Dynamics of voting propensity: Experimental tests of adaptive learning models

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Abstract

This paper aims to deliver experimental evidence on the dispute between two behavioral models of electoral turnout (Bendor, Diermeier & Ting, APSR 2003; Fowler, JoP 2006). Both models share the idea that the subjects’ voting propensities are updated from their past propensities, aspirations and realized payoffs. However, they differ in the exact specification of the feedback mechanism. The first model has a strong feedback mechanism toward 50%, while the other has only moderate feedback. This difference leads to two distinct distributions of voter types: the first model generates more casual voters who vote and abstain from time to time. The latter generates more habitual voting behavior. Thus far, the latter model seemed to be better supported empirically since survey data reveal more habitual voters and abstainers than casual voters. Given that the two models differ in their propensity updating mechanism in dynamic processes, a more direct test of this term with survey data is still pending. We designed a laboratory experiment in which subjects repeatedly make turnout and voting decisions. The results from experimental data is mixed, but more supportive of the first model with casual voters. We further find some specific circumstances in which the first model generates habitual voters and abstainers and vice versa, which might explain previous empirical evidence in survey data in favor of the latter model.

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1 Introduction

Electoral turnout is one of the most widely investigated phenomena in political science and is also known as a paradox for rational choice approaches based on cost benefit calculation (see for literature reviews, e.g. Aldrich, 1993; Laver, 1997; Dewan and Shepsle, 2008; Kittel and Marcinkiewicz, 2012). Criticizing previous solutions of the voting paradox, Bendor, Diermeier and Ting (2003, hereafter BDT) proposed an alternative behavioral model. Although their model is also based on a cost-benefit core, the actors do not optimize their decision based on subjective expectations, but adapt their voting propensity retrospectively. More specifically, in their model, actors are assumed to possess a certain aspiration level which is compared to payoffs (benefit minus cost). If an agent’s behavior in an election (vote or abstain) results in higher payoffs than her aspiration level, the agent’s initial propensity is reinforced, and vice versa. Simultaneously, her aspiration level is updated by current payoffs. By simulating multiple agents deciding to vote or not at sequential elections, in which their aspiration and propensity continue to be updated, BDT achieved stable turnout rate around 50% on average even with substantial voting cost.

A few years later, Fowler (2006) confronted the BDT model with another alternative behavioral model. He criticized the updating mechanism of voting propensity in the BDT model because of its strong tendency toward 50%, which too much suppressed the effect of voting cost on the turnout rate. Because of this so-called moderating feedback, most agents are casual voters who vote and abstain from time to time. Fowler argues, in contrast, that most real citizens are either habitual voters or habitual abstainers. For empirical evidence, he referred to data from South Bend (Huckfeldt and Sprague, 1991) which resulted in a unimodal distribution of turnout at the level of individual respondents. In order to reconstruct this distribution with more habitual voters and habitual abstainers, Fowler proposed an alternative behavioral model. Similar to that of BDT, agents compare their aspiration and actual payoffs to update their voting propensity. However, the updating mechanism has a much weaker moderating feedback so that the voting propensity is not concentrated around 50%. His corresponding simulation model in fact realized more habitual voters and abstainers than casual voters.

Empirical support for the superiority of Fowler’s against BDT’s model, however, exists only in terms of the individual turnout rate. While both models differ in their propensity updating mechanism in dynamic processes, a more direct test of this term is still pending. A corresponding test can hardly be conducted by using conventional survey data. Therefore, we utilize a laboratory experimental design in which experimental subjects make repeated decisions whether to vote or not.

In the remainder of this paper, we proceed as follows: In the next section, we compare and rerun the simulation models corresponding to the Fowler and BDT-model as well as to our experimental setting. This is, in particular, necessary since our experimental setting allows for only small number of subjects compared to the original simulations of Fowler and BDT. The third section introduces
the experimental design in detail, the fourth section presents the experimental results. This section begins with a macro-level inspection of our data and then looks into the micro mechanism of experimental subjects’ voting decisions. In particular, we construct a full Bayesian probability model corresponding to both theoretical models and obtain the posterior information using Markov-Chain-Monte-Carlo methods. The last section summarizes and discusses the results.
2 Simulation models and their results

