012)	827.89	≈	853.09	≈	839.97	≈	851.01	≈	841.77	≈	843.55
Dal Bó (2005)	667.03	≈	655.4	≈	653.05	≈	653.05	≈	667.82	≈	672.66
Dal Bó and Fréchette (2011)	7378.08	≈	7433.78	≈	7391.89	≈	7453.78	≈	7410.56	≈	7426.49
Dal Bó and Fréchette (2015)	8826.62	≈	8852.04	≈	8893.78	≈	8946.72	≈	8929.45	≈	8959.61
Dreber et al. (2008)	888.62	≈	876.1	≈	863.47	≈	863.47	≈	875.14	≈	879.91
Duffy and Ochs (2009)	1414.26	≈	1407.43	≈	1426.34	≈	1446.74	≈	1429.36	≈	1440.65
Fréchette and Yuksel (2017)	322.84	≈	324.71	≈	317.35	≈	317.35	<	330.66	≈	334.41
Fudenberg et al. (2012)	433.05	≈	432.32	≈	463.4	≈	469.22	≈	465.31	≈	467.27
Kagel and Schley (2013)	2710.64	≈	2739.15	≈	2730.66	≈	2737.32	≈	2733.03	≈	2737.72
Sherstyuk et al. (2013)	1386.14	≈	1369.48	≈	1398.69	≈	1416.84	≈	1400.69	≈	1403.5
Pooled	**27115.51**	≈	**27128.29**	≈	**27115.38**	≈	**27263.8**	≈	**27362.62**	≈	**27509.48**

(b) Second halves per session

	Gen M2		Gen M1		Best Pure M2		Pure M1		+ G2, TFT2, T2		+ 2TFT
Specification											
# Models evaluated	1		1		5		1		1		1
# Pars estimated (by treatment)	9		6		32		3		6		7
# Parameters accounted for	9		6		3–8		3		6		7
AF09–34	417.68	≈	416.51	≪	540.47	≈	543.34	≈	546.38	≈	544.96
BOS11–9	96.6	≈	92.33	>	84.22	≈	84.22	<	88.72	≈	90.22
BOS11–14	49.8	>	45.31	≈	40.82	≈	40.82	≪	45.31	≈	46.81
BOS11–15	24.51	≈	20.01	≈	15.52	≈	15.52	≈	20.01	≈	21.51
BOS11–16	173.27	≈	162.81	≈	157.48	≈	157.48	≈	161.97	≈	163.73
BOS11–17	240.94	≈	234.24	≈	228.36	≈	229.75	≈	229.86	≈	231.36
BOS11–26	374.59	≈	375.35	≈	374.79	≈	375.99	≈	376.63	≈	379.73
BOS11–27	243.46	≈	290.73	≈	281.24	≈	286.24	≈	282.74	≈	284.24
BOS11–30	147.13	≈	148.34	≈	146.49	≈	146.49	≈	150.98	≈	152.47
BOS11–31	160.84	≈	159.57	≈	196.99	≈	200.65	≈	198.49	≈	200.23
BK12–28	575.98	≈	592.59	≈	567.99	≈	587.38	≈	569.78	≈	571.6
D05–18	346.26	≈	356.38	≈	350.59	≈	350.59	≈	354.41	≈	356.81
D05–19	386.44	≈	396.31	≈	388.48	≈	388.48	≈	397.6	≈	399.62
DF11–6	755.12	≈	752.32	≈	747.77	≈	747.77	≈	753.45	≈	755.34
DF11–7	1571.64	≈	1591.36	≈	1566.58	≈	1585.49	≈	1568.54	≈	1570.53
DF11–8	1140.35	<	1223.57	≈	1153.72	<	1217.82	≈	1155.64	≈	1157.54
DF11–22	1171.84	≈	1224.33	≈	1152.14	≈	1218.65	≈	1154.03	≈	1153.84
DF11–23	776.24	≈	785.37	≈	782.51	≈	863.26	>	786.34	≈	782.51
DF11–24	462.37	≈	450.61	<	530.97	≈	540.78	≈	533.31	≈	536.77
DF15–4	352.57	≈	347.64	≈	342.05	≈	342.05	≈	346.85	≈	348.81
DF15–5	1688.11	≈	1688.45	≈	1712.9	≈	1722.43	≈	1715.36	≈	1723.94
DF15–20	1563.94	≈	1628.58	≈	1582.66	≈	1622.15	≈	1585.03	≈	1587.38
DF15–21	1684.16	≈	1692.13	≈	1754.9	≈	1796.63	≈	1761.1	≈	1769.78
DF15–33	2856.1	<	2973.69	≈	2935.81	≈	2990.83	≈	2936.64	≈	2941.36
DF15–35	758.55	≈	774.14	≈	789.09	≈	842.27	>	790.87	≈	792.66
DRFN08–10	302.05	≈	303.34	≈	301.08	≈	301.08	≈	306.08	≈	307.74
DRFN08–11	336.84	≈	349.04	≈	345.37	≈	345.37	≈	349.75	≈	351
DO09–32	1888.67	≈	1914.18	≈	2003.41	≈	2034.56	≈	2005.7	≈	2009.16
FY17–25	444.26	≈	438.55	<	464.23	≈	464.23	≈	472.21	≈	474.13
FRD12–29	477.91	≈	514.87	≈	534.47	≈	562.1	≈	536.37	≈	537.09
KS13–12	1806.93	≪	1923.93	>	1830.26	<	1924.38	>	1832.61	≈	1835.1
STS13–13	1029.88	<	1249.12	≫	1023.43	<	1109.62	>	1025.44	≈	1027.45
Aoyagi and Frechette (2009)	417.68	≈	416.51	≪	540.47	≈	543.34	≈	546.38	≈	544.96
Blonski et al. (2011)	1601.27	≈	1588.79	≈	1564.48	≈	1567.21	≈	1614.81	≈	1640.42
Bruttel and Kamecke (2012)	575.98	≈	592.59	≈	567.99	≈	587.38	≈	569.78	≈	571.6
Dal Bó (2005)	739.07	<	756.94	≈	741.2	≈	741.2	≈	756.26	≈	761.39
Dal Bó and Fréchette (2011)	5926.01	<	6059.85	≈	5960.78	≪	6189.93	>	5983.61	≈	5994.24
Dal Bó and Fréchette (2015)	8955.93	<	9139.62	≈	9143.98	<	9333.86	>	9170.84	≈	9204.77
Dreber et al. (2008)	645.2	≈	656.58	≈	648.55	≈	648.55	<	660.03	≈	663.65
Duffy and Ochs (2009)	1888.67	≈	1914.18	≈	2003.41	≈	2034.56	≈	2005.7	≈	2009.16
Fréchette and Yuksel (2017)	444.26	≈	438.55	<	464.23	≈	464.23	≈	472.21	≈	474.13
Fudenberg et al. (2012)	477.91	≈	514.87	≈	534.47	≈	562.1	≈	536.37	≈	537.09
Kagel and Schley (2013)	1806.93	≪	1923.93	>	1830.26	<	1924.38	>	1832.61	≈	1835.1
Sherstyuk et al. (2013)	1029.88	<	1249.12	≫	1023.43	<	1109.62	>	1025.44	≈	1027.45
Pooled	**24837.07**	≪	**25470.38**	≈	**25177.57**	≪	**25815.79**	≫	**25392.89**	≈	**25519.27**

Note: Notation of treatments and meaning of relation signs are all as defined above, see Table A.9.

Table A.39: Comparison of 1- and 2-memory Semi-Grim with two and three parameters, pure and generalized strategies (no switching, Grim scheme) (ICL-BIC of the models, less is better and relation signs point toward better models)

	SGs M2"General"		SGs M2 "Grim"		Semi-Grim		Gen M2"Grim"		Gen M1		Best Pure M2
Specification											
# Models evaluated	1		1		1		1		1		5
# Pars estimated (by treatment)	5		3		3		9		6		32
# Parameters accounted for	5		3		3		9		6		3–8
First halves per session											
Aoyagi and Frechette (2009)	865.91	>	843.09	≈	835.89	>	764.25	≈	757.68	≪	884.86
Blonski et al. (2011)	1421.49	≫	1375.08	≫	1089.36	<	1167.82	≈	1208.25	>	1105.96
Bruttel and Kamecke (2012)	969.35	≈	966.75	≫	817.24	≈	827.89	≈	853.09	≈	839.97
Dal Bó (2005)	798.82	≈	791.74	≫	653.33	≈	667.03	≈	655.4	≈	653.05
Dal Bó and Fréchette (2011)	8512.04	≈	8479.3	≫	7282.65	≈	7378.08	≈	7433.78	≈	7391.89
Dal Bó and Fréchette (2015)	11283.53	≈	11280.81	≫	8887.67	≈	8826.62	≈	8852.04	≈	8893.78
Dreber et al. (2008)	1177.21	≈	1170.29	≫	838.33	≈	888.62	≈	876.1	≈	863.47
Duffy and Ochs (2009)	1588.23	≈	1586.14	≫	1437.86	≈	1414.26	≈	1407.43	≈	1426.34
Fréchette and Yuksel (2017)	362.68	≈	359.65	≈	335.07	≈	322.84	≈	324.71	≈	317.35
Fudenberg et al. (2012)	440.73	≈	440.31	>	398.38	≈	433.05	≈	432.32	≈	463.4
Kagel and Schley (2013)	3490.59	≈	3478.42	≫	2912.53	>	2710.64	≈	2739.15	≈	2730.66
Sherstyuk et al. (2013)	1601.7	≈	1600.41	≫	1413	≈	1386.14	≈	1369.48	≈	1398.69
Pooled	**32694.65**	>	**32481.42**	≫	**27010.74**	≈	**27115.51**	≈	**27128.29**	≈	**27115.38**
Second halves per session											
Aoyagi and Frechette (2009)	498.38	≈	495.48	≈	494.93	>	417.68	≈	416.51	≪	540.47
Blonski et al. (2011)	2277.26	≫	2230.87	≫	1441.28	<	1601.27	≈	1588.79	≈	1564.48
Bruttel and Kamecke (2012)	1013.73	≈	1010.14	≫	595.23	≈	575.98	≈	592.59	≈	567.99
Dal Bó (2005)	904.41	≈	902.58	≫	748.55	≈	739.07	<	756.94	≈	741.2
Dal Bó and Fréchette (2011)	8322.63	≈	8283.81	≫	6160.5	≈	5926.01	<	6059.85	≈	5960.78
Dal Bó and Fréchette (2015)	14925.81	≈	14901.44	≫	9015.88	≈	8955.93	<	9139.62	≈	9143.98
Dreber et al. (2008)	827.1	≈	820.93	≫	665.13	≈	645.2	≈	656.58	≈	648.55
Duffy and Ochs (2009)	1973.39	≈	1968.89	≫	1794.26	≈	1888.67	≈	1914.18	≈	2003.41
Fréchette and Yuksel (2017)	526.45	≈	525.79	≈	481.62	≈	444.26	≈	438.55	<	464.23
Fudenberg et al. (2012)	510.99	≈	507.45	≈	485.43	≈	477.91	≈	514.87	≈	534.47
Kagel and Schley (2013)	2675.61	≈	2673.64	≫	2261.67	≫	1806.93	≪	1923.93	>	1830.26
Sherstyuk et al. (2013)	1261.23	≈	1259.78	≫	1087.07	≈	1029.88	<	1249.12	≫	1023.43
Pooled	**35899.35**	>	**35690.23**	≫	**25340.99**	≈	**24837.07**	≪	**25470.38**	≈	**25177.57**

Note: Relation signs, bootstrap procedure, and derived p-values are exactly as above, see Table 1.2. Pure M1 refers to TFT, Grim, and AD. For definitions of pure strategies see Table A.7. Gen M1 refers to generalized versions of TFT, Grim, and AD with memory-1. SGs refers to a two parameter version of SG $(1-\theta_1, \theta_2, \theta_2, \theta_1)$. "Gen M2" refers to memory-2 versions of the generalized strategies that allow parameters to depend on the prevalence of joint cooperation in $t-2$ (Grim Scheme).

Table A.40: Comparison of 1- and 2-memory Semi-Grim, pure and generalized strategies (no switching, TFT scheme) (ICL-BIC of the models, less is better and relation signs point toward better models)

	SGs M2“General”		SGs M2 “TFT”		Semi-Grim		Gen M2“TFT”		Gen M1		Best Pure M2
Specification											
# Models evaluated	1		1		1		1		1		5
# Pars estimated (by treatment)	5		3		3		9		6		32
# Parameters accounted for	5		3		3		9		6		3–8
First halves per session											
Aoyagi and Frechette (2009)	846.43	≈	842.85	≈	835.89	>	761.5	≈	757.68	≪	884.86
Blonski et al. (2011)	1806.09	>	1764.42	≫	1089.36	<	1166.9	≈	1208.25	>	1105.98
Bruttel and Kamecke (2012)	969.46	≈	966.85	≫	817.24	≈	830.04	≈	853.09	≈	839.97
Dal Bó (2005)	798.82	≈	792.19	≫	653.33	≈	670.93	≈	655.4	≈	653.05
Dal Bó and Fréchette (2011)	8766.46	≈	8857.14	≫	7282.65	≈	7356.81	≈	7433.78	≈	7391.89
Dal Bó and Fréchette (2015)	11201.12	≈	11195.82	≫	8887.67	≈	8772.73	≈	8852.04	≈	8893.78
Dreber et al. (2008)	1080.21	≈	1074.01	≫	838.33	≈	885.14	≈	876.1	≈	863.47
Duffy and Ochs (2009)	1588.23	≈	1589.78	≫	1437.86	≈	1408.4	≈	1407.43	≈	1426.34
Fréchette and Yuksel (2017)	362.68	≈	359.82	≈	335.07	≈	317.71	≈	324.71	≈	317.35
Fudenberg et al. (2012)	440.73	≈	438.77	>	398.38	≈	434.18	≈	432.32	≈	463.4
Kagel and Schley (2013)	3482.28	≈	3478.98	≫	2912.53	>	2679.23	≈	2739.15	≈	2730.66
Sherstyuk et al. (2013)	1601.7	≈	1599.88	≫	1413	≈	1361.19	≈	1369.48	≈	1398.69
Pooled	**33126.57**	≈	**33069.94**	≫	**27010.74**	≈	**26973**	≈	**27128.29**	≈	**27115.39**
Second halves per session											
Aoyagi and Frechette (2009)	498.38	≈	496.8	≈	494.93	>	420.25	≈	416.51	≪	540.47
Blonski et al. (2011)	2534.05	≈	2515.52	≫	1441.28	<	1585.85	≈	1588.79	≈	1564.48
Bruttel and Kamecke (2012)	798.72	≈	802.37	≫	595.23	≈	565.54	≈	592.59	≈	567.99
Dal Bó (2005)	904.46	≈	903.44	≫	748.55	≈	736.51	<	756.94	≈	741.2
Dal Bó and Fréchette (2011)	8180.26	≈	8163	≫	6160.5	≈	5907.5	<	6059.85	≈	5960.78
Dal Bó and Fréchette (2015)	12011.36	≈	12036.08	≫	9015.88	≈	8931.28	<	9139.62	≈	9143.98
Dreber et al. (2008)	994.91	≈	990.52	≫	665.13	≈	640.2	≈	656.58	≈	648.55
Duffy and Ochs (2009)	1973.39	≈	1969	≫	1794.26	≈	1866.23	≈	1914.18	≈	2003.41
Fréchette and Yuksel (2017)	526.45	≈	524.04	≈	481.62	≈	442.91	≈	438.55	<	464.23
Fudenberg et al. (2012)	510.99	≈	508.14	≈	485.43	≈	503.36	≈	514.87	≈	534.47
Kagel and Schley (2013)	2675.61	≈	2675.31	≫	2261.67	≫	1786.55	≪	1923.93	>	1830.26
Sherstyuk et al. (2013)	1261.23	≈	1260.14	≫	1087.07	≈	1015.79	≪	1249.12	≫	1023.43
Pooled	**33052.2**	≈	**32953.79**	≫	**25340.99**	>	**24730.23**	≪	**25470.38**	≈	**25177.57**

Note: Relation signs, bootstrap procedure, and derived p-values are exactly as above, see Table 1.2. Pure M1 refers to TFT, Grim, and AD. For definitions of pure strategies see Table A.7. “Gen M1” refers to generalized versions of TFT, Grim, and AD with memory-1. SGs refers to a two parameter version of SG $(1-\theta_1, \theta_2, \theta_2, \theta_1)$. “Gen M2” refers to memory-2 versions of the generalized strategies that allow parameters to depend on opponent’s behavior in $t-2$ (TFT Scheme).

Table A.41: Examining all mixtures of Semi-Grim with pure or generalized pure strategies as secondary components

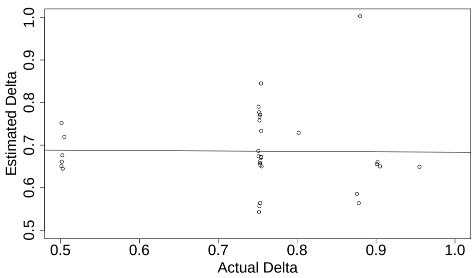
Component 1	First component is always Semi-Grim														
Component 2	Gen WSLS		Gen TFT		Gen Grim		Gen AD/AC		AD		Grim		TFT		WSLS
Specification															
# Models evaluated	1		1		1		1		1		1		1		1
# Pars estimated (by treatment)	5		5		5		5		4		4		4		4
# Parameters accounted for	5		5		5		5		4		4		4		4
First halves per session															
Aoyagi and Frechette (2009)	833.07	≈	827.61	>	781.52	≈	781.72	≈	781.86	≈	836.15	≈	839.39	≈	838.34
Blonski et al. (2011)	1104.67	≪	1205.21	≫	1078.98	≈	1077.49	≈	1069.28	≈	1078.78	≈	1084.91	≈	1116.68
Bruttel and Kamecke (2012)	788.3	≈	774.29	≈	781.67	≈	801.91	≈	800.12	≈	785.63	≈	791.16	≈	805.34
Dal Bó (2005)	626.71	≈	615.03	≈	618.81	≈	633.79	≈	629.17	≈	622.09	≈	620.42	≪	665.94
Dal Bó and Fréchette (2011)	6792.73	≈	6741.75	≈	6717.88	≈	6613.74	≈	6597.93	<	6776.33	≈	6768.78	≪	7019.27
Dal Bó and Fréchette (2015)	8296.9	>	8219.32	≈	8146.3	≈	8032.68	≈	8017.59	≪	8282.13	≈	8244.33	≪	8578.97
Dreber et al. (2008)	783.18	≈	778.8	≈	780.25	≈	786.29	≈	782.37	≈	779.27	≈	801.73	≈	840.26
Duffy and Ochs (2009)	1400.27	≈	1392.67	≈	1378.77	≈	1375.28	≈	1372.97	≈	1398.16	≈	1427.86	≈	1368.08
Fréchette and Yuksel (2017)	296.99	≈	288.62	≈	291.8	≈	301.54	≈	299.62	≈	295.03	≈	301.61	<	341.67
Fudenberg et al. (2012)	407.24	≈	393.68	≈	396.2	≈	382.94	≈	381.01	≈	408.96	≈	391.66	≈	403.85
Kagel and Schley (2013)	2707.66	>	2615.48	≈	2659.78	≈	2564.13	≈	2561.76	<	2705.29	≈	2737.96	<	2909.82
Sherstyuk et al. (2013)	1344.97	≈	1288.49	≈	1290.74	≈	1305.81	≈	1303.8	≈	1342.96	≈	1322.1	<	1417.88
Pooled	**25601.53**	>	**25359.79**	>	**25141.55**	≈	**24876.16**	≈	**24779.85**	≪	**25493.16**	≈	**25514.29**	≪	**26488.47**
Second halves per session															
Aoyagi and Frechette (2009)	479.98	>	446.87	>	418.99	≈	425.42	≈	423.68	≈	479.95	≈	455.1	≈	485.31
Blonski et al. (2011)	1439.96	>	1403.78	≈	1398.73	≈	1366.99	≈	1346.79	≈	1416.3	≈	1397.1	≈	1449.29
Bruttel and Kamecke (2012)	515.73	≈	492.41	≈	512.72	≈	538.57	≈	536.77	≈	513.93	≈	503.46	≪	590.69
Dal Bó (2005)	693.22	>	673	≈	697.25	≈	710.27	≈	699.05	≈	688.6	≈	707.82	<	761.12
Dal Bó and Fréchette (2011)	5253.2	≈	5114.49	≈	5119.08	<	5500.38	>	5128.69	≈	5239.33	≈	5098.31	≪	5730.27
Dal Bó and Fréchette (2015)	7980.76	≫	7744.75	≈	7753.44	≈	7873.59	≈	7825.98	≈	8016.72	≈	7886.32	≪	8545.26
Dreber et al. (2008)	568.76	≈	551.89	≈	565.89	≈	593.75	≈	589.84	≈	564.85	≈	573.93	<	672.96
Duffy and Ochs (2009)	1647.29	≈	1715.88	≈	1710.22	≈	1661.28	≈	1761.6	≈	1747.49	≈	1755.26	≈	1795.33
Fréchette and Yuksel (2017)	464.38	≈	437.79	≈	431.82	≈	425.29	≈	423.34	≈	462.62	≈	457.07	<	487.74
Fudenberg et al. (2012)	463.31	≈	473.75	≈	481.89	≈	470.44	≈	452.6	≈	461.37	≈	483.91	≈	487.78
Kagel and Schley (2013)	1902.37	≫	1730.68	≈	1791.78	≈	1777.99	≈	1775.62	≈	1900	≈	1881.46	≪	2265.03
Sherstyuk et al. (2013)	1015.02	≈	969.34	≈	915.62	≈	953.35	≈	951.34	≈	1013.01	≈	986.2	<	1079.05
Pooled	**22642.83**	≫	**21973.48**	≈	**22016.28**	<	**22516.18**	>	**22097.67**	<	**22686.55**	>	**22368.31**	≪	**24532.19**

Note: Relation signs, bootstrap procedure, and derived p-values are exactly as above, see Table 1.2. For definitions of pure strategies see Table A.7. For definitions of generalized strategies see Section 3 main text.

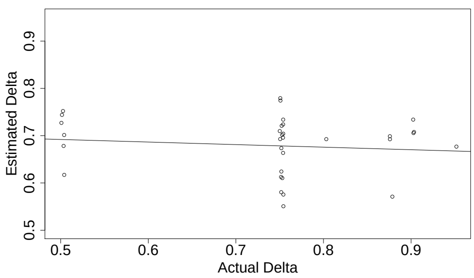
A.6 Robustness checks for section 1.5

Figure A.3: Relation of actual and estimated treatment parameters: Comparison of estimates based on regular and belief-free semi-grim MPEs (first halves of sessions)

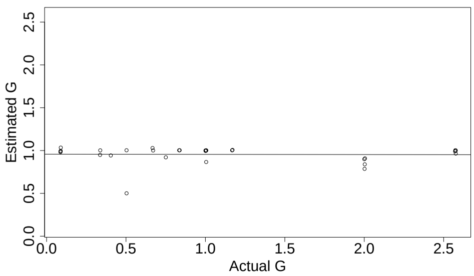
(a) RegSG: Actual vs. Estimated Delta



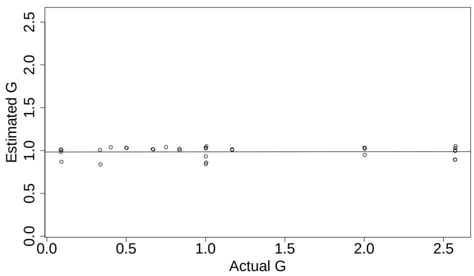
(b) BFSG: Actual vs. Estimated Delta



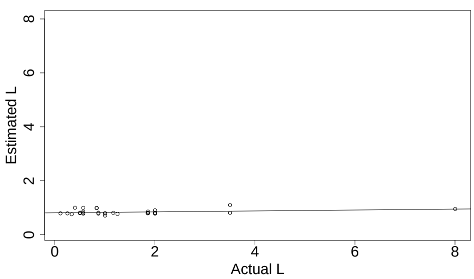
(c) RegSG: Actual vs. Estimated *g*



(d) BFSG: Actual vs. Estimated *g*



(e) RegSG: Actual vs. Estimated *l*



(f) BFSG: Actual vs. Estimated *l*

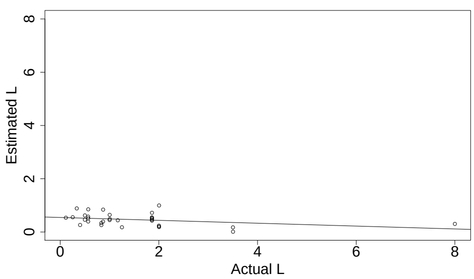
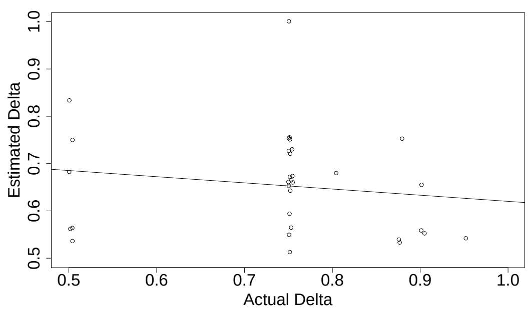
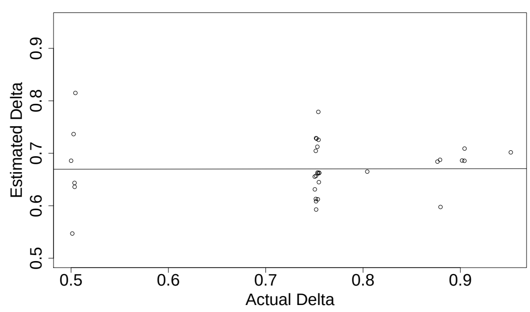


Figure A.4: Relation of actual and estimated treatment parameters: Comparison of estimates based on regular and belief-free semi-grim MPEs (second halves of sessions)

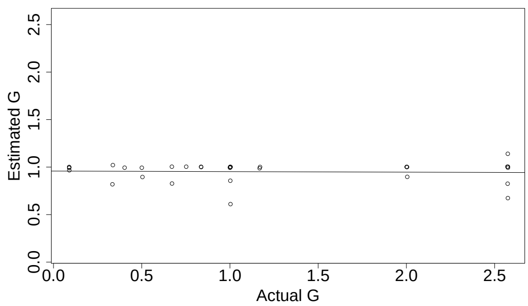
(a) RegSG: Actual vs. Estimated Delta



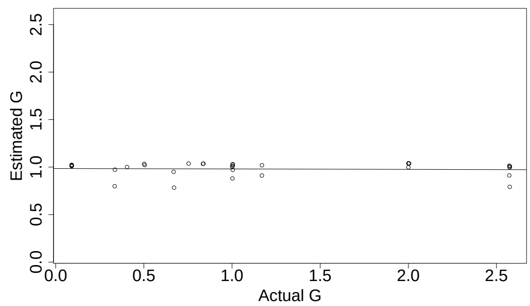
(b) BFSG: Actual vs. Estimated Delta



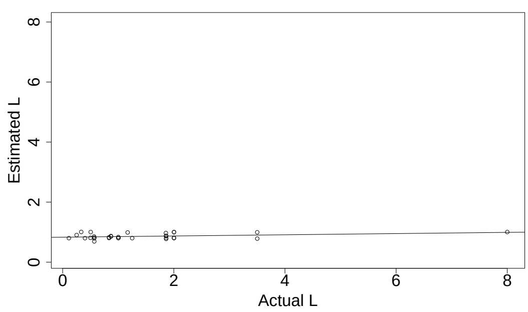
(c) RegSG: Actual vs. Estimated *g*



(d) BFSG: Actual vs. Estimated *g*



(e) RegSG: Actual vs. Estimated *l*



(f) BFSG: Actual vs. Estimated *l*

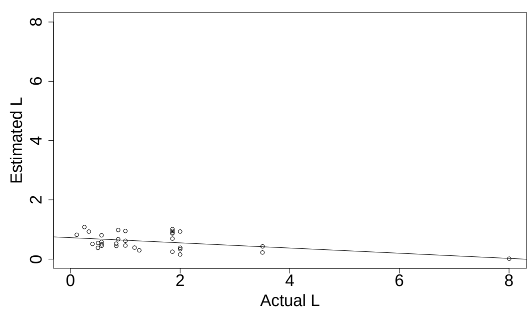


Table A.42: Distance to Semi-Grim MPEs (first halves of sessions)

	Empirical		Closest Reg-SG MPE		Closest BF-SG MPE	
Treatment	SG-Strategy	Game (δ, g, l)	MAD	in game (δ, g, l)	MAD	in game (δ, g, l)
AF09–34	(0.91,0.41,0.41,0.09)	(0.9,0.33,0.11)	0.18	(0.65,1,0.79)	0	(0.7,0.84,0.54)
BOS11–9	(0.95,0.2,0.2,0.05)	(0.5,2,2)	0	(0.75,0.9,0.79)	0	(0.62,1.02,0.2)
BOS11–14	(0.99,0.12,0.12,0.01)	(0.75,0.5,3.5)	0	(0.84,1,0.81)	0	(0.55,1.03,0.17)
BOS11–15	(1,0.22,0.22,0)	(0.75,1,8)	0	(0.76,0.87,0.96)	0	(0.58,1.05,0.3)
BOS11–16	(0.95,0.18,0.18,0.05)	(0.75,0.75,1.25)	0.1	(0.77,0.92,0.77)	0	(0.61,1.04,0.17)
BOS11–17	(1,0.38,0.38,0)	(0.75,0.83,0.5)	0	(0.65,1,0.8)	0	(0.62,1,0.62)
BOS11–26	(0.98,0.17,0.17,0.02)	(0.75,2,2)	0.03	(0.79,0.78,0.81)	0.05	(0.58,1.03,0.24)
BOS11–27	(0.89,0.45,0.45,0.11)	(0.75,1,1)	0.23	(0.55,1,0.71)	0	(0.77,0.84,0.64)
BOS11–30	(1,0,0,0)	(0.88,0.5,3.5)	0	(1,0.5,1.1)	0	(0.57,1.03,0.01)
BOS11–31	(0.98,0.51,0.51,0.02)	(0.88,2,2)	0.05	(0.56,0.84,0.91)	0	(0.69,0.95,1)
BK12–28	(0.92,0.29,0.29,0.08)	(0.8,1.17,0.83)	0.17	(0.73,1,0.99)	0	(0.69,1.01,0.33)
D05–18	(0.86,0.29,0.29,0.14)	(0.75,1.17,0.83)	0.28	(0.73,1,0.99)	0	(0.77,1.01,0.26)
D05–19	(0.91,0.34,0.34,0.09)	(0.75,0.83,1.17)	0.17	(0.67,1,0.81)	0	(0.72,1.02,0.44)
DF11–6	(0.92,0.4,0.4,0.08)	(0.5,2.57,1.86)	0.16	(0.65,1,0.8)	0	(0.7,0.89,0.54)
DF11–7	(0.89,0.32,0.32,0.11)	(0.5,0.67,0.87)	0.21	(0.68,1,0.81)	0	(0.74,1.02,0.39)
DF11–8	(0.91,0.42,0.42,0.09)	(0.5,0.09,0.57)	0.19	(0.64,1,0.78)	0	(0.73,0.86,0.58)
DF11–22	(0.92,0.38,0.38,0.08)	(0.75,2.57,1.86)	0.17	(0.65,1,0.8)	0	(0.7,0.89,0.5)
DF11–23	(0.95,0.46,0.46,0.05)	(0.75,0.67,0.87)	0.1	(0.56,1.03,0.78)	0	(0.72,1.01,0.84)
DF11–24	(0.95,0.36,0.36,0.05)	(0.75,0.09,0.57)	0.1	(0.66,0.99,0.8)	0	(0.67,1,0.52)
DF15–4	(0.9,0.36,0.36,0.1)	(0.5,2.57,1.86)	0.21	(0.66,0.99,0.8)	0	(0.75,0.99,0.46)
DF15–5	(0.93,0.31,0.31,0.07)	(0.5,0.09,0.57)	0.14	(0.72,0.98,1)	0	(0.67,1.01,0.39)
DF15–20	(0.92,0.32,0.32,0.08)	(0.75,2.57,1.86)	0.16	(0.68,0.96,0.85)	0	(0.71,1.05,0.43)
DF15–21	(0.94,0.47,0.47,0.06)	(0.75,0.09,0.57)	0.12	(0.54,1.03,0.85)	0	(0.73,0.98,0.85)
DF15–33	(0.93,0.37,0.37,0.07)	(0.9,2.57,1.86)	0.14	(0.66,1,0.81)	0	(0.7,1,0.53)
DF15–35	(0.97,0.42,0.42,0.03)	(0.95,2.57,1.86)	0.06	(0.64,1,0.79)	0	(0.67,1.03,0.72)
DRFN08–10	(0.95,0.18,0.18,0.05)	(0.75,2,2)	0.11	(0.77,0.91,0.79)	0.02	(0.61,1.03,0.18)
DRFN08–11	(0.93,0.33,0.33,0.07)	(0.75,1,1)	0.14	(0.67,1,0.8)	0	(0.69,1.03,0.44)
DO09–32	(0.9,0.37,0.37,0.1)	(0.9,1,1)	0.2	(0.65,0.99,0.79)	0	(0.73,0.93,0.48)
FY17–25	(0.93,0.25,0.25,0.07)	(0.75,0.4,0.4)	0.15	(0.76,0.94,1)	0	(0.66,1.03,0.26)
FRD12–29	(0.97,0.47,0.47,0.03)	(0.88,0.33,0.33)	0.06	(0.58,0.95,0.76)	0	(0.7,1.01,0.88)
KS13–12	(0.93,0.33,0.33,0.07)	(0.75,1,0.5)	0.14	(0.67,1,0.81)	0	(0.69,1.02,0.46)
STS13–13	(0.92,0.41,0.41,0.08)	(0.75,1,0.25)	0.16	(0.65,1,0.79)	0	(0.7,0.86,0.55)
Means			0.123	(0.69,0.95,0.84)	0.002	(0.68,0.98,0.47)

Note: "SG-Strategy" is the SG-continuation strategy estimated in the "1.5× SG + AD" model

Table A.43: Distance to Semi-Grim MPEs: closest equilibria (first halves of sessions)

Treatment	Empirical		Closest Reg-SG MPE	Closest BF-SG MPE
	SG-Strategy	Game	Strategy	Strategy
AF09–34	(0.91,0.41,0.41,0.09)	(0.9,0.33,0.11)	(1,0.41,0.41,0)	(0.91,0.41,0.41,0.09)
BOS11–9	(0.95,0.2,0.2,0.05)	(0.5,2,2)	(1,0.2,0.2,0)	(0.95,0.2,0.2,0.05)
BOS11–14	(0.99,0.12,0.12,0.01)	(0.75,0.5,3.5)	(1,0.12,0.12,0)	(1,0.15,0.15,0)
BOS11–15	(1,0.22,0.22,0)	(0.75,1,8)	(1,0.22,0.22,0)	(1,0.22,0.22,0)
BOS11–16	(0.95,0.18,0.18,0.05)	(0.75,0.75,1.25)	(1,0.18,0.18,0)	(0.95,0.18,0.18,0.05)
BOS11–17	(1,0.38,0.38,0)	(0.75,0.83,0.5)	(1,0.38,0.38,0)	(1,0.38,0.38,0)
BOS11–26	(0.98,0.17,0.17,0.02)	(0.75,2,2)	(1,0.17,0.17,0)	(0.98,0.2,0.2,0.02)
BOS11–27	(0.89,0.45,0.45,0.11)	(0.75,1,1)	(1,0.45,0.45,0)	(0.89,0.45,0.45,0.11)
BOS11–30	(1,0,0,0)	(0.88,0.5,3.5)	(1,0,0,0)	(0.95,0.06,0.06,0.05)
BOS11–31	(0.98,0.51,0.51,0.02)	(0.88,2,2)	(1,0.51,0.51,0)	(0.98,0.51,0.51,0.02)
BK12–28	(0.92,0.29,0.29,0.08)	(0.8,1.17,0.83)	(1,0.29,0.29,0)	(0.92,0.29,0.29,0.08)
D05–18	(0.86,0.29,0.29,0.14)	(0.75,1.17,0.83)	(1,0.29,0.29,0)	(0.86,0.29,0.29,0.14)
D05–19	(0.91,0.34,0.34,0.09)	(0.75,0.83,1.17)	(1,0.34,0.34,0)	(0.91,0.34,0.34,0.09)
DF11–6	(0.92,0.4,0.4,0.08)	(0.5,2.57,1.86)	(1,0.4,0.4,0)	(0.92,0.4,0.4,0.08)
DF11–7	(0.89,0.32,0.32,0.11)	(0.5,0.67,0.87)	(1,0.32,0.32,0)	(0.89,0.32,0.32,0.11)
DF11–8	(0.91,0.42,0.42,0.09)	(0.5,0.09,0.57)	(1,0.42,0.42,0)	(0.91,0.42,0.42,0.09)
DF11–22	(0.92,0.38,0.38,0.08)	(0.75,2.57,1.86)	(1,0.38,0.38,0)	(0.92,0.38,0.38,0.08)
DF11–23	(0.95,0.46,0.46,0.05)	(0.75,0.67,0.87)	(1,0.46,0.46,0)	(0.95,0.46,0.46,0.05)
DF11–24	(0.95,0.36,0.36,0.05)	(0.75,0.09,0.57)	(1,0.36,0.36,0)	(0.95,0.36,0.36,0.05)
DF15–4	(0.9,0.36,0.36,0.1)	(0.5,2.57,1.86)	(1,0.36,0.36,0)	(0.9,0.36,0.36,0.1)
DF15–5	(0.93,0.31,0.31,0.07)	(0.5,0.09,0.57)	(1,0.31,0.31,0)	(0.93,0.31,0.31,0.07)
DF15–20	(0.92,0.32,0.32,0.08)	(0.75,2.57,1.86)	(1,0.32,0.32,0)	(0.92,0.32,0.32,0.08)
DF15–21	(0.94,0.47,0.47,0.06)	(0.75,0.09,0.57)	(1,0.47,0.47,0)	(0.94,0.47,0.47,0.06)
DF15–33	(0.93,0.37,0.37,0.07)	(0.9,2.57,1.86)	(1,0.37,0.37,0)	(0.93,0.37,0.37,0.07)
DF15–35	(0.97,0.42,0.42,0.03)	(0.95,2.57,1.86)	(1,0.42,0.42,0)	(0.97,0.42,0.42,0.03)
DRFN08–10	(0.95,0.18,0.18,0.05)	(0.75,2,2)	(1,0.18,0.18,0)	(0.95,0.19,0.19,0.05)
DRFN08–11	(0.93,0.33,0.33,0.07)	(0.75,1,1)	(1,0.33,0.33,0)	(0.93,0.33,0.33,0.07)
DO09–32	(0.9,0.37,0.37,0.1)	(0.9,1,1)	(1,0.37,0.37,0)	(0.9,0.37,0.37,0.1)
FY17–25	(0.93,0.25,0.25,0.07)	(0.75,0.4,0.4)	(1,0.25,0.25,0)	(0.93,0.25,0.25,0.07)
FRD12–29	(0.97,0.47,0.47,0.03)	(0.88,0.33,0.33)	(1,0.47,0.47,0)	(0.97,0.47,0.47,0.03)
KS13–12	(0.93,0.33,0.33,0.07)	(0.75,1,0.5)	(1,0.33,0.33,0)	(0.93,0.33,0.33,0.07)
STS13–13	(0.92,0.41,0.41,0.08)	(0.75,1,0.25)	(1,0.41,0.41,0)	(0.92,0.41,0.41,0.08)

Note: “SG-Strategy” is the SG-continuation strategy estimated in the “1.5× SG + AD” model

Table A.44: Distance to Semi-Grim MPEs (second halves of sessions)

	Empirical		Closest Reg-SG MPE		Closest BF-SG MPE	
Treatment	SG-Strategy	Game (δ, g, l)	MAD	in game (δ, g, l)	MAD	in game (δ, g, l)
AF09–34	(0.97,0.46,0.46,0.03)	(0.9,0.33,0.11)	0.06	(0.55,1.02,0.8)	0	(0.68,0.97,0.82)
BOS11–9	(1,0.13,0.13,0)	(0.5,2,2)	0	(0.83,1,0.8)	0	(0.54,1.03,0.15)
BOS11–14	(0.99,0.3,0.3,0.01)	(0.75,0.5,3.5)	0	(0.72,0.99,0.99)	0	(0.61,1.02,0.43)
BOS11–15	(1,0,0,0)	(0.75,1,8)	0	(1,0.99,1)	0	(0.59,1.03,0.01)
BOS11–16	(0.97,0.21,0.21,0.03)	(0.75,0.75,1.25)	0.07	(0.75,1,0.8)	0.06	(0.61,1.03,0.29)
BOS11–17	(0.95,0.26,0.26,0.05)	(0.75,0.83,0.5)	0.1	(0.75,1,1)	0.07	(0.64,1.04,0.38)
BOS11–26	(0.94,0.29,0.29,0.06)	(0.75,2,2)	0.13	(0.73,1,1)	0.03	(0.66,1.04,0.38)
BOS11–27	(0.95,0.5,0.5,0.05)	(0.75,1,1)	0.1	(0.51,0.86,0.83)	0	(0.73,0.97,0.95)
BOS11–30	(0.96,0.2,0.2,0.04)	(0.88,0.5,3.5)	0.08	(0.75,0.89,0.78)	0.02	(0.6,1.03,0.22)
BOS11–31	(0.98,0.48,0.48,0.02)	(0.88,2,2)	0.04	(0.54,0.89,0.81)	0	(0.69,0.99,0.93)
BK12–28	(0.95,0.32,0.32,0.05)	(0.8,1.17,0.83)	0.1	(0.68,0.98,0.82)	0	(0.66,1.02,0.44)
D05–18	(0.88,0.4,0.4,0.12)	(0.75,1.17,0.83)	0.24	(0.65,1,0.8)	0	(0.78,0.91,0.52)
D05–19	(0.95,0.3,0.3,0.05)	(0.75,0.83,1.17)	0.11	(0.72,1,0.98)	0	(0.66,1.03,0.38)
DF11–6	(0.94,0.55,0.55,0.06)	(0.5,2.57,1.86)	0.13	(0.56,0.67,0.97)	0	(0.73,0.79,1.01)
DF11–7	(0.86,0.47,0.47,0.14)	(0.5,0.67,0.87)	0.27	(0.53,1,0.86)	0	(0.81,0.78,0.67)
DF11–8	(0.97,0.45,0.45,0.03)	(0.5,0.09,0.57)	0.06	(0.56,0.99,0.69)	0	(0.68,1.01,0.8)
DF11–22	(0.96,0.47,0.47,0.04)	(0.75,2.57,1.86)	0.08	(0.55,1,0.81)	0	(0.7,1,0.86)
DF11–23	(0.96,0.51,0.51,0.04)	(0.75,0.67,0.87)	0.09	(0.56,0.83,0.87)	0	(0.72,0.95,0.98)
DF11–24	(0.98,0.33,0.33,0.02)	(0.75,0.09,0.57)	0.04	(0.67,1,0.79)	0	(0.63,1.02,0.5)
DF15–4	(0.94,0.23,0.23,0.06)	(0.5,2.57,1.86)	0.12	(0.75,1.14,0.87)	0	(0.63,1.01,0.25)
DF15–5	(0.96,0.32,0.32,0.04)	(0.5,0.09,0.57)	0.08	(0.68,0.96,0.85)	0	(0.64,1.01,0.45)
DF15–20	(0.94,0.42,0.42,0.06)	(0.75,2.57,1.86)	0.12	(0.64,0.99,0.77)	0	(0.71,0.99,0.69)
DF15–21	(0.97,0.37,0.37,0.03)	(0.75,0.09,0.57)	0.07	(0.66,1,0.81)	0	(0.66,1.01,0.58)
DF15–33	(0.96,0.48,0.48,0.04)	(0.9,2.57,1.86)	0.07	(0.55,1,0.87)	0	(0.7,1,0.9)
DF15–35	(0.97,0.51,0.51,0.03)	(0.95,2.57,1.86)	0.07	(0.54,0.82,0.87)	0	(0.7,0.91,0.95)
DRFN08–10	(0.97,0.25,0.25,0.03)	(0.75,2,2)	0.07	(0.75,1,1)	0.03	(0.61,1.03,0.34)
DRFN08–11	(0.95,0.33,0.33,0.05)	(0.75,1,1)	0.1	(0.67,1,0.8)	0	(0.66,1.02,0.45)
DO09–32	(0.95,0.39,0.39,0.05)	(0.9,1,1)	0.09	(0.65,1,0.8)	0	(0.68,1,0.62)
FY17–25	(0.96,0.35,0.35,0.04)	(0.75,0.4,0.4)	0.09	(0.66,0.99,0.79)	0	(0.66,1,0.51)
FRD12–29	(0.96,0.54,0.54,0.04)	(0.88,0.33,0.33)	0.07	(0.53,0.82,1)	0	(0.68,0.8,0.93)
KS13–12	(0.96,0.36,0.36,0.04)	(0.75,1,0.5)	0.07	(0.66,0.99,0.81)	0	(0.65,1.01,0.54)
STS13–13	(0.95,0.55,0.55,0.05)	(0.75,1,0.25)	0.09	(0.59,0.61,0.9)	0.01	(0.73,0.88,1.08)
Means			0.088	(0.65,0.95,0.86)	0.007	(0.67,0.98,0.59)