This section presents some simulation results of two theoretical models: Bendor, Diermeier and Ting (2003) and Fowler (2006) adaptation model. Both of these models are commonly characterized by aspiration-based adaptive rules (ABAR) for the agents’ decisions. The basic idea of ABAR is simple: An agent takes an action based on her action propensities. If the action succeeds, that is, the agent’s payoff is larger than or the same as her aspiration level, then the corresponding action propensity increases and the actors becomes more likely to take the same action again. This is called positive feedback. If the action does not succeed, that is, the agent’s payoff is less than her aspiration level, then the corresponding action propensity decreases and the agent becomes less likely to take the same action again. This is negative feedback. Besides these two feedback mechanisms, the third important element of both models is the adjustment of aspirations. An agent’s aspiration level is constantly adjusted by its past level and the payoffs of the previous period. If an agent receives higher payoffs than her aspiration level, then her aspiration level increases, and vice versa.

The BDT and Fowler models only differ in their feedback mechanisms introduced above. To formalize, we use the following notation:

- $V_{i,t}$: citizen $i$’s action in period $t$ (vote=1; abstain=0)
- $p_{i,t}(V)$: citizen $i$’s propensity to take action $V$ in period $t$.
- $a_{i,t}$: citizen $i$’s aspiration in period $t$.
- $\pi_{i,t}$: citizen $i$’s payoff in period $t$.

According to the BDT model, citizens update their propensity after their action $I$ as follows:\footnote{This model is called Bush-Mosteller rule by BDT since it was originally proposed by Bush and Mosteller (1955).}

$$p_{i,t+1}(I) = \begin{cases} 
  p_{i,t}(I) + \alpha(1 - p_{i,t}(I)) & \text{if } \pi_{it} > a_{it} \\
  p_{i,t}(I) & \text{if } \pi_{it} = a_{it} \\
  p_{i,t}(I) - \alpha p_{i,t}(I) & \text{if } \pi_{it} < a_{it}
\end{cases} \quad (1)$$

The parameter $\alpha \in (0, 1]$ controls the magnitude of the update parameter. The magnitude is, however, also determined by the current propensity $p_{i,t}$.

According to the Fowler model, in contrast, the magnitude of the update parameter is solely controlled by $\alpha$:

$$p_{i,t+1}(I) = \begin{cases} 
  \min(1, p_{i,t}(I) + \alpha) & \text{if } \pi_{it} > a_{it} \\
  p_{i,t}(I) & \text{if } \pi_{it} = a_{it} \\
  \max(0, p_{i,t}(I) - \alpha) & \text{if } \pi_{it} < a_{it}
\end{cases} \quad (2)$$

The difference is depicted in Figure 1. The left panel shows the update magnitude ($\Delta p_{i,t+1}$) on the vertical axis in dependence of $p_{i,t}$ on the horizontal
axis according to BDT model. If a citizen obtains higher payoffs than her aspiration after voting, her vote propensity increases up to the level shown by the solid line. The magnitude is highest ($\alpha$) at $p_{i,t} = 0$ and lowest (zero) at $p_{i,t} = 1$. If we assume the same probability for $\pi_{it} > a_{it}$ and $\pi_{it} < a_{it}$, the mid of the solid and the dashed lines represents the expected change of propensity. Accordingly, if an individual has propensity less than 0.5 she is expected to have a higher propensity level, and vice versa. This is the moderating feedback which drives the propensity toward 50%. This phenomenon is clearly absent in the Fowler model. Except for the two boundaries, the mid of the solid and dashed lines corresponds to zero, which means that individuals can stay at a certain propensity level for a longer time.