Note: "SG-Strategy" is the SG-continuation strategy estimated in the "1.5× SG + AD" model

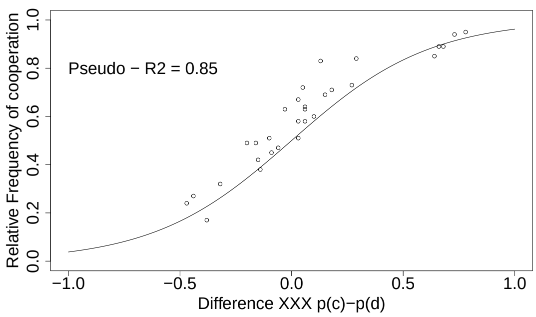
Table A.45: Distance to Semi-Grim MPEs: closest equilibria (second halves of sessions)

	Empirical		Closest Reg-SG MPE	Closest BF-SG MPE
Treatment	SG-Strategy	Game	Strategy	Strategy
AF09–34	(0.97,0.46,0.46,0.03)	(0.9,0.33,0.11)	(1,0.46,0.46,0)	(0.97,0.46,0.46,0.03)
BOS11–9	(1,0.13,0.13,0)	(0.5,2,2)	(1,0.13,0.13,0)	(1,0.13,0.13,0)
BOS11–14	(0.99,0.3,0.3,0.01)	(0.75,0.5,3.5)	(1,0.3,0.3,0)	(0.99,0.3,0.3,0.01)
BOS11–15	(1,0,0,0)	(0.75,1,8)	(1,0,0,0)	(0.93,0.08,0.08,0.07)
BOS11–16	(0.97,0.21,0.21,0.03)	(0.75,0.75,1.25)	(1,0.21,0.21,0)	(0.97,0.24,0.24,0.03)
BOS11–17	(0.95,0.26,0.26,0.05)	(0.75,0.83,0.5)	(1,0.26,0.26,0)	(0.96,0.29,0.29,0.04)
BOS11–26	(0.94,0.29,0.29,0.06)	(0.75,2,2)	(1,0.29,0.29,0)	(0.94,0.29,0.29,0.06)
BOS11–27	(0.95,0.5,0.5,0.05)	(0.75,1,1)	(1,0.5,0.5,0)	(0.95,0.5,0.5,0.05)
BOS11–30	(0.96,0.2,0.2,0.04)	(0.88,0.5,3.5)	(1,0.2,0.2,0)	(0.97,0.2,0.2,0.03)
BOS11–31	(0.98,0.48,0.48,0.02)	(0.88,2,2)	(1,0.48,0.48,0)	(0.98,0.48,0.48,0.02)
BK12–28	(0.95,0.32,0.32,0.05)	(0.8,1.17,0.83)	(1,0.32,0.32,0)	(0.95,0.32,0.32,0.05)
D05–18	(0.88,0.4,0.4,0.12)	(0.75,1.17,0.83)	(1,0.4,0.4,0)	(0.88,0.4,0.4,0.12)
D05–19	(0.95,0.3,0.3,0.05)	(0.75,0.83,1.17)	(1,0.3,0.3,0)	(0.95,0.3,0.3,0.05)
DF11–6	(0.94,0.55,0.55,0.06)	(0.5,2.57,1.86)	(1,0.55,0.55,0)	(0.94,0.55,0.55,0.06)
DF11–7	(0.86,0.47,0.47,0.14)	(0.5,0.67,0.87)	(1,0.47,0.47,0)	(0.86,0.47,0.47,0.14)
DF11–8	(0.97,0.45,0.45,0.03)	(0.5,0.09,0.57)	(1,0.45,0.45,0)	(0.97,0.45,0.45,0.03)
DF11–22	(0.96,0.47,0.47,0.04)	(0.75,2.57,1.86)	(1,0.47,0.47,0)	(0.96,0.47,0.47,0.04)
DF11–23	(0.96,0.51,0.51,0.04)	(0.75,0.67,0.87)	(1,0.51,0.51,0)	(0.96,0.51,0.51,0.04)
DF11–24	(0.98,0.33,0.33,0.02)	(0.75,0.09,0.57)	(1,0.33,0.33,0)	(0.98,0.33,0.33,0.02)
DF15–4	(0.94,0.23,0.23,0.06)	(0.5,2.57,1.86)	(1,0.23,0.23,0)	(0.94,0.23,0.23,0.06)
DF15–5	(0.96,0.32,0.32,0.04)	(0.5,0.09,0.57)	(1,0.32,0.32,0)	(0.96,0.32,0.32,0.04)
DF15–20	(0.94,0.42,0.42,0.06)	(0.75,2.57,1.86)	(1,0.42,0.42,0)	(0.94,0.42,0.42,0.06)
DF15–21	(0.97,0.37,0.37,0.03)	(0.75,0.09,0.57)	(1,0.37,0.37,0)	(0.97,0.37,0.37,0.03)
DF15–33	(0.96,0.48,0.48,0.04)	(0.9,2.57,1.86)	(1,0.48,0.48,0)	(0.96,0.48,0.48,0.04)
DF15–35	(0.97,0.51,0.51,0.03)	(0.95,2.57,1.86)	(1,0.51,0.51,0)	(0.97,0.51,0.51,0.03)
DRFN08–10	(0.97,0.25,0.25,0.03)	(0.75,2,2)	(1,0.25,0.25,0)	(0.98,0.26,0.26,0.02)
DRFN08–11	(0.95,0.33,0.33,0.05)	(0.75,1,1)	(1,0.33,0.33,0)	(0.95,0.33,0.33,0.05)
DO09–32	(0.95,0.39,0.39,0.05)	(0.9,1,1)	(1,0.39,0.39,0)	(0.95,0.39,0.39,0.05)
FY17–25	(0.96,0.35,0.35,0.04)	(0.75,0.4,0.4)	(1,0.35,0.35,0)	(0.96,0.35,0.35,0.04)
FRD12–29	(0.96,0.54,0.54,0.04)	(0.88,0.33,0.33)	(1,0.54,0.54,0)	(0.96,0.54,0.54,0.04)
KS13–12	(0.96,0.36,0.36,0.04)	(0.75,1,0.5)	(1,0.36,0.36,0)	(0.96,0.36,0.36,0.04)
STS13–13	(0.95,0.55,0.55,0.05)	(0.75,1,0.25)	(1,0.55,0.55,0)	(0.95,0.55,0.55,0.05)

Note: “SG-Strategy” is the SG-continuation strategy estimated in the “1.5× SG + AD” model

Table A.46: Incentives in state ∅ (second halves of sessions)

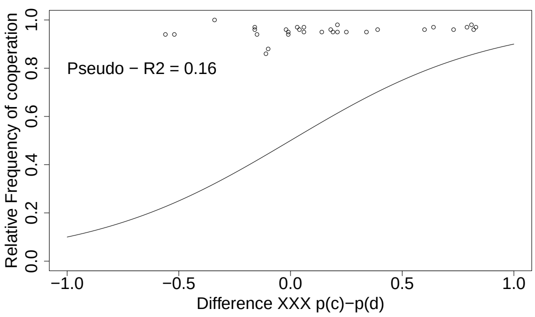
Treatment	Game	Observation $\hat{\sigma}_0$	$\hat{\pi}(c)$	$\hat{\pi}(d)$	Fit σ_0^*	Deviat
AF09–34	(0.9,0.33,0.11)	0.94	7.7	6.46	0.99	-0.05
BOS11–9	(0.5,2,2)	0.27	0.75	1.18	0.19	0.08
BOS11–14	(0.75,0.5,3.5)	0.03	0.75	1	0.3	-0.27
BOS11–15	(0.75,1,8)	0	0.75	1	0.3	-0.3
BOS11–16	(0.75,0.75,1.25)	0.63	1.32	1.28	0.53	0.1
BOS11–17	(0.75,0.83,0.5)	0.6	1.69	1.5	0.66	-0.06
BOS11–26	(0.75,2,2)	0.49	0.99	1.12	0.39	0.1
BOS11–27	(0.75,1,1)	0.47	1.27	1.23	0.53	-0.06
BOS11–30	(0.88,0.5,3.5)	0.45	0.95	1	0.46	-0.01
BOS11–31	(0.88,2,2)	0.58	1.11	1.09	0.52	0.06
BK12–28	(0.8,1.17,0.83)	0.58	1.44	1.36	0.57	0.01
D05–18	(0.75,1.17,0.83)	0.51	1.5	1.59	0.42	0.09
D05–19	(0.75,0.83,1.17)	0.67	1.3	1.26	0.53	0.14
DF11–6	(0.5,2.57,1.86)	0.17	0.76	1.07	0.26	-0.09
DF11–7	(0.5,0.67,0.87)	0.32	0.98	1.24	0.29	0.03
DF11–8	(0.5,0.09,0.57)	0.64	1.53	1.43	0.58	0.06
DF11–22	(0.75,2.57,1.86)	0.38	1.08	1.18	0.42	-0.04
DF11–23	(0.75,0.67,0.87)	0.83	1.79	1.61	0.65	0.18
DF11–24	(0.75,0.09,0.57)	0.95	2.54	1.73	0.94	0.01
DF15–4	(0.5,2.57,1.86)	0.24	0.68	1.1	0.19	0.05
DF15–5	(0.5,0.09,0.57)	0.69	1.65	1.52	0.61	0.08
DF15–20	(0.75,2.57,1.86)	0.42	1.06	1.17	0.41	0.01
DF15–21	(0.75,0.09,0.57)	0.85	2.19	1.56	0.89	-0.04
DF15–33	(0.9,2.57,1.86)	0.51	1.22	1.18	0.53	-0.02
DF15–35	(0.95,2.57,1.86)	0.63	1.27	1.21	0.55	0.08
DRFN08–10	(0.75,2,2)	0.49	0.98	1.11	0.39	0.1
DRFN08–11	(0.75,1,1)	0.72	1.52	1.44	0.57	0.15
DO09–32	(0.9,1,1)	0.71	1.53	1.36	0.64	0.07
FY17–25	(0.75,0.4,0.4)	0.89	2.66	1.95	0.92	-0.03
FRD12–29	(0.88,0.33,0.33)	0.89	3.18	2.41	0.93	-0.04
KS13–12	(0.75,1,0.5)	0.84	2.29	1.93	0.77	0.07
STS13–13	(0.75,1,0.25)	0.73	3.87	3.39	0.84	-0.11



Note: For each treatment in each experiment, the table reviews the treatment parameters, the observed relative frequency of cooperation (in state ∅ in second halves of sessions), the expected payoff cooperating in that state $\hat{\pi}(c)$, the expected payoff of defecting in that state $\hat{\pi}(d)$, the "predicted" probability of cooperation based on the logistic regression of cooperation rates on monetary incentive $\hat{\pi}(c) - \hat{\pi}(c)$, and the absolute deviation of that prediction.

Table A.47: Incentives in state *cc* (second halves of sessions)

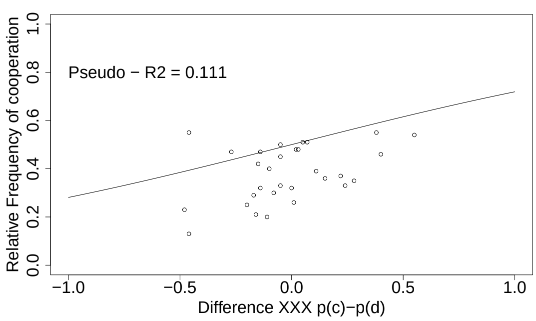
		Observation			Fit	
Treatment	Game	$\hat{\sigma}_{cc}$	$\hat{\pi}(c)$	$\hat{\pi}(d)$	σ_0^*	Deviat
AF09–34	(0.9,0.33,0.11)	0.97	7.86	6.61	0.98	-0.01
BOS11–9	(0.5,2,2)	1	1.46	1.75	0.28	0.72
BOS11–14	(0.75,0.5,3.5)	0.99	1.25	1.1	0.62	0.37
BOS11–15	(0.75,1,8)	1	1.12	1.06	0.55	0.45
BOS11–16	(0.75,0.75,1.25)	0.97	1.59	1.42	0.63	0.34
BOS11–17	(0.75,0.83,0.5)	0.95	2.57	2.03	0.85	0.1
BOS11–26	(0.75,2,2)	0.94	1.35	1.37	0.48	0.46
BOS11–27	(0.75,1,1)	0.95	1.8	1.62	0.64	0.31
BOS11–30	(0.88,0.5,3.5)	0.96	1.15	1.03	0.59	0.37
BOS11–31	(0.88,2,2)	0.98	1.38	1.23	0.62	0.36
BK12–28	(0.8,1.17,0.83)	0.95	1.9	1.65	0.69	0.26
D05–18	(0.75,1.17,0.83)	0.88	1.83	1.9	0.44	0.44
D05–19	(0.75,0.83,1.17)	0.95	1.64	1.43	0.66	0.29
DF11–6	(0.5,2.57,1.86)	0.94	1.42	1.85	0.2	0.74
DF11–7	(0.5,0.67,0.87)	0.86	1.81	1.9	0.43	0.43
DF11–8	(0.5,0.09,0.57)	0.97	2.61	2	0.88	0.09
DF11–22	(0.75,2.57,1.86)	0.96	1.46	1.56	0.42	0.54
DF11–23	(0.75,0.67,0.87)	0.96	1.96	1.74	0.67	0.29
DF11–24	(0.75,0.09,0.57)	0.98	2.59	1.75	0.94	0.04
DF15–4	(0.5,2.57,1.86)	0.94	1.41	1.87	0.19	0.75
DF15–5	(0.5,0.09,0.57)	0.96	2.57	1.97	0.87	0.09
DF15–20	(0.75,2.57,1.86)	0.94	1.42	1.52	0.42	0.52
DF15–21	(0.75,0.09,0.57)	0.97	2.47	1.68	0.93	0.04
DF15–33	(0.9,2.57,1.86)	0.96	1.4	1.34	0.55	0.41
DF15–35	(0.95,2.57,1.86)	0.97	1.36	1.29	0.56	0.41
DRFN08–10	(0.75,2,2)	0.97	1.4	1.37	0.52	0.45
DRFN08–11	(0.75,1,1)	0.95	1.79	1.62	0.63	0.32
DO09–32	(0.9,1,1)	0.95	1.67	1.45	0.67	0.28
FY17–25	(0.75,0.4,0.4)	0.96	3.03	2.15	0.94	0.02
FRD12–29	(0.88,0.33,0.33)	0.96	3.38	2.57	0.93	0.03
KS13–12	(0.75,1,0.5)	0.96	2.71	2.25	0.81	0.15
STS13–13	(0.75,1,0.25)	0.95	4.54	4.32	0.67	0.28



Note: For each treatment in each experiment, the table reviews the treatment parameters, the observed relative frequency of cooperation (in state *cc* in second halves of sessions), the expected payoff cooperating in that state $\hat{\pi}(c)$, the expected payoff of defecting in that state $\hat{\pi}(d)$, the "predicted" probability of cooperation based on the logistic regression of cooperation rates on monetary incentive $\hat{\pi}(c) - \hat{\pi}(c)$, and the absolute deviation of that prediction.

Table A.48: Incentives in state cd, dc (second halves of sessions)

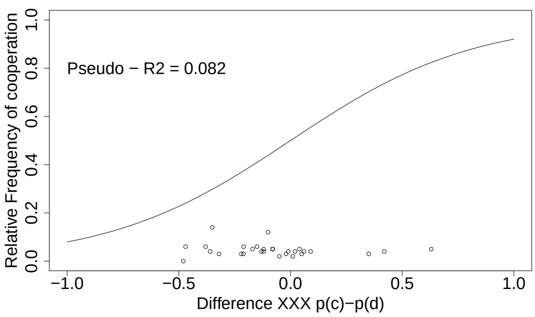
		Observation			Fit	
Treatment	Game	$\hat{\sigma}_{cd,dc}$	$\hat{\pi}(c)$	$\hat{\pi}(d)$	σ_0^*	Deviat
AF09–34	(0.9,0.33,0.11)	0.46	6.66	5.49	0.63	-0.17
BOS11–9	(0.5,2,2)	0.13	0.64	1.1	0.45	-0.32
BOS11–14	(0.75,0.5,3.5)	0.3	0.9	1.02	0.49	-0.19
BOS11–15	(0.75,1,8)	0	0.75	1	0.47	-0.47
BOS11–16	(0.75,0.75,1.25)	0.21	1.06	1.15	0.49	-0.28
BOS11–17	(0.75,0.83,0.5)	0.26	1.42	1.33	0.51	-0.25
BOS11–26	(0.75,2,2)	0.29	0.99	1.12	0.48	-0.19
BOS11–27	(0.75,1,1)	0.5	1.41	1.33	0.51	-0.01
BOS11–30	(0.88,0.5,3.5)	0.2	0.92	1	0.49	-0.29
BOS11–31	(0.88,2,2)	0.48	1.15	1.11	0.5	-0.02
BK12–28	(0.8,1.17,0.83)	0.32	1.31	1.27	0.5	-0.18
D05–18	(0.75,1.17,0.83)	0.4	1.44	1.52	0.49	-0.09
D05–19	(0.75,0.83,1.17)	0.3	1.09	1.15	0.49	-0.19
DF11–6	(0.5,2.57,1.86)	0.55	1.11	1.49	0.46	0.09
DF11–7	(0.5,0.67,0.87)	0.47	1.31	1.51	0.48	-0.01
DF11–8	(0.5,0.09,0.57)	0.45	1.57	1.45	0.51	-0.06
DF11–22	(0.75,2.57,1.86)	0.47	1.19	1.28	0.49	-0.02
DF11–23	(0.75,0.67,0.87)	0.51	1.56	1.43	0.52	-0.01
DF11–24	(0.75,0.09,0.57)	0.33	1.57	1.29	0.53	-0.2
DF15–4	(0.5,2.57,1.86)	0.23	0.79	1.22	0.45	-0.22
DF15–5	(0.5,0.09,0.57)	0.32	1.26	1.32	0.49	-0.17
DF15–20	(0.75,2.57,1.86)	0.42	1.13	1.24	0.49	-0.07
DF15–21	(0.75,0.09,0.57)	0.37	1.58	1.29	0.53	-0.16
DF15–33	(0.9,2.57,1.86)	0.48	1.24	1.2	0.5	-0.02
DF15–35	(0.95,2.57,1.86)	0.51	1.27	1.21	0.51	0
DRFN08–10	(0.75,2,2)	0.25	0.95	1.1	0.48	-0.23
DRFN08–11	(0.75,1,1)	0.33	1.23	1.25	0.5	-0.17
DO09–32	(0.9,1,1)	0.39	1.38	1.27	0.51	-0.12
FY17–25	(0.75,0.4,0.4)	0.35	1.83	1.49	0.54	-0.19
FRD12–29	(0.88,0.33,0.33)	0.54	2.74	2.06	0.58	-0.04
KS13–12	(0.75,1,0.5)	0.36	1.73	1.51	0.53	-0.17
STS13–13	(0.75,1,0.25)	0.55	3.64	3.07	0.57	-0.02



Note: For each treatment in each experiment, the table reviews the treatment parameters, the observed relative frequency of cooperation (in states cd, dc in second halves of sessions), the expected payoff cooperating in that state $\hat{\pi}(c)$, the expected payoff of defecting in that state $\hat{\pi}(d)$, the "predicted" probability of cooperation based on the logistic regression of cooperation rates on monetary incentive $\hat{\pi}(c) - \hat{\pi}(c)$, and the absolute deviation of that prediction.