For both updating mechanisms, we ran 1000 simulations. We set voting costs higher (0.30) for one half and lower (0.18) for the other half of these 1000 simulation runs. In each simulation run, 10 supporters of one party and 10 of the other party repeated 1000 election periods. For the other simulation parameters, we used the following set of parameters, which are identical with those of BDT and Fowler with one exception:

- $\alpha = 0.1$: update speed of propensity level
- $\lambda = 0.95$: update speed of aspiration level
- $\epsilon = 0.5$: inertia
- support = 0.2

The only parameter which differs from BDT and Fowler is the agent’s inertia in updating their propensity ($\epsilon$). We set a much higher value (0.5) than the original studies (0.05) because of the smaller number of agents that can be
Table 1: Predicted turnout for different levels of voting cost

<table>
<thead>
<tr>
<th></th>
<th>c=.70</th>
<th>c=.50</th>
<th>c=.30</th>
<th>c=.18</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>BDT</strong></td>
<td>.49</td>
<td>.52</td>
<td>.57</td>
<td>.58</td>
</tr>
<tr>
<td><strong>Fowler</strong></td>
<td>.33</td>
<td>.41</td>
<td>.45</td>
<td>.49</td>
</tr>
<tr>
<td><strong>EU</strong></td>
<td>–</td>
<td>0</td>
<td>1</td>
<td>.20</td>
</tr>
</tbody>
</table>

handled in an experimental setting. Otherwise, no agent would update her propensity in a series of elections. This change of parameter has, however, no relevant impact on the results below.

Table 1 presents the turnout rates of 500 simulation runs over 1000 periods. As a reference, we also gives the predicted value based on the expected utility model in the style of Palfrey and Rosenthal (1985). The simulated turnout rates are consistent with the results of BDT and Fowler, revealing only a small impact of voting costs in comparison with the expected utility model. Among the two simulation models, the Fowler model is more sensitive to the cost due to the lack of the moderating feedback mechanism (Fowler p. 341). The impact of voting costs is, however, smaller than the results in Fowler (2006) due to the small population size (n=20) in our simulation runs.

![Individual turnout density graphs](image1)

**Figure 2**: individual turnout rate in the last 30 periods

The more relevant difference between the two simulation models, however, relates to the individual turnout rates. Figure 2 gives the distribution of turnout rates of individual voters for the last 30 periods. As Fowler has already shown, most agents in the BDT model are casual voters who vote and abstain from time to time. Therefore, the mode of the individual turnout lies around 50%. In contrast, agents in the Fowler Model tend to be habitual voters or abstainers
so that the turnout distribution is bimodal.

Behind the distributions presented in Figure 2 are different system dynamics. Figure 3 gives the frequency of propensity changes depending on the previous propensity level. That is, this figure adds information on frequencies in our simulation runs to Figure 1. The size of the circles represents the frequency, with larger circles indicating larger numbers, and the solid red lines are the mean propensity change conditional on the previous propensities. The mean propensity change conditional on the previous propensities show clear difference between the two system dynamics. In the BDT model, high voting propensities in the previous period tend to reduce current propensities on average and vice versa. This generates means-reverting system dynamics, resulting in the observed mid-level propensities around 50%. In the Fowler model, especially with c=.18, agents with high voting propensities tend to increase their propensities
and vice versa. This generates system dynamics toward the extreme high and low level of propensities.

![Figure 3: Dynamics of propensities in simulation runs](image)

The red lines represent mean propensity changes conditional on previous propensities.

Why do we have these two different system dynamics in simulation runs? Although the Fowler model lacks the moderating feedback, it also has no feedback in favor of the two extreme values (0% and 100%). Accordingly, we should rather expect a uniform distribution of individual turnout rates instead of a bimodal distribution. Fowler (2006) himself presented the corresponding simu-
We propose to explore the simulation results in more depth in order to solve this puzzle. First, we have to note that the bimodal distribution is not based on the full 1000 periods of the simulations but only on the last set of 30 periods. If we observe the individual turnout rate for the whole 1000 periods the bimodal distribution disappears. That is, most individuals habitually vote or abstain for a relatively short period, and change their habits over time. The bimodal distribution in Fowler (2006) is based on a total of 1000 simulation runs. All of the 1000 runs do not necessarily have a bimodal distribution.

In view of this fact, what makes voters habitually vote or abstain? Also the Fowler model assumes that agents’ decisions are based on their voting propensity, which is updated through the aspiration and payoffs. If an agent continues to vote she keeps a high propensity, which means, in turn, that payoffs remains higher than her aspiration. This situation can only happen if her party continues to win in a series and her aspiration is updated at a slower rate. At the same time, an agent can continue to abstain even if her party loses multiple elections in a series. This is because her aspiration is adjusted toward a lower level through the losing series. This is confirmed by Figure 4 which compares each period’s vote margin with the variance of individual average turnout in the preceding 30 periods. In the Fowler model, the larger the margin in favor of one party, the larger the variance of individual turnout rates, that is, the more likely the corresponding distribution is bimodal. A similar, though weaker tendency can be also observed in the BDT model. This is due to the feedback
effect which makes the race between the parties more close. And this is the reason for producing rather homogeneous casual voters\textsuperscript{2}

\textsuperscript{2}The presented results are based on a single simulation run with higher voting cost (c=0.30). The other simulation runs with the same level of cost show different cycles of the margin of the turnout rate. However, the relationship between the margin and the variance of the turnout rate can be always observed. Analogous results can also be observed in the simulation runs with lower voting cost. In these simulations, the size of the margin swing and the variance of the turnout rate tend to be slightly smaller than in those with higher voting cost.
3 Experimental design

In order to study whether the propensity updating process described by BDT or by Fowler generates real behavior, we set up a laboratory experiment. This is because the laboratory experiment enables us to test the two different propensity updating mechanisms in a more direct way than other methods would allow. A corresponding test can hardly be conducted by using conventional survey data for various reasons. First, they track only respondents’ turnout at a small number of elections. Second, turnout rate based on surveys in general suffers from over-reporting due to social desirability (McDonald, 2003; Holbrook, Green and Krosnick, 2003; Holbrook and Krosnick, 2010; Karp and Brockington, 2005) and/or worse response rate of abstainers (Clausen, 1968; Yalc, 1976; Burden, 2000). The South Bend data cited by Fowler tracked seven elections with official turnout records, but also this data suffer from the second problem. That is, survey data can at best provide measures of benefit, cost and aspiration at a low quality. And this prevent us to directly compare the two different propensity updating mechanisms. We, therefore, utilize a laboratory experiment design in which experimental persons repeatedly make decisions whether to vote at 30 elections in series.

More specifically, our laboratory experiment used the following setup. We invited 120 subjects from the subject pool of the experimental laboratory at the University of Oldenburg. They participated in one of six sessions which consist of 20 subjects, respectively. Out of six sessions, three are under the high-cost treatment and the other are under the low-cost treatment (for more detail see below).

In each session, 10 subjects are randomly assigned to one group (A) and the other 10 to the other group (B). Each session repeats a collective decision between two alternative, A and B for 30 periods. In each period, subjects decide to participate in the collective decision or not. If a subject decided to participate she has to pay voting cost. This is 0.30 Euro under the high-cost treatment and 0.18 Euro under the low-cost treatment. Independent of their second decision for which alternative to vote, the participants have to pay the corresponding cost. If a subject decides to participate, she further has to vote for one of the two alternatives: A or B. After these decisions, the alternative with more votes wins. In case of a tie, the winning alternative is decided by a random draw. Individual payoffs in each period depend on the vote result as well as on the subject’s first decision to participate or not. Depending on the vote results, individuals receive payoffs according to Table 2.

Subjects have 20 seconds for every decision. If she has not decided within those 20 seconds in the first decision, she does not participate in the second stage. If she does not take a decision in the second stage between alternatives, she is assumed to vote for the alternative with the same label (A for A and B for B).

3The experiments were programmed and conducted in z-Tree (Fischbacher, 2007).
4We utilized ORSEE for the recruitment of participants (Greiner, 2004).
Table 2: Payoff depending on the vote result

<table>
<thead>
<tr>
<th></th>
<th>Gruppe A</th>
<th>Gruppe B</th>
</tr>
</thead>
<tbody>
<tr>
<td>A wins</td>
<td>1 Euro</td>
<td>0 Euro</td>
</tr>
<tr>
<td>B wins</td>
<td>0 Euro</td>
<td>1 Euro</td>
</tr>
</tbody>
</table>

In each period, after the decisions and before the announcement of the result, subjects are also asked to estimate the likelihood of the result using a 11 point scale. The leftmost point on this scale corresponds to a certain victory of A and the rightmost point a certain victory of B. The mid-point of the scale represents an equal likelihood of victory of both alternatives. In the following analysis, we interpret this expected result as an approximation of aspirations.