Table A.49: Incentives in state *dd* (second halves of sessions)

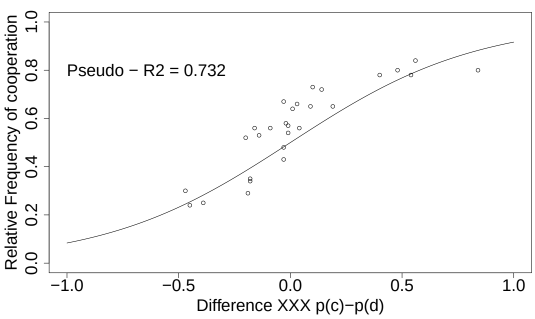
		Observation			Fit	
Treatment	Game	$\hat{\sigma}_{dd}$	$\hat{\pi}(c)$	$\hat{\pi}(d)$	σ_0^*	Deviat
AF09–34	(0.9,0.33,0.11)	0.03	5.71	4.6	0.64	-0.61
BOS11–9	(0.5,2,2)	0	0.54	1.02	0.44	-0.44
BOS11–14	(0.75,0.5,3.5)	0.01	0.75	1	0.47	-0.46
BOS11–15	(0.75,1,8)	0	0.75	1	0.47	-0.47
BOS11–16	(0.75,0.75,1.25)	0.03	0.91	1.08	0.48	-0.45
BOS11–17	(0.75,0.83,0.5)	0.05	1.06	1.12	0.49	-0.44
BOS11–26	(0.75,2,2)	0.06	0.85	1.03	0.48	-0.42
BOS11–27	(0.75,1,1)	0.05	1.04	1.06	0.5	-0.45
BOS11–30	(0.88,0.5,3.5)	0.04	0.87	0.99	0.48	-0.44
BOS11–31	(0.88,2,2)	0.02	0.99	1.03	0.49	-0.47
BK12–28	(0.8,1.17,0.83)	0.05	1.06	1.11	0.49	-0.44
D05–18	(0.75,1.17,0.83)	0.12	1.21	1.3	0.49	-0.37
D05–19	(0.75,0.83,1.17)	0.05	0.89	1.05	0.48	-0.43
DF11–6	(0.5,2.57,1.86)	0.06	0.73	1.03	0.46	-0.4
DF11–7	(0.5,0.67,0.87)	0.14	0.82	1.12	0.46	-0.32
DF11–8	(0.5,0.09,0.57)	0.03	0.77	1.03	0.47	-0.44
DF11–22	(0.75,2.57,1.86)	0.04	0.95	1.05	0.49	-0.45
DF11–23	(0.75,0.67,0.87)	0.04	1.14	1.1	0.51	-0.47
DF11–24	(0.75,0.09,0.57)	0.02	1.07	1.06	0.5	-0.48
DF15–4	(0.5,2.57,1.86)	0.06	0.61	1.04	0.44	-0.38
DF15–5	(0.5,0.09,0.57)	0.04	0.71	1.05	0.46	-0.42
DF15–20	(0.75,2.57,1.86)	0.06	0.93	1.05	0.48	-0.42
DF15–21	(0.75,0.09,0.57)	0.03	1.07	1.07	0.5	-0.47
DF15–33	(0.9,2.57,1.86)	0.04	1.1	1.08	0.5	-0.46
DF15–35	(0.95,2.57,1.86)	0.03	1.17	1.12	0.51	-0.48
DRFN08–10	(0.75,2,2)	0.03	0.82	1.02	0.47	-0.44
DRFN08–11	(0.75,1,1)	0.05	0.97	1.08	0.49	-0.44
DO09–32	(0.9,1,1)	0.05	1.2	1.16	0.51	-0.46
FY17–25	(0.75,0.4,0.4)	0.04	1.24	1.16	0.51	-0.47
FRD12–29	(0.88,0.33,0.33)	0.04	2.1	1.55	0.57	-0.53
KS13–12	(0.75,1,0.5)	0.04	1.2	1.12	0.51	-0.47
STS13–13	(0.75,1,0.25)	0.05	2.54	1.55	0.63	-0.58



Note: For each treatment in each experiment, the table reviews the treatment parameters, the observed relative frequency of cooperation (in state *dd* in second halves of sessions), the expected payoff cooperating in that state $\hat{\pi}(c)$, the expected payoff of defecting in that state $\hat{\pi}(d)$, the "predicted" probability of cooperation based on the logistic regression of cooperation rates on monetary incentive $\hat{\pi}(c) - \hat{\pi}(c)$, and the absolute deviation of that prediction.

Table A.50: Incentives in state 0 (first halves of sessions)

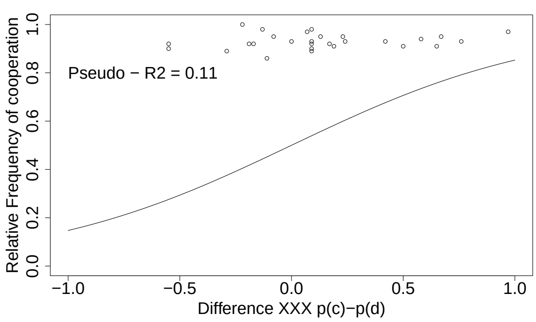
		Observation			Fit	
Treatment	Game	$\hat{\sigma}_{\emptyset}$	$\hat{\pi}(c)$	$\hat{\pi}(d)$	σ^*_0	Deviat
AF09–34	(0.9,0.33,0.11)	0.78	6.24	5.51	0.87	-0.09
BOS11–9	(0.5,2,2)	0.36	0.76	1.18	0.26	0.1
BOS11–14	(0.75,0.5,3.5)	0.11	0.78	0.99	0.37	-0.26
BOS11–15	(0.75,1,8)	0.2	0.76	1	0.35	-0.15
BOS11–16	(0.75,0.75,1.25)	0.57	1.26	1.25	0.51	0.06
BOS11–17	(0.75,0.83,0.5)	0.52	1.7	1.83	0.42	0.1
BOS11–26	(0.75,2,2)	0.29	0.96	1.14	0.39	-0.1
BOS11–27	(0.75,1,1)	0.56	1.17	1.2	0.48	0.08
BOS11–30	(0.88,0.5,3.5)	0.69	0.95	0.99	0.47	0.22
BOS11–31	(0.88,2,2)	0.64	1.18	1.14	0.53	0.11
BK12–28	(0.8,1.17,0.83)	0.54	1.43	1.44	0.49	0.05
D05–18	(0.75,1.17,0.83)	0.53	1.43	1.54	0.43	0.1
D05–19	(0.75,0.83,1.17)	0.58	1.21	1.24	0.48	0.1
DF11–6	(0.5,2.57,1.86)	0.24	0.77	1.15	0.27	-0.03
DF11–7	(0.5,0.67,0.87)	0.25	0.89	1.22	0.3	-0.05
DF11–8	(0.5,0.09,0.57)	0.48	1.41	1.43	0.49	-0.01
DF11–22	(0.75,2.57,1.86)	0.35	1.04	1.19	0.41	-0.06
DF11–23	(0.75,0.67,0.87)	0.65	1.51	1.42	0.56	0.09
DF11–24	(0.75,0.09,0.57)	0.8	2.04	1.6	0.75	0.05
DF15–4	(0.5,2.57,1.86)	0.3	0.75	1.16	0.26	0.04
DF15–5	(0.5,0.09,0.57)	0.73	1.68	1.59	0.56	0.17
DF15–20	(0.75,2.57,1.86)	0.34	1.02	1.18	0.4	-0.06
DF15–21	(0.75,0.09,0.57)	0.78	1.94	1.56	0.73	0.05
DF15–33	(0.9,2.57,1.86)	0.43	1.13	1.16	0.48	-0.05
DF15–35	(0.95,2.57,1.86)	0.56	1.24	1.21	0.52	0.04
DRFN08–10	(0.75,2,2)	0.56	1.08	1.2	0.42	0.14
DRFN08–11	(0.75,1,1)	0.67	1.34	1.35	0.49	0.18
DO09–32	(0.9,1,1)	0.66	1.35	1.32	0.52	0.14
FY17–25	(0.75,0.4,0.4)	0.84	2.43	1.87	0.81	0.03
FRD12–29	(0.88,0.33,0.33)	0.8	3.06	2.18	0.9	-0.1
KS13–12	(0.75,1,0.5)	0.72	1.99	1.81	0.61	0.11
STS13–13	(0.75,1,0.25)	0.65	3.33	3.09	0.65	0



Note: For each treatment in each experiment, the table reviews the treatment parameters, the observed relative frequency of cooperation (in state $\emptyset$ in first halves of sessions), the expected payoff cooperating in that state $\hat{\pi}(c)$, the expected payoff of defecting in that state $\hat{\pi}(d)$, the "predicted" probability of cooperation based on the logistic regression of cooperation rates on monetary incentive $\hat{\pi}(c) - \hat{\pi}(c)$, and the absolute deviation of that prediction.

Table A.51: Incentives in state *cc* (first halves of sessions)

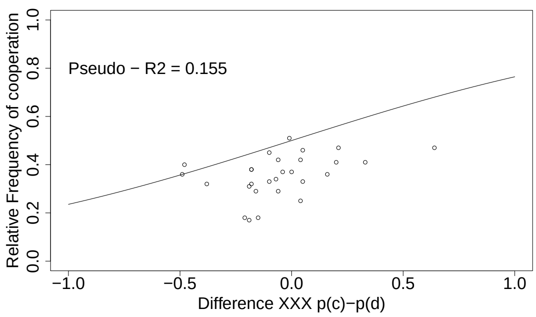
		Observation			Fit	
Treatment	Game	$\hat{\sigma}_{cc}$	$\hat{\pi}(c)$	$\hat{\pi}(d)$	σ_0^*	Deviat
AF09–34	(0.9,0.33,0.11)	0.91	6.53	5.77	0.85	0.06
BOS11–9	(0.5,2,2)	0.95	1.41	1.71	0.33	0.62
BOS11–14	(0.75,0.5,3.5)	0.99	1.09	1.07	0.51	0.48
BOS11–15	(0.75,1,8)	1	1.05	1.03	0.51	0.49
BOS11–16	(0.75,0.75,1.25)	0.95	1.55	1.39	0.59	0.36
BOS11–17	(0.75,0.83,0.5)	1	2.08	2.21	0.43	0.57
BOS11–26	(0.75,2,2)	0.98	1.33	1.39	0.47	0.51
BOS11–27	(0.75,1,1)	0.89	1.6	1.52	0.55	0.34
BOS11–30	(0.88,0.5,3.5)	1	1.2	1.03	0.6	0.4
BOS11–31	(0.88,2,2)	0.98	1.39	1.26	0.57	0.41
BK12–28	(0.8,1.17,0.83)	0.92	1.79	1.7	0.55	0.37
D05–18	(0.75,1.17,0.83)	0.86	1.74	1.8	0.47	0.39
D05–19	(0.75,0.83,1.17)	0.91	1.56	1.43	0.57	0.34
DF11–6	(0.5,2.57,1.86)	0.92	1.4	1.88	0.25	0.67
DF11–7	(0.5,0.67,0.87)	0.89	1.84	1.92	0.45	0.44
DF11–8	(0.5,0.09,0.57)	0.91	2.38	2	0.71	0.2
DF11–22	(0.75,2.57,1.86)	0.92	1.39	1.53	0.42	0.5
DF11–23	(0.75,0.67,0.87)	0.95	1.89	1.67	0.62	0.33
DF11–24	(0.75,0.09,0.57)	0.95	2.32	1.73	0.8	0.15
DF15–4	(0.5,2.57,1.86)	0.9	1.33	1.81	0.25	0.65
DF15–5	(0.5,0.09,0.57)	0.93	2.36	1.95	0.72	0.21
DF15–20	(0.75,2.57,1.86)	0.92	1.39	1.52	0.43	0.49
DF15–21	(0.75,0.09,0.57)	0.94	2.3	1.75	0.78	0.16
DF15–33	(0.9,2.57,1.86)	0.93	1.31	1.29	0.51	0.42
DF15–35	(0.95,2.57,1.86)	0.97	1.33	1.28	0.53	0.44
DRFN08–10	(0.75,2,2)	0.95	1.37	1.38	0.49	0.46
DRFN08–11	(0.75,1,1)	0.93	1.69	1.57	0.57	0.36
DO09–32	(0.9,1,1)	0.9	1.48	1.4	0.55	0.35
FY17–25	(0.75,0.4,0.4)	0.93	2.78	2.06	0.84	0.09
FRD12–29	(0.88,0.33,0.33)	0.97	3.4	2.43	0.9	0.07
KS13–12	(0.75,1,0.5)	0.93	2.52	2.23	0.66	0.27
STS13–13	(0.75,1,0.25)	0.92	4.13	3.96	0.6	0.32



Note: For each treatment in each experiment, the table reviews the treatment parameters, the observed relative frequency of cooperation (in state *cc* in first halves of sessions), the expected payoff cooperating in that state $\hat{\pi}(c)$, the expected payoff of defecting in that state $\hat{\pi}(d)$, the "predicted" probability of cooperation based on the logistic regression of cooperation rates on monetary incentive $\hat{\pi}(c) - \hat{\pi}(c)$, and the absolute deviation of that prediction.

Table A.52: Incentives in state cd,dc (first halves of sessions)

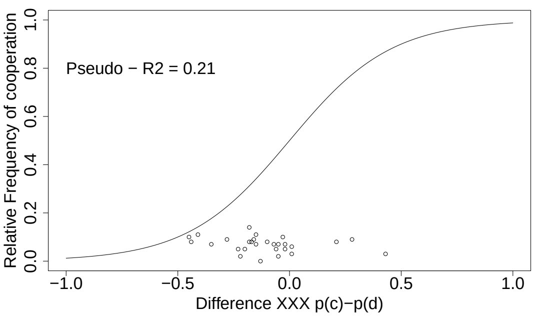
Treatment	Game	Observation			Fit	
		$\hat{\sigma}_{cd,dc}$	$\hat{\pi}(c)$	$\hat{\pi}(d)$	σ_0^*	Deviat
AF09–34	(0.9,0.33,0.11)	0.41	5.62	4.94	0.69	-0.28
BOS11–9	(0.5,2,2)	0.2	0.73	1.15	0.38	-0.18
BOS11–14	(0.75,0.5,3.5)	0.12	0.8	1	0.44	-0.32
BOS11–15	(0.75,1,8)	0.22	0.79	1	0.44	-0.22
BOS11–16	(0.75,0.75,1.25)	0.18	0.99	1.12	0.46	-0.28
BOS11–17	(0.75,0.83,0.5)	0.38	1.63	1.76	0.46	-0.08
BOS11–26	(0.75,2,2)	0.17	0.91	1.1	0.44	-0.27
BOS11–27	(0.75,1,1)	0.45	1.27	1.28	0.5	-0.05
BOS11–30	(0.88,0.5,3.5)	0	0.88	0.98	0.47	-0.47
BOS11–31	(0.88,2,2)	0.51	1.18	1.14	0.51	0
BK12–28	(0.8,1.17,0.83)	0.29	1.27	1.32	0.49	-0.2
D05–18	(0.75,1.17,0.83)	0.29	1.26	1.4	0.46	-0.17
D05–19	(0.75,0.83,1.17)	0.34	1.13	1.19	0.48	-0.14
DF11–6	(0.5,2.57,1.86)	0.4	0.97	1.38	0.38	0.02
DF11–7	(0.5,0.67,0.87)	0.32	1.07	1.36	0.42	-0.1
DF11–8	(0.5,0.09,0.57)	0.42	1.5	1.49	0.5	-0.08
DF11–22	(0.75,2.57,1.86)	0.38	1.11	1.25	0.46	-0.08
DF11–23	(0.75,0.67,0.87)	0.46	1.41	1.35	0.52	-0.06
DF11–24	(0.75,0.09,0.57)	0.36	1.49	1.35	0.54	-0.18
DF15–4	(0.5,2.57,1.86)	0.36	0.89	1.32	0.38	-0.02
DF15–5	(0.5,0.09,0.57)	0.31	1.15	1.32	0.45	-0.14
DF15–20	(0.75,2.57,1.86)	0.32	1.06	1.21	0.46	-0.14
DF15–21	(0.75,0.09,0.57)	0.47	1.65	1.42	0.57	-0.1
DF15–33	(0.9,2.57,1.86)	0.37	1.14	1.16	0.49	-0.12
DF15–35	(0.95,2.57,1.86)	0.42	1.2	1.19	0.5	-0.08
DRFN08–10	(0.75,2,2)	0.18	0.89	1.09	0.44	-0.26
DRFN08–11	(0.75,1,1)	0.33	1.16	1.23	0.48	-0.15
DO09–32	(0.9,1,1)	0.37	1.27	1.27	0.5	-0.13
FY17–25	(0.75,0.4,0.4)	0.25	1.51	1.39	0.53	-0.28
FRD12–29	(0.88,0.33,0.33)	0.47	2.6	1.85	0.71	-0.24
KS13–12	(0.75,1,0.5)	0.33	1.64	1.54	0.53	-0.2
STS13–13	(0.75,1,0.25)	0.41	2.93	2.64	0.58	-0.17



Note: For each treatment in each experiment, the table reviews the treatment parameters, the observed relative frequency of cooperation (in state cd,dc in first halves of sessions), the expected payoff cooperating in that state $\hat{\pi}(c)$, the expected payoff of defecting in that state $\hat{\pi}(d)$, the "predicted" probability of cooperation based on the logistic regression of cooperation rates on monetary incentive $\hat{\pi}(c) - \hat{\pi}(c)$, and the absolute deviation of that prediction.

Table A.53: Incentives in state *dd* (first halves of sessions)

		Observation			Fit	
Treatment	Game	$\hat{\sigma}_{dd}$	$\hat{\pi}(c)$	$\hat{\pi}(d)$	σ_0^*	Deviat
AF09–34	(0.9,0.33,0.11)	0.09	5	4.39	0.87	-0.78
BOS11–9	(0.5,2,2)	0.05	0.58	1.03	0.2	-0.15
BOS11–14	(0.75,0.5,3.5)	0.01	0.74	0.99	0.32	-0.31
BOS11–15	(0.75,1,8)	0	0.75	1	0.32	-0.32
BOS11–16	(0.75,0.75,1.25)	0.05	0.87	1.06	0.36	-0.31
BOS11–17	(0.75,0.83,0.5)	0	1.46	1.59	0.4	-0.4
BOS11–26	(0.75,2,2)	0.02	0.83	1.04	0.34	-0.32
BOS11–27	(0.75,1,1)	0.11	0.98	1.07	0.43	-0.32
BOS11–30	(0.88,0.5,3.5)	0	0.87	0.98	0.42	-0.42
BOS11–31	(0.88,2,2)	0.02	1.02	1.04	0.48	-0.46
BK12–28	(0.8,1.17,0.83)	0.08	1.11	1.21	0.42	-0.34
D05–18	(0.75,1.17,0.83)	0.14	1.13	1.29	0.38	-0.24
D05–19	(0.75,0.83,1.17)	0.09	0.92	1.07	0.39	-0.3
DF11–6	(0.5,2.57,1.86)	0.08	0.69	1.06	0.24	-0.16
DF11–7	(0.5,0.67,0.87)	0.11	0.75	1.12	0.24	-0.13
DF11–8	(0.5,0.09,0.57)	0.09	0.85	1.11	0.31	-0.22
DF11–22	(0.75,2.57,1.86)	0.08	0.94	1.09	0.39	-0.31
DF11–23	(0.75,0.67,0.87)	0.05	1.08	1.14	0.45	-0.4
DF11–24	(0.75,0.09,0.57)	0.05	1.16	1.2	0.47	-0.42
DF15–4	(0.5,2.57,1.86)	0.1	0.67	1.07	0.22	-0.12
DF15–5	(0.5,0.09,0.57)	0.07	0.8	1.14	0.26	-0.19
DF15–20	(0.75,2.57,1.86)	0.08	0.91	1.08	0.37	-0.29
DF15–21	(0.75,0.09,0.57)	0.06	1.21	1.19	0.52	-0.46
DF15–33	(0.9,2.57,1.86)	0.07	1.06	1.1	0.47	-0.4
DF15–35	(0.95,2.57,1.86)	0.03	1.15	1.16	0.49	-0.46
DRFN08–10	(0.75,2,2)	0.05	0.82	1.04	0.34	-0.29
DRFN08–11	(0.75,1,1)	0.07	0.97	1.11	0.39	-0.32
DO09–32	(0.9,1,1)	0.1	1.18	1.21	0.48	-0.38
FY17–25	(0.75,0.4,0.4)	0.07	1.16	1.21	0.46	-0.39
FRD12–29	(0.88,0.33,0.33)	0.03	1.92	1.37	0.85	-0.82
KS13–12	(0.75,1,0.5)	0.07	1.24	1.22	0.52	-0.45
STS13–13	(0.75,1,0.25)	0.08	2.23	1.88	0.75	-0.67



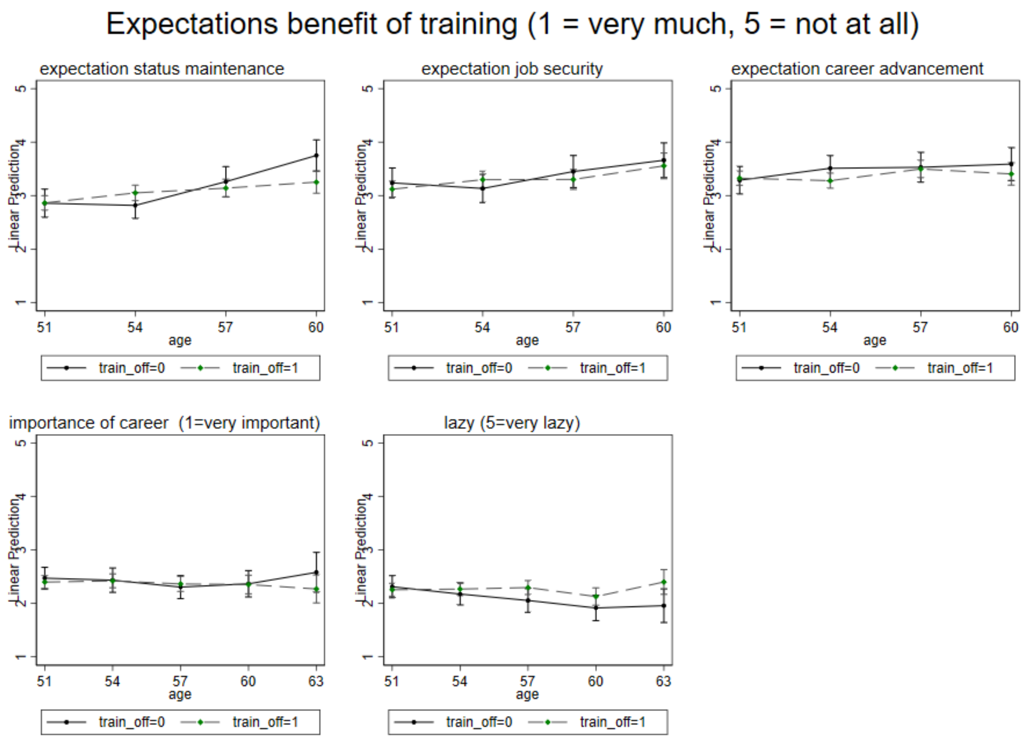
Note: For each treatment in each experiment, the table reviews the treatment parameters, the observed relative frequency of cooperation (in state *dd* in first halves of sessions), the expected payoff cooperating in that state $\hat{\pi}(c)$, the expected payoff of defecting in that state $\hat{\pi}(d)$, the "predicted" probability of cooperation based on the logistic regression of cooperation rates on monetary incentive $\hat{\pi}(c) - \hat{\pi}(c)$, and the absolute deviation of that prediction.

Appendix B

Appendix to Chapter 2

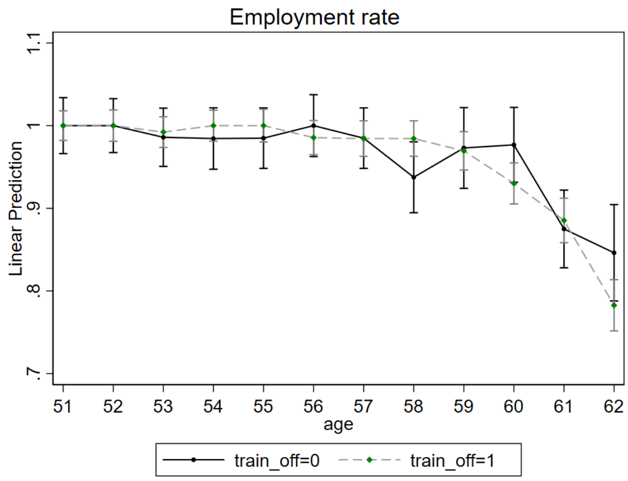
B.1 Descriptives

Figure B.1: Expectations and ambitions by training offers



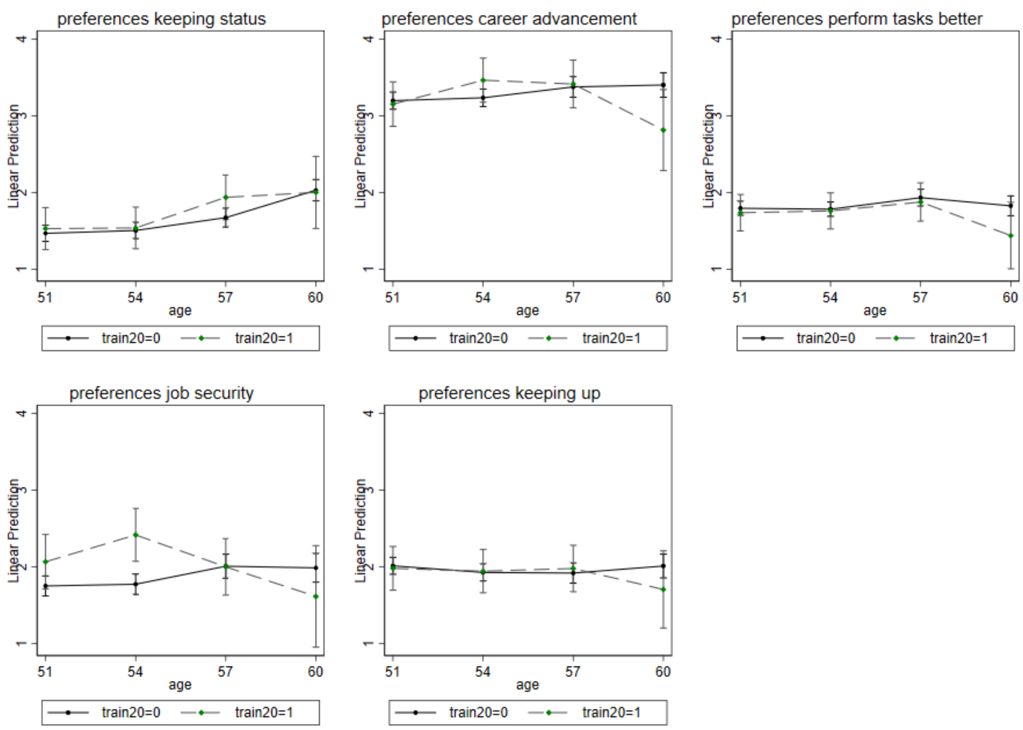
Notes: Male less educated employees only. Top row expectations; bottom row ambitions. *Source:* NEPS; own calculations based on estimation sample.

Figure B.2: Employment by training offers



Source: NEPS; own calculations bases on estimation sample. Male employees, less-educated only.

Figure B.3: Career ambitions by training participation



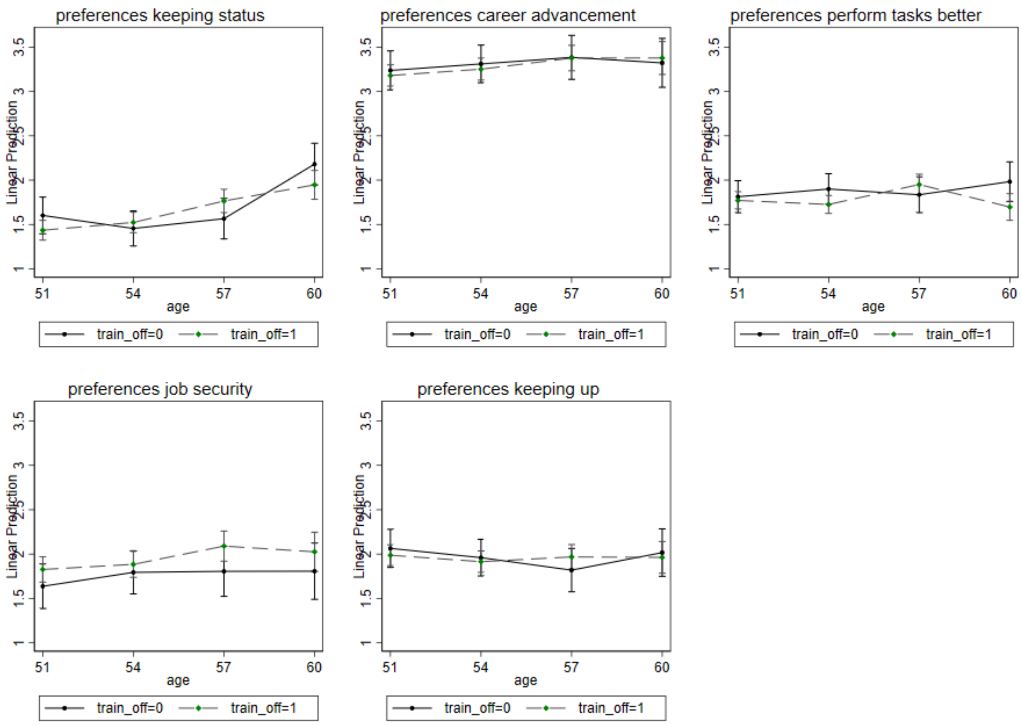
Notes: Scale ranges from 1 ="very important" to 5 ="very unimportant". Less-educated male employees only. Training participation defined as having participated at least in 20hrs of training. Age is grouped into three year intervals, i.e. the data point at age 51 refers to ages 50-52. *Source:* NEPS, subsample; own calculations.

Table B.1: Individual characteristics by training offers

Variable	**No training offer**	**Training offer**
Ambitions		
Importance of status maintenance	1.994	1.971
	(1.303)	(1.292)
Importance career advancement	3.528	3.331
	(1.122)	(1.105)
Importance perform tasks better	1.977	1.891
	(1.018)	(0.883)
Importance job security	2.038	2.087
	(1.312)	(1.341)
Importance of keeping up	2.109	2.038
with colleges	(1.177)	(1.065)
Attitudes		
Lazy	2.132	2.248
	(1.072)	(1.131)
Importance of career	2.593	2.583
	(1.091)	(1.105)
Wages		
Gross wage	2990.9	3797.9
	(1235.7)	(1502.8)
Net wage	2034.4	2529.3
	(1035.7)	(949.1)

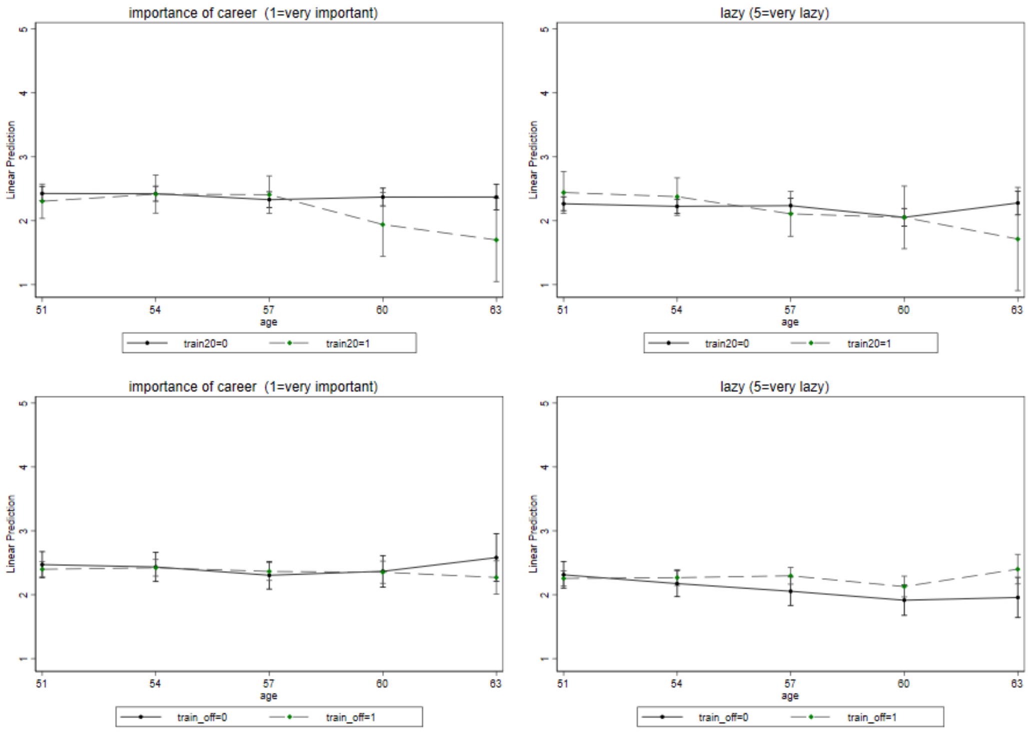
Notes: Mean values, standard deviations in parentheses. Ambitions: 1 = very important, 5= very unimportant. Lazyness: 1= not lazy at all, 5 very lazy. For a brake down by age see Figures B.4 and B.5 *Source*: NEPS data, less-educated male employees in full-time employment only.

Figure B.4: Career Ambitions by training offers (TO)



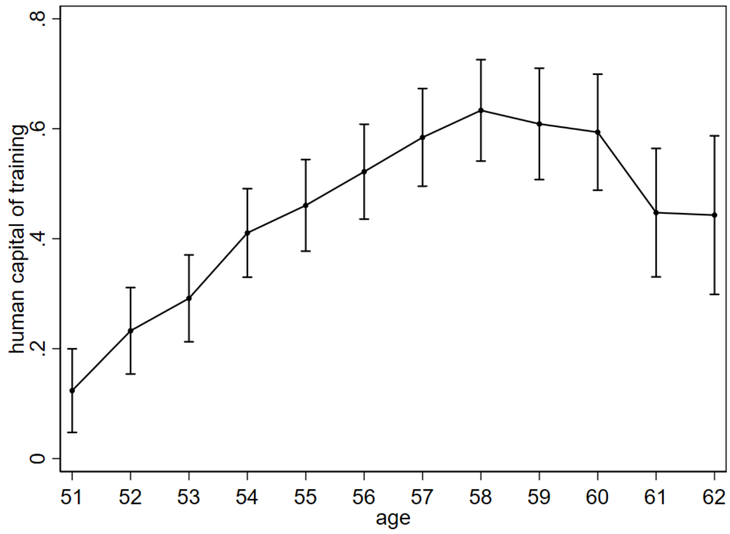
Notes: Scale ranges from 1 ="very important" to 5 ="very unimportant". Less educated male employees only. *Source:* NEPS, subsample; own calculations.

Figure B.5: Ambitions by training offers and training participation



Source: NEPS; own calculations bases on estimation sample. Male less-educated employees only. Top row training participation; bottom row training offers.

Figure B.6: Pre-choice human capital of training by age



Notes: Human capital of training as defined in section 2.3.3. *Source:* NEPS; own calculations base.

B.2 Estimation

I use a multinomial-logit model to approximate the choices. First, the dynamic programming problem is solved using backward induction. I use linear interpolation for expected value functions of periods that are more than two periods ahead from the decision period. Interpolation is used for the state variables of wages and human capital of training only.[1]

The log-likelihood function is defined as follows:

$$L = \sum_{i=1}^{N} log\big[\prod_{t=t0}^{\bar{t}} P(d_{it}|\theta, s_{it}) f(w_{it}^{obs}|\theta, s_{it})\big] \tag{B.1}$$

with parameter vector θ and state-variables $s_{it} = \{train_{it}, TO_{it}, wage_{it}, JS_{it}\}$

Individual likelihood contributions for parameters θ and state variables s_{it}:

$$Pr(d = \ell t|s_{it}, \theta) = P(D_{it} = \{u, \ell, \ell t\}|s_{it}, \theta) \frac{exp(\bar{V}_{\ell t}(s_{it}, \theta))}{\sum_{c \in \{\ell t, \ell, u\}} exp(\bar{V}_c(s_{it}, \theta))} f(wage^{obs}|s_{it}, \theta)$$

$$\begin{aligned} &Pr(d = \ell|s_{it}, \theta) = \\ &\big[Pr(D_{it} = \{u, \ell, \ell t\}|s_{it}, \theta) \frac{exp(\bar{V}_{\ell}(s_{it}, \theta))}{\sum_{c \in \{\ell t, \ell, u\}} exp(\bar{V}_c(s_{it}, \theta))} \\ &+ Pr(D_{it} = \{u, \ell\}|s_{it}, \theta) \frac{exp(\bar{V}_{\ell}(s_{it,\theta}))}{\sum_{c \in \{\ell, u\}} exp(\bar{V}_c(s_{it}, \theta))}\big] f(wage^{obs}|s_{it}, \theta) \end{aligned}$$

$$\begin{aligned} &Pr(d = u|s_{it}, \theta) = \\ &Pr(D_{it} = \{u, \ell, \ell t\}|s_{it}, \theta) \frac{exp(\bar{V}_u(s_{it}, \theta))}{\sum_{c \in \{\ell t, \ell, u\}} exp(\bar{V}_c(s_{it}, \theta))} \\ &+ Pr(D_{it} = \{u, \ell\}|s_{it}, \theta) \frac{exp(\bar{V}_u(s_{it}, \theta))}{\sum_{c \in \{\ell, u\}} exp(\bar{V}_c(s_{it}, \theta))} + Pr(D_{it} = \{u\}|s_{it}, \theta) \end{aligned}$$

where $\bar{V}()$ is the systematic component of the value function without the preference shock. I estimate the parameters of the model with the maximum-likelihood method using nonlinear minimization with a Newton-type method in R (nlm). Several starting values were tested to ensure the parameters represent the global optimum. The standard errors at the optimum are derived using the information matrix equality (BHHH method) with numerical gradient (see Henningsen and Toomet, 2011).

[1] The grid for net-monthly wages is $\{1500, 2000, 2500, 3000, 3500, 4200, 5000, 10000\}$, for training $\{0, 0.8, 1, 1.8, 3\}$.

Appendix C

Appendix to Chapter 3

C.1 Supplementary tables for section 3.5

Table C.1: Shares of employees with gross hourly wages $>$ 8.50€ per hour among employees with gross hourly wages $<$ 8.50€ per hour in 2012

Year	Share with wage > 8.50€ per hour	CI	Observations
2012	0.000	[0.000,0.000]	551
2013	0.424	[0.357,0.491]	551
2014	0.544	[0.478,0.609]	551

Only employees eligible for the minimum wage and employed in all years 2012-2014. *Source:* SOEP, waves 2012-2014; own calculations.

Table C.2: Share of job changers by deciles of the gross hourly wage distribution, years 2011-2014 pooled

Decile	Share of job changes	CI	Observations
1	0.39	[0.36,0.41]	5,052
2	0.33	[0.31,0.35]	5,047
3	0.27	[0.25,0.29]	5,090
4	0.23	[0.21,0.25]	5,013
5	0.19	[0.17,0.20]	5,114
6	0.14	[0.13,0.16]	4,976
7	0.12	[0.11,0.14]	5,065
8	0.11	[0.10,0.13]	5,032
9	0.09	[0.08,0.10]	5,045
10	0.11	[0.09,0.12]	5,046

Source: SOEP, waves 2011-2014; own calculations.

Descriptive evidence over time on the employment levels and sectors of affected employees shows that employment conditions of low-wage employees were hardly affected by the reform (Table C.3). Most employees belonging to the bottom 11% of the hourly wage distribution in a respective year are full-time employed. The full-time share does not change significantly over time. The share of part-time employment increases in post-reform years. In 2016 the part-time share is significantly above pre-reform years. The proportion of marginal employment decreases, albeit not significantly. These findings are consistent with previous evidence pointing towards some transformation of marginal jobs into part-time employment (Garloff, 2019; Schmitz, 2019; Bonin et al., 2019; Bachmann et al., 2017; vom Berge and Weber, 2017).

Table C.3: Eligible individuals in the bottom 11% of the hourly wage distribution

	2012	**2013**	**2014**	**2015**	**2016**
Employment categories in %					
- full time	53.99	54.85	49.36	56.19	50.81
- part time	18.43	18.58	17.61	20.47	24.47
- marginal	25.25	24.48	29.84	20.89	22.89
Contractual working hours per week					
- mean	29.67	29.86	28.40	29.93	28.26
- median	31.54	32.46	29.54	32.54	30.46
Sectors (in %)					
Agriculture	0.47	0.38	0.54	0.42	0.43
Energy	0.35	0.46	0.30	0.19	0.06
Manufacturing	14.62	14.67	11.18	12.81	12.81
Construction	6.58	7.48	4.37	5.87	7.44
Trade	26.75	31.90	29.91	30.64	28.53
Transport	5.20	4.92	4.58	4.62	4.49
Bank, Insurance	1.06	1.17	0.87	0.95	0.53
Services	38.88	38.52	38.98	41.30	35.44
Observations	1348	1534	1289	1482	1244

Notes: Affected individuals: bottom 11% of the hourly wage distribution – reference: share of individuals who earned less than 8.50€ per hour in 2013.
Individual frequency weights used. Bootstrapped confidence intervals based on 500 replications.
For confidence intervals see tables C.4 and C.5, Appendix.
Source: SOEP, waves 2012-2016; own calculations.

There is some fluctuation in mean and median working hours before and after the minimum wage reform. Yet, this variation is not statistically significant. Large shares of low-wage employees work in the trade, service, and manufacturing sectors: About 40% work in the service sector, about 30% in the trade sector, and around 13% in the manufacturing sector. Sectoral shares also fluctuate, however they do not change significantly over time. Selection through a reduction of, or compositional changes working hours is not a problem under the statutory level of 8.50€ per hour. However, ruling out negative employment effects by assumption in the counterfactual scenarios with full compliance, especially with a markedly higher minimum wage level of 12€ per hour, would be too restrictive. Redistributive effects can thus only be interpreted as upper bounds in those counterfactual scenarios.

Table C.4: Confidence intervals for Table C.3 – employment & working hours

Year	Employment categories						Weekly working hours			
	full-time		part-time		marginal		mean		median	
		CI		CI		CI		CI		CI
2012	54.0	[49.4;57.5]	18.4	[15.2;21.9]	25.2	[22.1;28.8]	29.7	[28.7;30.7]	31.5	[29.5;35.0]
2013	54.9	[50.6;58.7]	18.6	[15.9;21.4]	24.5	[21.1;28.6]	29.9	[28.9;30.8]	32.5	[29.6;35.0]
2014	49.4	[44.6;54.4]	17.6	[14.6;21.2]	29.8	[25.3;33.6]	28.4	[27.3;29.8]	29.5	[29.5;30.0]
2015	56.2	[52.2;60.1]	20.5	[17.4;23.8]	20.9	[17.8;24.3]	29.9	[28.8;31.0]	32.5	[29.5;34.5]
2016	50.8	[46.2;55.6]	24.7	[21.0;29.0]	22.9	[18.5;27.0]	28.3	[27.1;29.4]	30.5	[29.5;33.5]

Source: SOEP, waves 2011-2016; own calculations.

Table C.5: Confidence intervals for Table C.3 – sectors

Year	Agriculture		Energy		Manufacturing		Construction	
		CI		CI		CI		CI
2012	0.5	[0.2;0.9]	0.4	[0.1;0.8]	14.6	[11.6;17.3]	6.6	[4.9;8.4]
2013	0.4	[0.1;0.8]	0.5	[0.1;1.1]	14.7	[12.0;17.5]	7.5	[5.3;9.8]
2014	0.5	[0.2;1.1]	0.3	[0.0;0.7]	11.2	[8.9;13.7]	4.4	[2.8;6.2]
2015	0.4	[0.1;0.8]	0.2	[0.0;0.5]	12.8	[10.6;15.7]	5.9	[4.2;7.7]
2016	0.4	[0.0;0.9]	0.1	[0.0;0.2]	12.8	[10.1;15.6]	7.4	[4.7;10.4]
Year	Trade		Transport		Bank / Ins.		Services	
		CI		CI		CI		CI
2012	26.7	[23.4;30.5]	5.2	[3.7;7.1]	1.1	[0.4;1.9]	38.9	[35.0;43.6]
2013	31.9	[28.3;35.9]	4.9	[3.6;6.6]	1.2	[0.2;2.5]	38.5	[33.9;42.7]
2014	29.9	[25.8;33.9]	4.6	[2.8;7.0]	0.9	[0.3;1.7]	39.0	[34.6;43.0]
2015	30.6	[26.9;34.2]	4.6	[3.5;5.9]	0.9	[0.1;2.4]	41.3	[37.2;45.6]
2016	28.5	[24.0;32.5]	4.5	[3.1;5.8]	0.5	[0.1;1.0]	35.4	[31.6;40.3]

Source: SOEP, waves 2011-2016; own calculations.

C.2 Supplementary tables for the wage analysis in subsection 3.6.1

This part of the Appendix provides supplementary tables for the wage analysis of subsection 3.6.1. It contains tables on distributional moments or measures and on the differences of these statistics between years or scenarios. All tables contain results based on observed data and five different counterfactual scenarios:

- Scenario A is a full compliance scenario for the statutory minimum wage level of 8.50€ per hour. All wages of eligible employees below 8.50€ are set to 8.50€. All other variables are kept unchanged.

- Scenario B is a full compliance scenario for a markedly higher minimum wage level of 12€ per hour. All wages of eligible employees below 12€ are set to 12€. All other variables are kept unchanged.