After 30 voting periods, participants are asked to fill a questionnaire. After that, participants received their payoff which is the sum of the payoffs of 10 randomly selected periods. On average, a session lasted about 45 minutes and average payment was 7.96 Euro.
4  Experiment results

4.1  Aggregate and individual level results

We begin our data analysis by inspecting aggregate-level results. Figure 5 presents each session's development of turnout over the periods. We observe at least two important findings: First, there are no clear differences in turnout between the high-cost (solid lines) and low-cost (dashed lines) treatment. Second, in general, turnout has a decreasing trend over the periods, even if this does not hold for all sessions. Both findings are also confirmed by Table 3, which compares turnout in each treatment. Accordingly, there are no significant differences ($\alpha = 5\%$) between the two treatments. This is also the case when we compare both treatments in the first, second and third set of ten periods separately.

Figure 5: Turnout for each session-period

<table>
<thead>
<tr>
<th></th>
<th>High cost</th>
<th>Low cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Session: 51%</td>
<td>Session: 53%</td>
</tr>
<tr>
<td>2</td>
<td>Session: 47%</td>
<td>Session: 49%</td>
</tr>
<tr>
<td>3</td>
<td>Session: 42%</td>
<td>Session: 49%</td>
</tr>
<tr>
<td>4</td>
<td>Session: 42%</td>
<td>Session: 49%</td>
</tr>
<tr>
<td>5</td>
<td>Session: 42%</td>
<td>Session: 49%</td>
</tr>
<tr>
<td>6</td>
<td>Session: 42%</td>
<td>Session: 49%</td>
</tr>
</tbody>
</table>

Table 3: Average turnout of each treatment

<table>
<thead>
<tr>
<th></th>
<th>high cost</th>
<th>low cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c = 0.30$</td>
<td>$c = 0.18$</td>
<td></td>
</tr>
<tr>
<td>overall</td>
<td>46.8%</td>
<td>48.4%</td>
</tr>
<tr>
<td>1-10</td>
<td>51.7%</td>
<td>53.0%</td>
</tr>
<tr>
<td>11-20</td>
<td>46.7%</td>
<td>47.3%</td>
</tr>
<tr>
<td>21-30</td>
<td>42.2%</td>
<td>45.0%</td>
</tr>
</tbody>
</table>
Comparing this result with the predictions in Table 1, we conclude that the expected utility model shows the least congruence with the data with regard to the predicted substantive differences between the two treatments as well as the predicted level of turnout. In contrast, these aggregate-level results do not allow us to rank the fit of the two aspiration-based models, since the level of turnout depends on the periods under study. In the first ten periods, the data seem to be right between the predictions of BDT and Fowler. In the second ten periods, the Fowler model seems to fit the data best. In the last ten periods, however, the level of turnout further decreases.

As discussed above, the aggregate-level result is only a limited indicator to differentiate between the BDT and Fowler model. The difference between the two should be more remarkable at the individual level. More specifically, the simulated data suggested that the BDT-model produces a unimodal distribution of individual turnout rates over the periods around 50%, while the Fowler-model realizes a bimodal distribution with habitual voters and abstainers. Figure 6 displays the corresponding results for each session separately. Most results seem to correspond more to the BDT model since they have a mode near 50% which means there are many casual voters. The exception is Session 5, whose distribution has no clear mode and rather resembles an uniform distribution.

In the aggregate-level analysis, we observe a slightly decreasing trend over the periods. This suggests to observe the results separately for sequences of ten periods. Figure 7 shows the developments of the distribution over the time. In the first ten periods (the second row), there is a more or less unimodal distribution with a mode near 50%, which corresponds more to BDT. In the second ten periods, the number of the habitual abstainers begins to grow and it becomes a mode in the last ten periods. This can be interpreted more in favor of the Fowler model. We also have to note, however, that our simulation results based on the Fowler model predicted a clearer bimodal distribution while our experimental data miss frequent habitual voters.

Figure 8 presents the development of the vote margin in individual sessions. The figure shows that the vote results in later periods tend to be one-sided in multiple sessions. This might hint at the reason why we observe a decreasing trend of the turnout rate and an increasing number of habitual abstainers. From the simulation results above, we know that bimodality is correlated with the vote margin. This seems to be replicated in the experimental data, at least on the side of abstainers. That is, participants in the losing group keep very low aspiration levels and thus continue to have a higher expected payoff than their aspiration level by abstaining. Interestingly, the analogous scenario for the participants in the winning group does not seem to work.
Figure 6: Distribution of individual turnout rate in each session

- **c=0.18**
  - Session 2
  - Session 4
  - Session 6

- **c=0.30**
  - Session 1
  - Session 3
  - Session 5
Figure 7: Distribution of individual turnout rate in different periods

c=.18: Period 1–10

c=.30: Period 1–10

c=.18: Period 11–20

c=.30: Period 11–20

c=.18: Period 21–30

c=.30: Period 21–30
Figure 8: Development of vote margin in each session

- Session 1: 53%
- Session 2: 51%
- Session 3: 47%
- Session 4: 43%
- Session 5: 42%
- Session 6: 49%

The graphs show the margin of votes over periods for different sessions, with varying vote percentages for each session.
4.2 A Bayesian full probability model based on the BDT- and Fowler-Model

As the analysis above has shown, differences between the BDT and Fowler models are minor at the aggregate level. Therefore, we shift our focus to individual choice processes. We measure the fit of both models to our data by estimating the parameters of the corresponding feedback mechanisms. Both models have, as described above, three types of input information (propensity, aspiration and payoffs) and one type of output information (vote choice). With corresponding experimental data we can estimate the model parameters, predict individual choices, and evaluate the fit of the models to the data. Out of the four variables, we have direct measures of two: payoffs and vote choice. In contrast, we have no direct measures of propensity and aspiration. For aspiration, however, we have measured an expectation of vote results using an 11 point scale (see above). Based on this information, we can devise an indicator of expected payoff:

\[
\hat{\pi}_{i,t} = e_{it} \times (1 - c_{it})
\]

(3)

where \(c_{it}\) equals 0.30 (High cost) and 0.18 (Low cost) if the subject voted. Otherwise \(c_{it} = 0\). We thus assume expected payoff is driven by aspiration. To test this assumption we estimate the following model:

\[
\hat{\pi}_{i,t} = \beta_0 + \beta_1 \hat{\pi}_{i,t-1} + \beta_2 \pi_{it} - 1
\]

(4)

This corresponds to the updating mechanism of aspiration which both BDT and Fowler assume. Since expected payoff can have certain elements of idiosyncracy, we also estimate random intercept (Model 2) and random slope models (Model 3). The estimation results in Table 4 show that both expected and realized payoff in the previous period have a positive impact on current expected payoff. This corresponds to the mechanism assumed by BDT and Fowler and can be interpreted as evidence in favor of our measure. Further, expected payoffs at \(t\) are more strongly affected by expected payoffs at \(t - 1\) than by payoffs at \(t - 1\). This indicates that the parameter choice of BDT, Fowler and our simulation (\(\lambda = 0.95\)) is not far from the laboratory results.

<table>
<thead>
<tr>
<th>Model</th>
<th>Estimate</th>
<th>SE</th>
<th>Estimate</th>
<th>SE</th>
<th>Estimate</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.106</td>
<td>0.009</td>
<td>0.292</td>
<td>0.013</td>
<td>0.256</td>
<td>0.016</td>
</tr>
<tr>
<td>(\hat{\pi}_{i,t-1})</td>
<td>0.495</td>
<td>0.015</td>
<td>0.277</td>
<td>0.016</td>
<td>0.262</td>
<td>0.025</td>
</tr>
<tr>
<td>(\pi_{it})</td>
<td>0.078</td>
<td>0.008</td>
<td>0.079</td>
<td>0.008</td>
<td>0.085</td>
<td>0.013</td>
</tr>
<tr>
<td>Variance</td>
<td>Std.Dev.</td>
<td>Variance</td>
<td>Std.Dev.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(random intercept for (i))</td>
<td>0.012</td>
<td>0.107</td>
<td>0.019</td>
<td>0.130</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(random (\beta_1) for (i))</td>
<td>0.038</td>
<td>0.195</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(random (\beta_2) for (i))</td>
<td>0.013</td>
<td>0.112</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residuals</td>
<td>0.046</td>
<td>0.213</td>
<td>0.041</td>
<td>0.202</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