Table C.6: Quantiles of the hourly gross wage distribution (in € per hour), eligible employees, 2012-2016

Year			**Percentiles**				**Median**	
	P1		P5		P10			
		CI		CI		CI		CI
2012	4.66	[4.19;4.72]	7.11	[6.98;7.34]	8.45	[8.26;8.61]	15.17	[14.97;15.53]
2013	4.72	[4.25;4.95]	7.08	[6.99;7.26]	8.43	[8.17;8.64]	15.15	[14.95;15.36]
2014	4.72	[4.47;4.81]	7.13	[6.99;7.24]	8.51	[8.21;8.65]	15.69	[15.35;15.88]
2015	4.72	[4.22;5.31]	7.72	[7.49;7.99]	9.01	[8.80;9.20]	16.33	[16.09;16.61]
2016	5.31	[4.99;5.88]	8.12	[7.90;8.29]	9.11	[8.99;9.32]	16.32	[15.96;16.74]
***Scenario A**: Full compliance scenario, minimum wage level: 8.50€ per hour*								
2015	8.50	[8.50;8.50]	8.50	[8.50;8.50]	9.01	[8.80;9.20]	16.33	[16.09;16.64]
2016	8.50	[8.50;8.50]	8.50	[8.50;8.50]	9.11	[8.99;9.32]	16.32	[15.97;16.64]
***Scenario B**: Full compliance scenario, minimum wage level: 12€ per hour*								
2015	12.00	[12.00;12.00]	12.00	[12.00;12.00]	12.00	[12.00;12.00]	16.33	[16.03;16.66]
2016	12.00	[12.00;12.00]	12.00	[12.00;12.00]	12.00	[12.00;12.00]	16.32	[15.96;16.66]

Notes: Individual frequency weights used. Bootstrapped confidence intervals based on 500 replications. In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. For significance of differences see Table C.7. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.7: Differences in quantiles of the hourly gross wage distribution (in € per hour), eligible employees, 2012-2016

Year			**Percentiles**				**Median**		
	P1		P5		P10				N
		CI		CI		CI		CI	
2013-2012	0.05	[0.00;0.53]	-0.03	[-0.26;0.10]	-0.02	[-0.17;0.17]	-0.02	[-0.38;0.18]	13,992
2014-2013	0.00	[-0.24;0.47]	0.05	[-0.13;0.14]	0.08	[-0.13;0.34]	0.53	[0.33;0.74]	12,373
2015-2014	0.00	[-0.10;0.24]	0.59	[0.48;0.73]	0.50	[0.36;0.80]	0.64	[0.45;0.98]	12,144
2016-2014	0.59	[0.49;0.83]	0.99	[0.88;1.13]	0.60	[0.46;0.91]	0.63	[0.44;0.97]	10,732
***Scenario A**: Full compliance scenario, minimum wage level: 8.50€ per hour*									
2015-2014	3.78	[3.69;4.03]	1.37	[1.26;1.51]	0.50	[0.36;0.80]	0.64	[0.45;0.98]	12,144
2016-2014	3.78	[3.69;4.03]	1.37	[1.26;1.51]	0.60	[0.46;0.91]	0.63	[0.44;0.97]	10,732
***Scenario B**: Full compliance scenario, minimum wage level: 12€ per hour*									
2015-2014	7.28	[7.19;7.53]	4.87	[4.76;5.01]	3.49	[3.35;3.79]	0.64	[0.45;0.98]	12,144
2016-2014	7.28	[7.19;7.53]	4.87	[4.76;5.01]	3.49	[3.35;3.79]	0.63	[0.44;0.97]	10,732

Notes: This table contains differences and confidence intervals of these differences for the values in Table C.6. All values of the counterfactual scenarios are compared to the observed 2014 values. Bootstrapped confidence intervals based on 500 replications. In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.8: Inequality and poverty measures for the hourly gross wage distribution, eligible employees, 2012-2016

Year	**Inequality**				**Poverty measures**				
	Atkinson		Poverty rate		Poverty gap		FGT(2)		Poverty
		CI		CI		CI		CI	line
2012	0.20	[0.19;0.21]	13.10	[12.20;14.38]	2.73	[2.52;3.02]	0.94	[0.84;1.08]	9.10
2013	0.20	[0.19;0.21]	13.15	[12.25;14.14]	2.70	[2.46;2.97]	0.90	[0.79;1.02]	9.09
2014	0.21	[0.20;0.22]	15.39	[13.55;16.36]	3.04	[2.75;3.29]	1.02	[0.89;1.13]	9.41
2015	0.20	[0.19;0.21]	13.62	[12.66;15.04]	2.70	[2.43;3.00]	0.89	[0.76;1.03]	9.80
2016	0.19	[0.18;0.21]	14.21	[12.63;15.39]	2.36	[2.09;2.68]	0.72	[0.61;0.86]	9.79
***Scenario A** Full compliance scenario, minimum wage level: 8.50€ per hour*									
2015	0.17	[0.16;0.18]	13.62	[12.79;15.08]	1.41	[1.24;1.65]	0.17	[0.13;0.22]	9.80
2016	0.17	[0.16;0.18]	14.21	[12.72;15.41]	1.35	[1.13;1.60]	0.16	[0.12;0.21]	9.79
***Scenario B** Full compliance scenario, minimum wage level: 12€ per hour*									
2015	0.13	[0.12;0.14]	0.00	[0.00;0.00]	0.00	[0.00;0.00]	0.00	[0.00;0.00]	9.80
2016	0.13	[0.12;0.14]	0.00	[0.00;0.00]	0.00	[0.00;0.00]	0.00	[0.00;0.00]	9.79

Notes: Individual frequency weights used. Bootstrapped confidence intervals based on 500 replications. For inequality and poverty measures see definition in sub-section 3.5.5.
In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. For significance of differences see Table C.9.
Source: SOEP, waves 2012-2016; own calculations.

Table C.9: Differences in inequality & poverty measures for the hourly gross wage distribution, eligible employees, 2012-2016

Year	**Inequality**		**Poverty measures**					
	Atkinson		Poverty rate		Poverty gap		FGT(2)	
		CI		CI		CI		CI
2013-2012	0.00	[-0.02;0.02]	0.05	[-1.61;1.32]	-0.03	[-0.44;0.29]	-0.04	[-0.23;0.11]
2014-2013	0.01	[-0.01;0.02]	2.23	[0.25;3.50]	0.34	[-0.05;0.69]	0.12	[-0.06;0.28]
2015-2014	-0.01	[-0.03;0.01]	-1.77	[-3.11;0.63]	-0.34	[-0.75;0.10]	-0.12	[-0.31;0.09]
2016-2014	-0.02	[-0.03;0.00]	-1.18	[-2.92;1.09]	-0.68	[-1.05;-0.25]	-0.30	[-0.47;-0.11]
Scenario A *Full compliance scenario, minimum wage level: 8.50€ per hour*								
2015-2014	-0.04	[-0.05;-0.02]	-1.77	[-2.97;0.54]	-1.63	[-1.89;-1.25]	-0.85	[-0.97;-0.71]
2016-2014	-0.04	[-0.06;-0.02]	-1.18	[-3.06;0.91]	-1.68	[-2.03;-1.30]	-0.86	[-0.98;-0.72]
Scenario B *Full compliance scenario, minimum wage level: 12€ per hour*								
2015-2014	-0.08	[-0.10;-0.07]	-15.39	[-16.36;-13.55]	-3.04	[-3.29;-2.75]	-1.02	[-1.13;-0.89]
2016-2014	-0.08	[-0.10;-0.07]	-15.39	[-16.36;-13.55]	-3.04	[-3.29;-2.75]	-1.02	[-1.13;-0.89]

Notes: This table contains differences and confidence intervals of these differences for the values in Table C.8. All values of the counterfactual scenarios are compared to the observed 2014 values. Bootstrapped confidence intervals based on 500 replications. For inequality and poverty measures see definition in sub-section 3.5.5. For number of observations see Table C.7. In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. *Source:* SOEP, waves 2012-2016; own calculations.

C.3 Supplementary figures and tables for the income analysis in sub-section 3.6.2

This part of the Appendix provides supplementary tables for the income analysis of sub-section 3.6.2. It contains tables on distributional moments or measures and on the differences of these statistics between years or scenarios. All tables contain results based on observed data and five different counterfactual scenarios:

- Scenario A is a full compliance scenario for the statutory minimum wage level of 8.50€ per hour. All wages of eligible employees below 8.50€ are set to 8.50€. All other variables are kept unchanged.

- Scenario B is a full compliance scenario for a markedly higher minimum wage level of 12€ per hour. All wages of eligible employees below 12€ are set to 12€. All other variables are kept unchanged.

Table C.10: Quantiles & moments of the monthly disposable household equivalence income distribution (in €), working-age households, 2012-2016

Year	**P5**		**P10**		**Mean**		**Median**		**N**
		CI		CI		CI		CI	
2012	622	[593;641]	708	[692;725]	1754	[1718;1788]	1488	[1451;1524]	11,320
2013	636	[623;647]	716	[703;733]	1795	[1762;1826]	1497	[1457;1527]	12,560
2014	664	[649;671]	735	[721;751]	1848	[1813;1887]	1546	[1508;1582]	10,773
2015	657	[633;672]	748	[728;767]	1875	[1837;1916]	1575	[1526;1616]	10,566
2016	650	[627;663]	742	[724;770]	1885	[1847;1931]	1610	[1571;1653]	10,214
***Scenario A**: Full compliance scenario, minimum wage level: 8.50€ per hour*									
2015	657	[639;672]	750	[728;770]	1882	[1842;1920]	1583	[1541;1618]	10,566
2016	653	[627;665]	747	[724;771]	1890	[1855;1928]	1611	[1574;1652]	10,214
***Scenario B**: Full compliance scenario, minimum wage level: 12€ per hour*									
2015	661	[641;673]	755	[729;773]	1904	[1864;1940]	1616	[1580;1649]	10,566
2016	654	[629;670]	751	[726;779]	1909	[1865;1952]	1642	[1599;1681]	10,214

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. For significance of differences see Table C.11. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.11: Differences in quantiles & moments of the monthly disposable household equivalence income distribution (in €), working-age households, 2012-2016

Year	P5		P10		Mean		Median		N
		CI		CI		CI		CI	
2013-2012	14	[-5;43]	8	[-9;24]	41	[-5;85]	9	[-27;46]	12,560
2014-2013	28	[17;41]	19	[2;32]	53	[4;105]	49	[19;89]	10,773
2015-2014	-7	[-14;8]	13	[-3;27]	27	[-26;77]	29	[-7;67]	10,566
2016-2014	-14	[-21;5]	7	[-9;21]	37	[-12;99]	64	[20;107]	10,214
Scenario A *Full compliance scenario, minimum wage level: 8.50€ per hour*									
2015-2014	-7	[-14;8]	15	[-1;29]	34	[-22;86]	37	[1;75]	10,566
2016-2014	-11	[-18;8]	12	[-3;26]	41	[-5;96]	65	[21;108]	10,214
Scenario B *Full compliance scenario, minimum wage level: 12€ per hour*									
2015-2014	-3	[-10;12]	20	[4;34]	56	[1;106]	70	[34;108]	10,566
2016-2014	-10	[-17;9]	16	[0;30]	61	[10;115]	96	[53;140]	10,214

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.12: Inequality & poverty measures of the monthly disposable household equivalence income distribution, working-age households, 2012-2016

Year	Inequality		Poverty measures						
	Atkinson		Poverty rate		Poverty gap		FGT(2)		Poverty
		CI		CI		CI		CI	line
2012	0.30	[0.29;0.31]	20.7	[19.4;21.8]	4.9	[4.5;5.3]	1.9	[1.7;2.1]	892.6
2013	0.30	[0.29;0.31]	21.1	[19.5;22.2]	4.6	[4.2;5.0]	1.6	[1.4;1.8]	898.2
2014	0.30	[0.29;0.31]	21.1	[19.6;22.3]	4.7	[4.3;5.1]	1.7	[1.5;1.9]	927.6
2015	0.30	[0.29;0.32]	22.5	[20.7;23.7]	5.0	[4.5;5.4]	1.8	[1.6;2.0]	945.2
2016	0.30	[0.28;0.32]	22.4	[21.2;23.8]	5.3	[4.8;5.7]	1.9	[1.7;2.1]	965.7
Scenario A*: Full compliance scenario, minimum wage level: 8.50€ per hour*									
2015	0.30	[0.28;0.31]	21.8	[20.3;23.0]	4.9	[4.4;5.3]	1.7	[1.5;1.9]	950.0
2016	0.30	[0.28;0.31]	21.8	[20.6;23.4]	5.1	[4.7;5.6]	1.9	[1.6;2.1]	966.5
Scenario B*: Full compliance scenario, minimum wage level: 12€ per hour*									
2015	0.30	[0.28;0.31]	21.9	[20.8;23.0]	5.1	[4.7;5.5]	1.8	[1.6;2.0]	969.8
2016	0.29	[0.28;0.31]	22.4	[20.8;23.5]	5.3	[4.8;5.7]	1.9	[1.7;2.2]	985.5

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. For inequality and poverty measures see definition in sub-section 3.5.5. Poverty line refers to respective year (flexible poverty line). In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. For significance of differences see Table C.13. For results with a fixed poverty line see Table C.14. For number of observations see table C.10 *Source:* SOEP, waves 2012-2016; own calculations.

Table C.13: Differences in inequality & poverty measures for the monthly disposable household equivalence income distribution, working-age households, 2012-2016

Year	**Inequality**		**Poverty measures**						
	Atkinson	CI	Poverty rate	CI	Poverty gap	CI	FGT(2)	CI	Poverty line
2013-2012	-0.00	[-0.02;0.02]	0.4	[-1.6;2.0]	-0.3	[-0.9;0.3]	-0.3	[-0.6;0.0]	898.2
2014-2013	0.00	[-0.02;0.02]	-0.0	[-1.8;2.0]	0.1	[-0.5;0.7]	0.1	[-0.2;0.4]	927.6
2015-2014	0.00	[-0.02;0.02]	1.4	[-0.7;3.3]	0.3	[-0.4;0.8]	0.1	[-0.2;0.4]	945.2
2016-2014	-0.00	[-0.02;0.02]	1.3	[-0.4;3.6]	0.5	[-0.1;1.2]	0.2	[-0.1;0.5]	965.7
***Scenario A**: Full compliance scenario, minimum wage level: 8.50€ per hour*									
2015-2014	-0.00	[-0.02;0.02]	0.7	[-1.5;2.4]	0.2	[-0.4;0.7]	0.0	[-0.2;0.3]	950.0
2016-2014	-0.00	[-0.03;0.02]	0.7	[-1.0;3.1]	0.4	[-0.2;1.1]	0.2	[-0.1;0.5]	966.5
***Scenario B**: Full compliance scenario, minimum wage level: 12€ per hour*									
2015-2014	-0.00	[-0.02;0.02]	0.9	[-0.8;2.7]	0.4	[-0.2;0.9]	0.1	[-0.2;0.4]	969.8
2016-2014	-0.01	[-0.03;0.01]	1.4	[-0.8;2.9]	0.6	[-0.1;1.2]	0.3	[-0.1;0.6]	985.5

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. For inequality and poverty measures see definition in sub-section 3.5.5. Poverty line refers to respective year (flexible poverty line). In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.14: Poverty measures of the monthly disposable household equivalence income distribution, working-age households, 2012-2016 – robustness: fixed poverty line

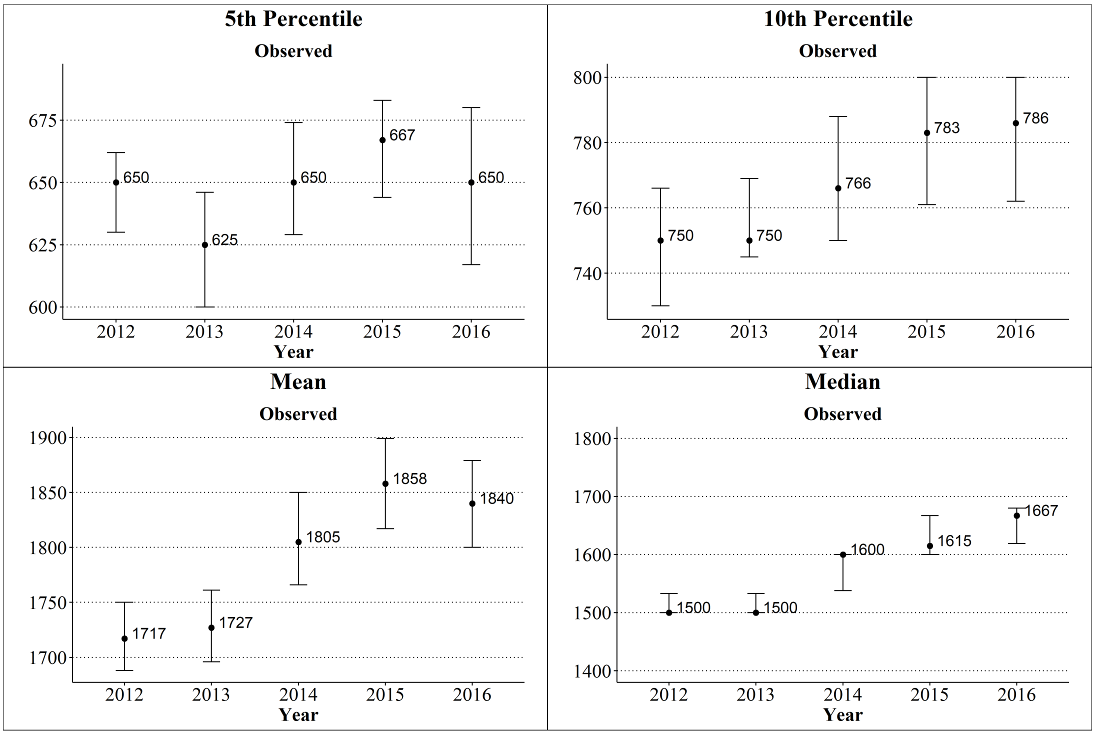
Year	**Poverty measures**						
	Poverty rate	CI	Poverty gap	CI	FGT(2)	CI	Poverty line
2012	22.87	[20.73;24.96]	5.55	[4.87;6.20]	2.13	[1.80;2.43]	927.62
2013	23.04	[21.15;25.31]	5.19	[4.66;5.83]	1.82	[1.59;2.08]	927.62
2014	21.06	[19.52;22.32]	4.72	[4.28;5.12]	1.69	[1.46;1.88]	927.62
2015	21.23	[19.07;23.52]	4.66	[4.12;5.28]	1.66	[1.43;1.92]	927.62
2016	20.37	[18.18;22.16]	4.59	[3.99;5.13]	1.66	[1.37;1.93]	927.62
***Scenario A**: Full compliance scenario, minimum wage level: 8.50€ per hour*							
2015	20.30	[17.79;22.39]	4.52	[3.95;5.08]	1.61	[1.37;1.85]	927.62
2016	19.73	[17.67;21.43]	4.48	[3.82;5.14]	1.62	[1.34;1.92]	927.62
***Scenario B**: Full compliance scenario, minimum wage level: 12€ per hour*							
2015	19.56	[17.56;21.52]	4.43	[3.89;5.00]	1.58	[1.36;1.82]	927.62
2016	19.19	[17.29;21.26]	4.38	[3.83;4.99]	1.57	[1.33;1.85]	927.62

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. For inequality and poverty measures see definition in sub-section 3.5.5. Poverty line is fixed to 2014 level. In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. *Source:* SOEP, waves 2012-2016; own calculations.

C.4 Robustness: results for observed disposable household incomes

This part of the Appendix provides additional material for robustness tests concerning the income analysis of sub-section 3.6.2. We re-analyze the distributional moments and quantiles as well as inequality and poverty measures for disposable household incomes reported directly by SOEP respondents. These results confirm the findings based on simulated disposable household incomes discussed in sub-section 3.6.2.

Figure C.1: Robustness for reported incomes: quantiles & moments of the monthly disposable household equivalence income distribution (in €), working-age households, 2012-2016



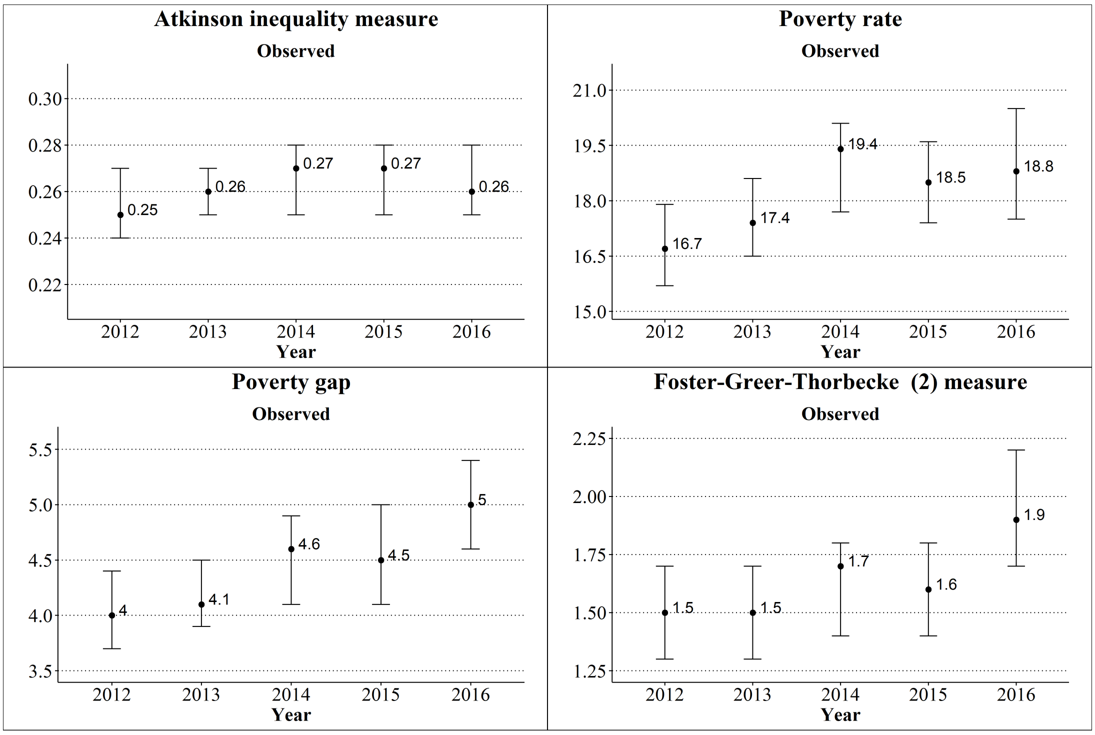
Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. For exact values of the confidence intervals see Table C.15, Appendix. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.15: Robustness for reported incomes: quantiles & moments of the monthly disposable household equivalence income distribution (in €), working-age households, 2012-2016

Year	P5	CI	P10	CI	Mean	CI	Median	CI	N
2012	650	[630;662]	750	[730;766]	1717	[1688;1750]	1500	[1500;1533]	11,305
2013	625	[600;646]	750	[745;769]	1727	[1696;1761]	1500	[1500;1533]	12,552
2014	650	[629;674]	766	[750;788]	1805	[1766;1850]	1600	[1538;1600]	10,767
2015	667	[644;683]	783	[761;800]	1858	[1817;1899]	1615	[1600;1667]	10,559
2016	650	[617;680]	786	[762;800]	1840	[1800;1879]	1667	[1619;1680]	10,201

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Disposable household incomes as reported in SOEP household questionnaires. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. *Source:* SOEP, waves 2012-2016; own calculations.