After clarifying the associations between payoff, vote choice, and aspiration, the issue remains how to integrate propensity. To solve this problem, we set
up a Bayesian full probability model in which propensity and aspiration are integrated as latent variables:

\[ V_{i,t} \sim BR(p_{i,t}) \]  
\[ \hat{\pi}_{i,t} \sim N(a_{i,t}, \sigma^2) \]  
\[ p_{i,t} = \tau f_{BDT}(p_{i,t}, \alpha, a_{i,t}, \pi_{i,t}) + (1 - \tau) f_{Fowler}(p_{i,t}, \alpha, a_{i,t}, \pi_{i,t}) \]  
\[ a_{i,t} = \lambda a_{i,t-1} + (1 - \lambda) \pi_{i,t-1} \]  
\[ \alpha \sim Unif(0,1) \]  
\[ \tau \sim Unif(0,1) \]  
\[ \lambda \sim Unif(0,1) \]  
\[ p_{i,1} \sim Unif(0,1) \]  
\[ a_{i,1} \sim N(0,1000) \]

The first two equations define vote choice and expected payoffs as probabilistic processes. Voting behavior is modeled as bernoulli trials with vote propensities as probabilities of success (Equation 5). In contrast, expected payoff is assumed to be distributed normal with aspiration as expected value (Equation 6). Both parameters, propensities and aspirations, are updated using their past values, past behavior, and past payoffs as the BDT and Fowler models assume (Equations 7 and 8). For these updating processes, we estimate three parameters, the magnitude of propensity update (\( \alpha \)), the weight of the BDT model (\( \tau \)) and aspiration inertia (\( \lambda \)). For these three parameters, we set flat priors between 0 and 1. Furthermore, we also set uninformative priors for the propensity and aspiration in the first period (Equations 12 and 13).

The posterior information of the parameters are obtained using Markov-Chain-Monte-Carlo techniques. The corresponding Markov-Chains were run separately for individual subjects for three sets of 10 period for several reasons. First, the adaptive process is individual-specific and there is no plausible reason to assume a common parameter value for all subjects. Second, the macro-level analysis showed some difference in the first, second and third ten periods. Thus, its parameters changed their values in the course of the experimental sessions. The third reason is a more practical one: Estimation of the model above is highly computation-intensive and it is not feasible to run the Markov-Chain for multiple individuals for all 30 periods.

As an example, Figure 9 shows the result for the 73rd subject in the first ten periods. The left panel shows the posterior distribution of propensity and the subsequent propensity change. The individual points are posterior means for each period. For example, this subject voted in the first period (see the upper right panel) and her payoff was higher than her aspiration (see the lower right panel). Therefore, she increased her voting propensity so that we can see the first point above 0. The further points can be interpreted analogously. The dotted line in the left panel is the estimated propensity update which is based
on the weighted average of the BDT and Fowler models. In the example, the weight of the BDT model is 0.60. Correspondingly, there is a dynamic toward the mid-level propensities, although it is less strong than in the pure BDT-model. This can also be found in the gray zone in the left panel which shows the density of posterior distributions.

In the next step, we compare the posterior distributions of different parameters between cost-treatments and different periods. First, we observe the posterior distribution of propensities in Figure 10. The right panel presents the posterior distributions in different periods under the low-cost treatments and the left panel under the high cost treatments. The posterior distributions in the first and second ten periods have a distribution with a mode around 50%. This corresponds more to the BDT-Model which drives the propensities toward the mid-level. This tendency becomes, however, weaker in the last ten periods whose posterior distributions have larger dispersions. In particular, the posterior distribution under the high-cost treatment has a local maximum near zero which indicates the existence of habitual nonvoters. These results imply that the BDT-model explains more in the first 20 periods while the Fowler model might have more explanatory power in the last ten periods. We can more directly observe the explanatory power of the two models by observing the posterior distribution of $\tau$ which corresponds to the weight of the BDT-model.