Figure C.2: Robustness for reported incomes: inequality and poverty measures for the monthly disposable household equivalence income distribution, working-age households, 2012-2016



Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. For inequality and poverty measures see definition in sub-section 3.5.5. Poverty line refers to respective year (flexible poverty line). For exact values of the confidence intervals and poverty lines see Table C.16, Appendix.
Source: SOEP, waves 2012-2016; own calculations.

Table C.16: Robustness for reported incomes: inequality & poverty measures for the monthly disposable household equivalence income distribution, working-age households, 2012-2016

Year	**Inequality**		**Poverty measures**						
	Atkinson		Poverty rate		Poverty gap		FGT(2)		Poverty
		CI		CI		CI		CI	line
2012	0.25	[0.24;0.27]	16.7	[15.7;17.9]	4.0	[3.7;4.4]	1.5	[1.3;1.7]	900.0
2013	0.26	[0.25;0.27]	17.4	[16.5;18.6]	4.1	[3.9;4.5]	1.5	[1.3;1.7]	900.0
2014	0.27	[0.25;0.28]	19.4	[17.7;20.1]	4.6	[4.1;4.9]	1.7	[1.4;1.8]	960.0
2015	0.27	[0.25,0.28]	18.5	[17.4;19.6]	4.5	[4.1;5.0]	1.6	[1.4;1.8]	969.2
2016	0.26	[0.25;0.28]	18.8	[17.5;20.5]	5.0	[4.6;5.4]	1.9	[1.7;2.2]	1000.0

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Disposable household incomes as reported in SOEP household questionnaires. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. For inequality and poverty measures see definition in sub-section 3.5.5. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.17: Means of household gross wages by deciles of the disposable household income distribution

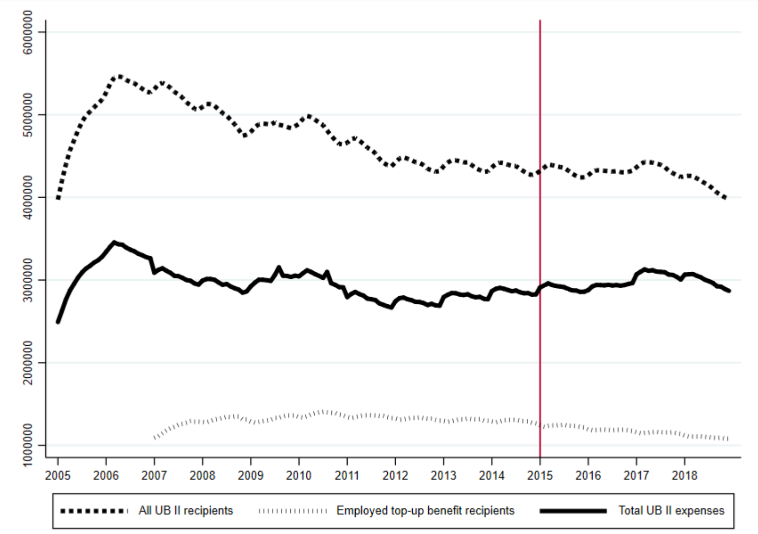
Decile	**Household gross wages**				
	2012	2013	2014	2015	2016
1	231	158	154	208	222
2	442	379	441	413	406
3	1229	1111	1224	1120	1184
4	1841	1776	1945	1861	1970
5	2291	2223	2254	2393	2598
6	2915	2782	2954	2993	3125
7	3386	3476	3618	3692	3702
8	3950	4147	4084	4324	4459
9	4728	4680	5095	5179	5212
10	5465	5476	5540	5766	6110

Notes: Table shows means of aggregated household gross wages deciles of the disposable household income distribution. Equivalence weights according to the new OECD scale. Household frequency weights used. *Source:* SOEP, waves 2012-2016; own calculations.

C.5 Supplementary figures and tables for the analysis of mechanisms in sub-section 3.6.3

This part of the Appendix provides supplementary material for the analysis of mechanisms that explain the (limited) pass-through from gross hourly wages to disposable household incomes in sub-section 3.6.3.

Figure C.3: Welfare recipients, top-up benefits, and unemployment assistance benefits, 2005-2018



Notes: The vertical line depicts the minimum wage introduction in 2015; total ALG II benefits in 1000€. *Source:* Federal employment agency, monthly data 2005-2018; own calculations.

Table C.18: Differences in top-up benefits and welfare receipt, working-age households, 2012-2016

	Top-up benefits (only working)[1]				**Social assistance transfer (all households)**							
					Calculated eligibility[1]				**stated take-up**[3]			
Year	eligibility	CI	avg. transfer €/year[3]	CI	eligibility	CI	avg. transfer €/year[3]	CI	take-up	CI	avg. transfer €/year[3]	CI
2013-2012	0.6	[-0.6;1.8]	49.0	[-31.2;123.0]	2.0	[0.3;3.7]	199.9	[51.7;360.6]	0.6	[-0.5;1.7]	71.5	[-14.5;163.9]
2014-2013	0.0	[-1.3;1.3]	-15.5	[-94.5;67.1]	-1.2	[-3.1;0.5]	-100.1	[-272.1;50.6]	0.1	[-1.3;1.3]	31.2	[-83.4;136.1]
2015-2014	-0.5	[-1.8;0.9]	11.9	[-70.5;102.2]	0.4	[-1.5;2.4]	112.2	[-51.2;294.9]	-0.4	[-1.6;1.0]	-25.2	[-132.5;86.2]
2016-2014	-0.2	[-1.5;1.3]	-3.3	[-83.6;91.4]	1.2	[-0.7;3.5]	146.0	[-40.5;325.2]	0.5	[-0.9;2.1]	43.7	[-97.3;179.7]
***Scenario A**: Full compliance scenario, minimum wage level: 8.50€ per hour*												
2015-2014	-1.4	[-2.7;-0.2]	-66.1	[-147.5;13.2]	-0.5	[-2.3;1.4]	28.1	[-145.7;204.0]				
2016-2014	-0.7	[-2.1;0.8]	-59.7	[-147.6;15.3]	0.8	[-1.3;2.7]	83.8	[-119.9;259.6]				
***Scenario B**: Full compliance scenario, minimum wage level: 12€ per hour*												
2015-2014	-2.6	[-3.9;-1.3]	-144.4	[-219.9;-61.7]	-1.8	[-3.7;0.2]	-69.1	[-227.9;119.4]				
2016-2014	-1.8	[-3.2;-0.6]	-137.4	[-217.5;-72.5]	-0.6	[-2.7;1.4]	-8.4	[-206.0;177.9]				

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications.

[1] The number of households eligible and average transfer as calculated in our model. We exclude minor transfer eligibility of less than 120€ per year.

[2] The number of households eligible and average transfer as stated in the survey (SOEP).

[3] Average transfer per year is an average over the entire sample, i.e. reflecting both, the number of households eligible and the amount that eligible households receive.

Table C.19: Share of affected by deciles of the disposable household equivalence income distribution, working-age households, 2012-2016

Decile	**Share in %**									
	2012	CI	2013	CI	2014	CI	2015	CI	2016	CI
1	2.4	[1.3;3.4]	2.6	[1.5;3.6]	2.7	[1.5;3.8]	2.5	[1.4;3.6]	2.0	[1.1;3.0]
2	9.0	[7.3;10.6]	8.3	[6.7;9.8]	7.4	[5.8;9.0]	8.3	[6.6;10.1]	8.0	[6.6;9.3]
3	20.1	[18.2;22.1]	18.9	[17.0;20.7]	19.4	[17.4;21.5]	19.2	[17.2;21.2]	19.2	[17.2;21.2]
4	15.2	[13.3;17.0]	15.3	[13.6;17.1]	18.6	[16.5;20.7]	17.2	[15.2;19.3]	19.3	[17.0;21.6]
5	13.1	[11.3;15.0]	13.4	[11.6;15.2]	12.9	[11.0;14.8]	13.7	[11.7;15.6]	12.1	[10.1;14.1]
6	9.8	[8.0;11.5]	10.6	[8.9;12.3]	10.5	[8.7;12.4]	9.3	[7.5;11.0]	12.8	[10.7;15.0]
7	10.8	[8.9;12.8]	5.7	[4.3;7.0]	5.8	[4.4;7.2]	8.3	[6.6;10.0]	7.0	[5.3;8.8]
8	4.5	[3.2;5.8]	5.1	[3.7;6.4]	5.3	[3.9;6.8]	5.2	[3.8;6.7]	8.9	[6.9;10.9]
9	3.5	[2.3;4.7]	2.8	[1.8;3.8]	3.6	[2.5;4.8]	4.0	[2.8;5.3]	2.6	[1.5;3.8]
10	1.7	[0.9;2.5]	1.9	[1.1;2.7]	3.2	[2.0;4.3]	2.0	[1.1;3.0]	2.7	[1.6;3.9]
Total	9.0	[8.5;9.5]	8.4	[8.0;8.9]	8.9	[8.4;9.5]	9.0	[8.4;9.5]	9.5	[8.9;10.0]

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.20: Mean disposable household income by deciles of disposable household equivalence income distribution, working-age households, 2012-2016

Decile	**Income in €**									
	2012	CI	2013	CI	2014	CI	2015	CI	2016	CI
1	553	[542;563]	579	[571;588]	592	[583;602]	596	[586;605]	590	[581;599]
2	795	[792;798]	802	[799;805]	826	[823;829]	829	[826;832]	840	[837;842]
3	966	[963;968]	959	[957;961]	996	[993;998]	994	[991;996]	1012	[1009;1015]
4	1158	[1155;1161]	1147	[1144;1150]	1194	[1191;1198]	1204	[1200;1207]	1235	[1231;1240]
5	1372	[1368;1375]	1369	[1365;1372]	1417	[1413;1421]	1446	[1442;1450]	1486	[1482;1491]
6	1611	[1606;1615]	1617	[1613;1621]	1671	[1667;1675]	1696	[1692;1700]	1737	[1732;1742]
7	1868	[1863;1873]	1887	[1883;1892]	1947	[1942;1953]	1986	[1980;1992]	2014	[2008;2020]
8	2182	[2175;2188]	2233	[2227;2240]	2299	[2292;2306]	2358	[2350;2365]	2348	[2341;2356]
9	2660	[2648;2672]	2776	[2763;2788]	2840	[2827;2854]	2921	[2907;2935]	2869	[2855;2883]
10	4384	[4304;4464]	4585	[4508;4661]	4701	[4612;4790]	4737	[4655;4820]	4728	[4640;4816]
Total	1754	[1733;1776]	1795	[1774;1816]	1848	[1825;1871]	1875	[1852;1899]	1885	[1861;1909]

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.21: Moments and Poverty measures of the monthly disposable household equivalence income distribution, households with *affected* employees, 2012-2016

Year	**Income measures**				**Poverty measures**						
	Mean		Median		Poverty rate		Poverty gap		FGT(2)		Poverty
		CI		CI		CI		CI		CI	line
2012	1410	[1341;1488]	1223	[1160;1302]	14.3	[10.7;18.1]	1.86	[1.40;2.39]	0.47	[0.31;0.68]	893
2013	1391	[1336;1449]	1227	[1151;1274]	14.0	[10.4;18.6]	1.92	1.29;2.61]	0.55	[0.33;0.80]	898
2014	1519	[1451;1619]	1251	[1204;1327]	13.2	[7.9;18.0]	1.54	[1.06;2.13]	0.39	[0.22;0.60]	928
2015	1487	[1420;1575]	1278	[1197;1367]	16.7	[11.2;20.3]	2.02	[1.38;2.68]	0.53	[0.33;0.76]	945
2016	1560	[1476;1678]	1335	[1266;1436]	14.7	[11.1;18.7]	2.03	[1.41;2.89]	0.64	[0.35;1.06]	966
***Scenario A**: Full compliance scenario, minimum wage level: 8.50€ per hour*											
2015	1516	[1453;1593]	1313	[1240;1384]	12.3	[;.9;16.4]	1.68	[1.08;2.30]	0.46	[0.25;0.66]	950
2016	1578	[1502;1683]	1351	[1290;1433]	12.1	[9.0;16.2]	1.73	[1.18;2.35]	0.58	[0.31;0.90]	967
***Scenario B**: Full compliance scenario, minimum wage level: 12€ per hour*											
2015	1655	[1611;1708]	1472	[1438;1498]	10.6	[7.6;12.8]	1.51	[1.11;1.91]	0.45	[0.30;0.61]	970
2016	1728	[1673;1782]	1515	[1478;1568]	10.1	[8.1;12.6]	1.44	[1.05;1.85]	0.40	[0.27;0.56]	985

Notes: Households are *affected* if at least one person in the household earns an hourly wage belonging to the bottom 11% of the wage distribution of the respective year. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. For inequality and poverty measures see definition in sub-section 3.5.5. Poverty line refers to respective year (flexible poverty line). In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. For significance of differences see Table C.22. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.22: Differences in moments and poverty measures for the monthly disposable household equivalence income distribution, households with *affected* employees, 2012-2016

Year	**Income measures**				**Poverty measures**					
	Mean		Median		Poverty rate		Poverty gap		FGT(2)	
		CI		CI		CI		CI		CI
2013-2012	-19	[-115;63]	4	[-121;82]	-0.3	[-6.2;4.9]	0.06	[-0.83;0.95]	0.07	[-0.28;0.36]
2014-2013	128	[41;248]	24	[-34;122]	-0.8	[-7.6;4.4]	-0.37	[-1.24;0.50]	-0.16	[-0.44;0.15]
2015-2014	-31	[-146;74]	27	[-90;117]	3.5	[-5.2;9.9]	0.48	[-0.57;1.22]	0.14	[-0.14;0.40]
2016-2014	41	[-74;175]	84	[-13;188]	1.5	[-4.4;8.1]	0.48	[-0.41;1.47]	0.26	[-0.10;0.71]
***Scenario A**: Full compliance scenario, minimum wage level: 8.50€ per hour*										
2015-2014	-3	[-129;102]	61	[-39;152]	-0.9	[-7.6;6.0]	0.14	[-0.77;0.98]	0.07	[-0.21;0.37]
2016-2014	60	[-76;189]	100	[7;192]	-1.1	[-7.0;4.7]	0.19	[-0.63;0.91]	0.19	[-0.11;0.55]
***Scenario B**:Full compliance scenario, minimum wage level: 12€ per hour*										
2015-2014	137	[24;221]	221	[141;263]	-2.6	[-8.1;3.1]	-0.03	[-0.73;0.68]	0.07	[-0.14;0.34]
2016-2014	209	[97;307]	264	[170;329]	-3.1	[-8.3;2.8]	-0.10	[-0.75;0.63]	0.02	[-0.24;0.29]

Notes: Households are *affected* if at least one person in the household earns an hourly wage belonging to the bottom 11% of the wage distribution of the respective year. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. For inequality and poverty measures see definition in sub-section 3.5.5. Poverty line refers to respective year (flexible poverty line). In scenario A (B) all wages below 8.50€ (12€) are lifted to this threshold, everything else unchanged, including employment. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.23: Employment shares by deciles of the monthly disposable household equivalence income distribution, working-age households, 2012-2016

Decile	**Full-time employment**					**Part-time employment**					**Marginal employment**				
	2012	2013	2014	2015	2016	2012	2013	2014	2015	2016	2012	2013	2014	2015	2016
1	0.21	0.22	0.18	0.17	0.19	0.09	0.08	0.07	0.11	0.12	0.06	0.06	0.07	0.07	0.05
2	0.25	0.23	0.19	0.21	0.16	0.14	0.13	0.17	0.14	0.14	0.08	0.10	0.10	0.12	0.12
3	0.35	0.32	0.34	0.33	0.34	0.18	0.20	0.19	0.21	0.23	0.09	0.10	0.12	0.10	0.10
4	0.46	0.45	0.45	0.44	0.46	0.17	0.20	0.22	0.22	0.18	0.08	0.09	0.10	0.09	0.08
5	0.50	0.50	0.47	0.51	0.51	0.17	0.18	0.20	0.20	0.19	0.08	0.08	0.08	0.07	0.07
6	0.65	0.59	0.62	0.65	0.65	0.15	0.17	0.17	0.15	0.17	0.05	0.05	0.05	0.04	0.06
7	0.68	0.70	0.66	0.64	0.66	0.15	0.14	0.15	0.18	0.18	0.05	0.04	0.04	0.04	0.03
8	0.72	0.72	0.75	0.74	0.71	0.14	0.16	0.13	0.15	0.16	0.03	0.03	0.03	0.02	0.04
9	0.74	0.75	0.74	0.76	0.74	0.15	0.13	0.14	0.14	0.16	0.03	0.03	0.02	0.03	0.03
10	0.79	0.79	0.79	0.78	0.78	0.12	0.12	0.12	0.12	0.12	0.02	0.03	0.03	0.03	0.03
Total	0.53	0.53	0.52	0.52	0.52	0.15	0.15	0.15	0.16	0.16	0.06	0.06	0.06	0.06	0.06

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Household frequency weights used. Shares displayed in the respective decile and year refer to households which have at least one person in full-time (part-time, marginal) employment. For confidence intervals see Tables C.25, C.26, and C.27, Appendix. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.24: Working time by employment status and deciles of the monthly disposable household equivalence income distribution, working-age households, 2012-2016

Decile	**Full-time employment**					**Part-time employment**					**Marginal employment**				
	2012	2013	2014	2015	2016	2012	2013	2014	2015	2016	2012	2013	2014	2015	2016
1	36.77	39.51	35.48	35.67	39.29	19.33	19.84	19.97	19.65	18.93	8.23	5.46	11.76	6.45	8.70
2	38.29	39.12	38.22	36.79	39.67	20.07	20.43	20.76	21.11	21.88	6.71	7.30	8.15	7.87	8.76
3	38.46	39.08	38.31	39.14	39.04	21.61	20.92	23.18	21.57	22.07	8.46	8.55	9.19	8.79	6.74
4	37.96	37.12	38.80	39.11	39.26	22.24	22.21	23.80	23.49	21.91	6.38	7.45	8.00	6.69	7.31
5	40.24	40.44	40.00	41.46	41.90	21.00	22.11	22.88	23.21	23.62	9.26	7.16	8.74	11.82	7.25
6	42.52	40.98	42.12	42.12	41.87	22.79	20.78	22.68	23.45	23.36	7.56	7.61	9.32	9.42	8.56
7	42.26	42.71	43.64	41.70	43.49	22.28	23.44	24.24	24.62	23.96	5.96	6.12	7.53	6.44	6.29
8	42.11	43.83	42.93	42.02	45.03	20.82	23.22	25.65	23.32	24.87	7.51	5.68	7.42	8.37	5.47
9	42.79	41.67	43.22	42.80	45.46	23.30	24.06	23.46	21.23	22.95	5.14	5.27	9.33	8.31	4.17
10	32.98	32.04	32.68	36.14	37.08	18.09	17.84	18.82	17.74	19.45	3.93	2.85	3.40	4.03	4.51
Total	39.79	39.75	40.10	40.38	41.72	21.36	21.68	22.83	22.26	22.60	7.25	6.80	8.37	8.04	7.13

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Values refer to averages of aggregate working hours in the household per employment status. I.e. within the household all hours are aggregated for each employment status (full-time, part-time, marginal employment), then the average over all households within this decile is computed. For confidence intervals see Tables C.28, C.29, and C.30, Appendix.
Source: SOEP, waves 2012-2016; own calculations.

Table C.25: Full-time employment shares by deciles of the monthly disposable household equivalence income distribution, working-age households, 2012-2016

Decile	**Share in %**									
	2012		2013		2014		2015		2016	
		CI		CI		CI		CI		CI
1	21.0	[18.3;23.7]	21.5	[18.9;24.1]	18.1	[15.5;20.8]	16.6	[14.1;19.0]	19.0	[16.5;21.6]
2	24.7	[22.5;27.0]	23.1	[21.0;25.2]	19.0	[16.9;21.2]	21.0	[18.6;23.3]	16.0	[14.3;17.6]
3	34.5	[32.6;36.4]	32.5	[30.6;34.3]	33.7	[31.7;35.8]	32.6	[30.6;34.6]	33.6	[31.6;35.5]
4	45.8	[43.8;47.7]	44.9	[43.0;46.7]	44.7	[42.6;46.8]	44.1	[41.9;46.2]	46.0	[43.8;48.3]
5	50.3	[48.3;52.4]	50.0	[48.0;52.0]	47.3	[45.2;49.5]	50.5	[48.3;52.7]	51.4	[49.2;53.6]
6	65.5	[63.4;67.6]	58.6	[56.6;60.6]	61.9	[59.8;63.9]	65.1	[63.0;67.2]	64.9	[62.6;67.1]
7	67.7	[65.6;69.7]	69.9	[67.9;71.8]	66.2	[64.1;68.3]	64.0	[61.8;66.1]	65.8	[63.4;68.2]
8	71.5	[69.5;73.6]	72.1	[70.2;74.1]	74.9	[72.8;76.9]	74.2	[72.2;76.1]	71.2	[68.9;73.4]
9	73.5	[71.5;75.6]	75.4	[73.5;77.2]	73.7	[71.8;75.6]	75.5	[73.6;77.4]	74.2	[72.0;76.3]
10	79.3	[77.7;81.0]	78.9	[77.2;80.5]	78.5	[76.7;80.4]	78.0	[76.1;79.9]	77.5	[75.6;79.5]
Total	53.4	[52.6;54.1]	52.7	[52.0;53.4]	51.8	[51.0;52.6]	52.1	[51.3;52.9]	51.9	[51.2;52.7]

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. Shares displayed in the respective decile and year refer to households which have at least one person in full-time employment. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.26: Part-time employment shares by deciles of the monthly disposable household equivalence income distribution, working-age households, 2012-2016

Decile	**Share in %**									
	2012		2013		2014		2015		2016	
		CI		CI		CI		CI		CI
1	8.7	[6.9;10.6]	8.0	[6.4;9.7]	7.2	[5.5;8.9]	11.3	[9.2;13.4]	11.7	[9.6;13.7]
2	13.7	[[11.9;15.5]	12.9	[11.2;14.6]	16.5	[14.4;18.7]	13.8	[11.8;15.8]	13.8	[12.2;15.4]
3	18.3	[16.7;19.9]	20.0	[18.3;21.7]	18.8	[17.0;20.6]	21.3	[19.4;23.2]	23.3	[21.4;25.1]
4	17.1	[15.4;18.8]	19.6	[18.0;21.3]	21.8	[19.9;23.7]	21.9	[19.9;23.9]	18.1	[16.2;20.0]
5	17.2	[15.5;18.9]	18.2	[16.5;19.9]	19.8	[18.0;21.7]	20.0	[18.1;21.9]	19.1	[17.2;21.1]
6	15.1	[13.4;16.8]	16.5	[15.0;18.1]	16.8	[15.1;18.5]	14.9	[13.2;16.6]	17.5	[15.6;19.4]
7	15.0	[13.5;16.6]	13.7	[12.3;15.1]	15.1	[13.5;16.7]	18.4	[16.6;20.1]	17.9	[16.0;19.9]
8	13.7	[12.1;15.3]	15.7	[14.2;17.3]	13.1	[11.5;14.8]	15.5	[13.9;17.1]	15.8	[14.0;17.6]
9	15.1	[13.4;16.8]	12.6	[11.2;14.0]	13.7	[12.2;15.2]	13.7	[12.1;15.2]	15.6	[13.8;17.3]
10	11.9	[10.6;13.2]	11.8	[10.5;13.1]	12.1	[10.6;13.5]	11.5	[10.1;13.0]	11.8	[10;.4;13.3]
Total	14.6	[14.1;15.1]	14.9	[14.4;15.4]	15.5	[14.9;16.1]	16.2	[15.7;16.8]	16.5	[15.9;17.0]

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. Shares displayed in the respective decile and year refer to households which have at least one person in part-time employment. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.27: Marginal employment shares by deciles of the monthly disposable household equivalence income distribution, working-age households, 2012-2016

Decile	**Share in %**									
	2012		2013		2014		2015		2016	
		CI		CI		CI		CI		CI
1	6.0	[4.4;7.6]	6.4	[4.9:7.9]	6.6	[4.9;8.2]	6.7	[5.0;8.3]	4.7	[3.3;6.0]
2	8.3	[6.9;9.8]	9.9	[8.4;11.5]	9.6	[8.0;11.2]	12.1	[10.2;14.0]	12.5	[10.9;14.0]
3	9.3	[8.0;10.5]	10.3	[9.0;11.6]	11.8	[10.3;13.3]	10.2	[8.9;11.6]	9.5	[8.3;10.8]
4	7.7	[6.6;8.8]	9.2	[8.0;10.3]	9.6	[8.2;10.9]	8.9	[7.7;10.2]	8.5	[7.1;9.9]
5	8.1	[6.9;9.3]	7.9	[6.7;9.1]	8.4	[7.1;9.7]	7.1	[5.9;8.3]	6.6	[5.4;7.7]
6	5.2	[4.3;6.2]	4.8	[3.9;5.8]	4.6	[3.6;5.6]	3.8	[2.9;4.7]	6.1	[4.9;7.3]
7	4.5	[3.6;5.5]	4.1	[3.3;5.0]	4.2	[3.3;5.1]	4.4	[3.5;5.3]	3.2	[2.4;4.1]
8	2.9	[2.2;3.7]	3.0	[2.2;3.8]	3.2	[2.4;4.1]	2.5	[1.8;3.2]	3.8	[2.8;4.8]
9	2.8	[2.1;3.5]	3.2	[2.4;4.0]	2.1	[1.5;2.7]	2.9	[2.2;3.7]	2.7	[1.9;3.6]
10	2.2	[1.6;2.8]	2.6	[2.0;3.2]	2.9	[2.2;3.6]	2.6	[1.9;3.3]	3.5	[2.6;4.3]
Total	5.7	[5.4;6.1]	6.1	[5.8;6.5]	6.3	[5.9;6.7]	6.1	[5.7;6.5]	6.1	[5.7;6.5]

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. Shares displayed in the respective decile and year refer to households which have at least one person in marginal employment. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.28: Working time of full-time employed by deciles of the monthly disposable household equivalence income distribution, working-age households, 2012-2016

Decile	2012		2013		2014		2015		2016	
		CI		CI		CI		CI		CI
1	36.8	[34.1;39.4]	39.5	[36.9;42.1]	35.5	[32.6;38.3]	35.7	[32.9;38.4]	39.3	[35.9;42.7]
2	38.3	[36.1;40.4]	39.1	[37.1;41.2]	38.2	[36.0;40.4]	36.8	[34.6;39.0]	39.7	[37.3;42.0]
3	38.5	[37.2;39.7]	39.1	[37.9;40.2]	38.3	[37.1;39.5]	39.1	[38.1;40.2]	39.0	[37.7;40.3]
4	38.0	[37.0;38.9]	37.1	[36.1;38.1]	38.8	[37.8;39.8]	39.1	[38.1;40.1]	39.3	[38.2;40.3]
5	40.2	[39.2;41.2]	40.4	[39.4;41.5]	40.0	[38.9;41.1]	41.5	[40.3;42.7]	41.9	[40.6;43.2]
6	42.5	[41.4;43.7]	41.0	[39.8;42.1]	42.1	[41.0;43.3]	42.1	[41.1;43.1]	41.9	[40.5;43.2]
7	42.3	[40.9;43.6]	42.7	[41.5;43.9]	43.6	[42.4;44.8]	41.7	[40.5;42.9]	43.5	[42.0;45.0]
8	42.1	[40.6;43.6]	43.8	[42.6;45.1]	42.9	[41.4;44.4]	42.0	[40.5;43.5]	45.0	[43.4;46.6]
9	42.8	[41.1;44.5]	41.7	[40.1;43.2]	43.2	[41.6;44.8]	42.8	[41.2;44.4]	45.5	[43.7;47.2]
10	33.0	[31.2;34.8]	32.0	[30.2;33.8]	32.7	[30.8;34.6]	36.1	[34.2;38.1]	37.1	[35.1;39.1]
Total	39.8	[39.3;40.3]	39.7	[39.3;40.2]	40.1	[39.6;40.6]	40.4	[39.9;40.9]	41.7	[41.2;42.2]

Notes: The sample includes all households without members exceeding age 65, irrespective of employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. Values refer to averages of aggregate working hours in the household per employment status. I.e. within the household all hours are aggregated for each employment status, then the average over all households within this decile is computed.
Source: SOEP, waves 2012-2016; own calculations.

Table C.29: Working time of part-time employed by deciles of the monthly disposable household equivalence income distribution, working-age households, 2012-2016

Decile	2012	CI	2013	CI	2014	CI	2015	CI	2016	CI
1	19.3	[17.3;21.3]	19.8	[17.6;22.1]	20.0	[17.7;22.2]	19.7	[17.5;21.8]	18.9	[16.2;21.7]
2	20.1	[18.7;21.4]	20.4	[19.1;21.8]	20.8	[19.3;22.2]	21.1	[19.8;22.5]	21.9	[20.1;23.7]
3	21.6	[20.7;22.5]	20.9	[20.0;21.8]	23.2	[22.0;24.4]	21.6	[20.6;22.6]	22.1	[21.0;23.1]
4	22.2	[21.2;23.3]	22.2	[21.3;23.1]	23.8	[22.9;24.7]	23.5	[22.5;24.5]	21.9	[20.7;23.1]
5	21.0	[20.0;22.0]	22.1	[21.1;23.1]	22.9	[21.9;23.8]	23.2	[21.9;24.5]	23.6	[22.5;24.8]
6	22.8	[21.4;24.1]	20.8	[19.6;22.0]	22.7	[21.6;23.7]	23.5	[22.3;24.6]	23.4	[22.1;24.6]
7	22.3	[21.3;23.3]	23.4	[22.4;24.5]	24.2	[23.2;25.3]	24.6	[23.5;25.7]	24.0	[22.7;25.2]
8	20.8	[19.6;22.0]	23.2	[22.1;24.3]	25.7	[24.5;26.8]	23.3	[22.2;24.4]	24.9	[23.5;26.2]
9	23.3	[22.1;24.5]	24.1	[22.9;25.2]	23.5	[22.3;24.6]	21.2	[20.1;22.3]	22.9	[21.7;24.2]
10	18.1	[16.7;19.5]	17.8	[16.5;19.2]	18.8	[17.3;20.4]	17.7	[16.0;19.4]	19.5	[17.8;21.1]
Total	21.4	[21.0;21.7]	21.7	[21.3;22.0]	22.8	[22.4;23.2]	22.3	[21.9;22.7]	22.6	[22.2;23.0]

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. Values refer to averages of aggregate working hours in the household per employment status. I.e. within the household all hours are aggregated for each employment status, then the average over all households within this decile is computed. *Source:* SOEP, waves 2012-2016; own calculations.

Table C.30: Working time of marginally employed by deciles of the monthly disposable household equivalence income distribution, working-age households, 2012-2016

Decile	2012	CI	2013	CI	2014	CI	2015	CI	2016	CI
1	8.2	[6.1;10.4]	5.5	[3.7;7.2]	11.8	[8.8;14.7]	6.4	[3.9;9.0]	8.7	[6.0;11.5]
2	6.7	[5.6;7.8]	7.3	[6.0;8.6]	8.2	[6.8;9.5]	7.9	[6.5;9.2]	8.8	[7.0;10.6]
3	8.5	[6.9;10.0]	8.5	[7.4;9.7]	9.2	[8.0;10.4]	8.8	[7.4;10.2]	6.7	[5.8;7.7]
4	6.4	[5.3;7.4]	7.5	[6.3;8.6]	8.0	[6.9;9.1]	6.7	[5.6;7.7]	7.3	[6.3;8.3]
5	9.3	[8.1;10.4]	7.2	[5.9;8.4]	8.7	[7.6;9.9]	11.8	[9.8;13.8]	7.3	[6.1;8.4]
6	7.6	[5.9;9.2]	7.6	[6.4;8.8]	9.3	[8.3;10.4]	9.4	[7.8;11.0]	8.6	[7.2;9.9]
7	6.0	[4.8;7.1]	6.1	[4.7;7.5]	7.5	[6.1;8.9]	6.4	[5.1;7.8]	6.3	[4.9;7.7]
8	7.5	[5.7;9.4]	5.7	[3.6;7.7]	7.4	[6.1;8.8]	8.4	[5.5;11.2]	5.5	[3.7;7.2]
9	5.1	[2.5;7.7]	5.3	[3.5;7.1]	9.3	[7.0;11.7]	8.3	[4.8;11.8]	4.2	[2.2;6.2]
10	3.9	[2.1;5.7]	2.8	[1.6;4.1]	3.4	[1.9;4.8]	4.0	[2.5;5.6]	4.5	[2.7;6.3]
Total	7.3	[6.8;7.7]	6.8	[6.4;7.2]	8.4	[7.9;8.8]	8.0	[7.5;8.6]	7.1	[6.7;7.6]

Notes: The sample includes all households without members exceeding age 65, irrespective of their employment status. Equivalence weights according to the new OECD scale and household frequency weights used. Bootstrapped confidence intervals based on 500 replications. Values refer to averages of aggregate working hours in the household per employment status. I.e. within the household all hours are aggregated for each employment status, then the average over all households within this decile is computed.
Source: SOEP, waves 2012-2016; own calculations.

Summary

This dissertation consists of three chapters in the field of applied microeconomics with a focus on labor economics and behavioral economics. It covers various topics and methods. A common theme is the importance of decisions. Our economy is the result of innumerable decisions made by individual and institutional agents. The decisions are constraint by resources and differ in complexity and impact. All three chapters contain empirical analyzes of such decisions reaching from binary decisions in the stylized context of the prisoners dilemma, over individual training and employment choices and consequences in late-careers, to the impact of the political choice of the minimum-wage introduction on income inequality and poverty.

In the first chapter we study how individuals make decisions in the stylized context of the repeated prisoners' dilemma. In a meta-study we reanalyze 12 experiments on the repeated prisoner's dilemma (PD) and identify three distinct types of players: defectors, cautious cooperators and strong cooperators. The defectors defect with a high probability in every round. Both cooperating types play semi-grim behavior strategies. This simple three-type mixture fits significantly better than any model consisting of combinations of (generalized) pure strategies from the literature, which we fitted at the treatment level (considering 10^{51} pure-strategy mixtures), even when we use constant specifications of the three types across all experiments. The three best fitting strategies vary slightly across experiments, however. Structurally analyzing these strategies, we find that subjects have limited foresight and subjectively assign utility values to the four states (cc,cd,dc,dd) of the supergame, which relate to the original stage-game payoffs in a manner compatible with inequity aversion. This subjectively transforms the prisoners dilemma game into a coordination game and can reliably explain the strategies used across all 32 treatments.

In the second chapter I study how individual decisions interplay with institutional factors in the context of late-career choices. I investigate decisions regarding on-the-job training and their impact on the employment outcomes of less-educated men in their late careers. Using survey data from the German National Education Panel Study adult cohort, I estimate a structural dynamic discrete-choice model reflecting the trade-offs of the employees' training participation decision. The data set enables me to distinguish whether non-participation is due to lack of availability of training or due to individual cost-benefit considerations. As a consequence, I can investigate whether future policy interventions should target the provision of training or the individual participation incentives. I find that on-the-job training has a positive impact on the

employees' employment prospects. Counterfactual simulations show that a reduction of the individual training costs would increase training participation and positively affect the employment rate near retirement. In contrast, an increase in the general availability of training would not be effective.

In the third chapter we study how the decision of the federal government in Germany about the introduction of the minimum wage has affected the disposable income of households. Minimum wages are increasingly discussed as an instrument against (in-work) poverty and income inequality in Europe. Recently, the German government opted for a substantial ad-hoc increase of the minimum-wage level by 22% to 12€ per hour citing poverty prevention as an explicit goal. We use the introduction of the federal minimum wage in Germany in 2015 to study its impact on poverty and the disposable household income distribution. Based on the German Socio-Economic Panel we analyze changes in poverty and income inequality, and investigate different mechanisms determining the transmission from individual gross wage-rates to disposable household incomes. We find that the minimum wage is an inadequate tool for income redistribution and poverty reduction because it does not target poor households effectively. Individuals affected by the minimum wage are spread across the entire income distribution and households at the bottom end are hardly affected. Consequently, welfare dependence decreases only marginally. A reduction in transfers or negative employment effects cannot explain the limited effect on poverty. Additional simulations show that a markedly higher level of 12€ per hour does not render the minimum wage more effective in reducing poverty.

German Summary

Diese Dissertation besteht aus drei Kapitel im Bereich der angewandten Mikroökonomie mit einem Fokus auf Arbeitsmarktökonomik und Verhaltensökonomik. Sie umfasst verschiedene Themen und Methoden. Ein gemeinsames Motiv ist die Bedeutung von Entscheidungen. Unsere Volkswirtschaft ist das Ergebnis unzähliger Entscheidungen, die von Individuen und Institutionen getroffen werden. Diese Entscheidungen werden durch verfügbare Ressourcen beschränkt und variieren in Komplexität und ihren Auswirkung. Alle drei Kapitel enthalten empirische Analysen solcher Entscheidungen, von binären Entscheidungen im stilisieren Kontext des Gefangenendilemmas, über individuelle Trainings- und Beschäftigungsentscheidungen und deren Auswirkungen, bis zum Einfluss der politischen Entscheidung der Mindestlohneinführung auf Einkommensungleichheit und Armut.

Im ersten Kapitel werden Entscheidungen von Individuen in der stilisierten Umgebung des wiederholten Gefangenendilemmas untersucht. In der Meta-Studie mit Daten aus zwölf Gefangenendilemmaexperimenten indentifizieren wir drei verschiedene Spieler-Typen: Defektierer, vorsichtige Kooperateure und überzeugte Kooperateure. Die Defektierer defektieren mit sehr hoher Wahrscheinlichkeit in jeder Runde. Beide Kooperateure spielen Semi-Grim Behavior-Strategien. Ein Modell dieser einfachen Drei-Typen-Mischung erzeugt einen signifikant besseren Fit als jedes Modell auf Basis von reinen Strategien aus der Literatur, das auf Treatmentebene optimiert wurde (unter Berücksichtingung von 10^{51} möglichen Mischungen), selbst wenn wir eine über alle Experimente konstante Drei-Typen-Mischung annehmen. Die am besten passendsten drei Strategien variieren aber leicht über die Experimente. In einer strukturellen Analyse dieser Strategien finden wir, dass die Spieler eine beschränkte Voraussicht haben und allen vier Spielstadien (cc,cd,dc,dd) bestimmte subjektive Nutzenwerte zuweisen, welche zu den jeweiligen Auszahlungsmatrizen der Experimente in einem Zusammenhang stehen, der sich über Ungleichheitsaversion erklären lässt. Dies transformiert das Gefangenendilemmaspiel subjektiv in ein Koordinationsspiel und kann zuverlässig die verwendeten Strategien über alle 32 Treatments in den analysierten Experimenten erklären.

Im zweiten Kapitel werden die Interaktion individueller Entscheidungen mit institutionellen Faktoren im Kontext von berufsbegleitender Weiterbildung von Arbeitnehmern im späten Verlauf ihrer Karriere analysiert. Ich untersuche wie sich Weiterbildung auf die Arbeitsmarktergebnisse von weniger gebildeten Arbeitnehmern gegen Ende ihrer Karriere auswirken kann. Mithilfe von Daten aus der Erwachsenenkohorte des Nationalen Bildungspanels, schätze ich ein strukturelles dynamisches diskretes Entscheidungsmodel, das die Abwägungen der Weiterbildungsentscheidung von Arbeitnehmern abbildet. Der Datensatz ermöglicht es mir Nichtteilnahme an beruflichen Weiterbildungsangeboten wegen mangelnder Verfügbarkeit von Weiterbildung von Nichtteilnahme aufgrund von individuellen Kosten-Nutzen-Abwägungen zu unterscheiden. Infolgedessen kann ich untersuchen, ob zukünftige Politikmaßnahmen die Bereitstellung von Weiterbildung oder die individuellen Teilnahmeanreize in den Fokus nehmen sollten. Ich finde heraus, dass Weiterbildung einen positiven Einfluss auf die Erwerbsperspektive der Arbeitnehmer hat. Kontrafaktische Simulationen zeigen, dass eine Reduktion der Weiterbildungskosten die Weiterbildungsteilnahme steigern würde und die Beschäftigungsquote kurz vor der Rente positiv beeinflussen würde. Im Gegensatz dazu wäre eine Steigerung der allgemeinen Verfügbarkeit von Weiterbildung nicht effektiv.

Im dritten Kapitel wird untersucht, welche Auswirkungen die Entscheidung der deutschen Bundesregierung zur Mindestlohneinführung auf die verfügbaren Einkommen der Haushalte hat. Mindestlöhne werden in Europa zunehmend als Mittel gegen (Erwerbs-)Armut und Einkommensungleichheit diskutiert. Vor kurzem hat die deutsche Regierung eine deutliche Erhöhung des Mindestlohnniveaus um 22% auf 12€ beschlossen. Die Armutsbekämpfung wurde dabei als explizites Ziel genannt. Wir nutzen die Einführung des bundeseinheitlichen deutschen Mindestlohns im Jahr 2015 um dessen Einfluss auf Armut und die Verteilung der verfügbaren Haushaltseinkommen zu untersuchen. Auf Basis von Daten aus dem Sozio-oekonomischen Panel analysieren wir Änderungen in Einkommensungleichheit und Armut, sowie unterschiedliche Mechanismen, die die Transmission von individuellen Bruttostundenlöhnen auf verfügbare Haushaltseinkommen beeinflussen. Wir finden heraus, dass der Mindestlohn kein effektives Werkzeug zur Haushaltseinkommensumverteilung und Armutsreduktion ist, da er nicht zielgerichtet auf arme Haushalte wirkt. Individuen, die vom Mindestlohn betroffen sind, sind über die gesamte Einkommensverteilung verteilt und Haushalte am unteren Ende sind kaum betroffen. Infolgedessen sinkt die Sozialleistungsabhängigkeit nur marginal. Weder eine Reduktion der Transferzahlungen noch negative Beschäftigungseffekte sind Grund für den begrenzten Effekt auf die Armut. Durch zusätzliche Simulationen zeigen wir, dass der Mindestlohn auch durch eine erhebliche Erhöhung auf 12€ nicht zu einem effektiverem Werkzeug zur Reduktion von Ungleichheit und Armut wird.

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Declaration

Erklärung gem. §4 Abs. 2 der Promotionsordnung

Hiermit erkläre ich, dass ich mich noch keinem Promotionsverfahren unterzogen oder um Zulassung zu einem solchen beworben habe, und die Dissertation in der gleichen oder einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule nicht bereits zur Überprüfung vorgelegen hat.

Berlin, Januar 2022

Teresa Backhaus

Erklärung gem. §10 Abs. 3 der Promotionsordnung

Hiermit erkläre ich, dass ich für die Dissertation folgende Hilfsmittel und Hilfen verwendet habe: Stata, R, Microsoft Excel, LaTeX, JabRef, genannte Koautoren und genannte Quellen.
Auf dieser Grundlage habe ich die Arbeit selbstständig verfasst.

Berlin, Januar 2022

Teresa Backhaus