According to Figure 11, the weight of the BDT model can be distributed quite widely between 0.1 and 0.9 over all periods under both treatments. However, the higher weight for the BDT-model in comparison with the Fowler model
tends to have higher probability and the mode of the posterior distributions is around 0.9. This indicates that voters update their propensities in a mixed form of the BDT and Fowler model whereby the weight of the BDT tends to exceed that of the Fowler model. More concretely, the mixed updating mechanism has a certain feedback tendency toward the mid level, although its intensity is less strong than the BDT model assumes. This seems to be the reason for the tendency of propensities and individual turnout rate to approach the mid-level with some dispersion.

We are still confronted with a puzzle about the cause of the larger number of habitual nonvoters in the last ten periods. According to this analysis, this does not seem to be due to the increasing impact of the Fowler model. Figure 11 shows no clear difference in the posterior distribution of $\tau$ between periods. One possible alternative cause is an increase in $\alpha$. As Figure 12 shows, the posterior distributions in the last ten periods have higher probabilities for larger values of $\alpha$. This indicates that the magnitude of propensity update increased in the last ten periods. This can reduce the tendency toward the mid-level propensity. To make this point clear, we come back to Figure 1 which visualizes both propensity update mechanisms. An increase of $\alpha$ in the BDT model means that the lines for reinforcement and inhibition are more distant from the horizontal line corresponding to no propensity change. If a subject with a lower propensity to vote votes in a specific period and becomes disappointed, then she will reduce her voting propensity by a larger margin in the case of a larger $\alpha$. In contrast, the same person would reduce her vote propensity less dramatically under a smaller $\alpha$. This can be a cause of a larger number of habitual nonvoters in the last ten periods. However, we also have to note that the cause of the increasing $\alpha$ in the last periods still remains unknown.
Figure 11: An example result

c=0.18
Fowler ← τ → BDT
Density

Per.1−10
Per.11−20
Per.21−30

Fowler ← τ → BDT
Density

Per.1−10
Per.11−20
Per.21−30

Figure 12: An example result

c=0.3
α
Density

Per.1−10
Per.11−20
Per.21−30

α
Density
5 Conclusion

This paper’s aim is to provide more direct empirical evidence for two competing adaptive behavioral models of turnout. Both models differ only in their feedback mechanisms which, however, leads to an interesting implication at the macro level. The BDT model generates more casual voters and the Fowler model more habitual voters and abstainers. Our empirical data from the lab experiments which allow us to test the feedback mechanisms more directly suggest that the BDT model with moderating feedback toward the mid-level of propensities tends to more closely fit our data. More specifically, we found that the experimental subjects uses some sort of mixed propensity update mechanism including a feedback mechanism of the style assumed by BDT. In the last ten periods, however, we found that the magnitude of propensity updating increased, resulting in the existence of a larger number of habitual non-voters.

In view of these results there still remains one puzzle to be solved. Fowler (2006) showed that the respondents of the South Bend Study are mostly habitual voters or abstainers. How can we explain the discrepancy between his and our results? One might attribute our results in favor of the BDT model to our laboratory setting. Actually, we avoided to use terms like “election”, “candidate”, “party”, etc. Instead, our experimental subjects decided whether to participate in a poll between two “alternatives”. According to this line of argument, our results in favor of the BDT model with casual voters may be due to the absence of a voting norm. In the “real world”, voting is considered a citizen duty, an incentive to vote which is absent in our laboratory setting. But this would also mean that the habitual voters of the South Bend Study would be the result of a voting norm instead of the Fowler model.

Even if this interpretation holds value, the assumption of a voting norm cannot explain the habitual abstainers. Another possible explanation might be a higher value of $\alpha$. The citizens in South Bend might have a larger magnitude of propensity updating. However, there is neither empirical evidence for a higher value of $\alpha$ nor a plausible reason why people in South Bend should have a larger $\alpha$. There is a further explanation: We might attribute the habitual voters and abstainers to the specific context of South Bend where the one-sided results characterized in particular the House of Representative race at that time. In the period during which the South-Bend-Study collected the actual voting data (1976-1984), Indiana’s 2nd congressional district was won by the Democrats without exception. This Democrats’ dominance in the district lasts from 1975 to 1995. As we have observed in our simulation results, the habitual voters and abstainers are more directly generated by a one-sided results which often occur in the Fowler model, but also sometimes in the BDT model.
References


