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ORIGINAL PAPER

# Learning to accept welfare-enhancing policies: an experimental investigation of congestion pricing

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**Abstract**

Welfare-enhancing policies such as congestion pricing are argued to improve efficiency in situations with externalities. Unfamiliarity and lack of any personal experience with such policies, however, can hinder their implementation; particularly the ex-ante uncertainties of incidences of gains and losses as well as debates regarding equity concerns and how to recycle revenues often stymies implementation. This paper employs a laboratory experiment with heterogeneous users to investigate the effectiveness and acceptability of a toll in a six-player-two-route congestion game. To measure acceptability and how it is affected by experience with the toll, we conduct referenda before, during, and after subjects experience a congestion problem and a toll. The experiment employs a $2 \times 2$ design that varies two treatments: the rate of revenue reallocation and the level of information before the final vote. After an experiential learning phase, congestion pricing is found to curb congestion effectively, and although some subjects do not vote in their monetary self-interest initially, the majority does so after experiencing the congestion pricing policy. Data on worldviews and beliefs are collected and matched to voting behavior to examine the evolution of how experience determines acceptability. Some worldviews and beliefs can predict voting behavior and the timing of when an individual finds a toll (un) acceptable.

**Keywords** Acceptability · Congestion pricing · Policy trial · Lab experiment · Revenue recycling · Voting behavior

**JEL Classification** C92 · R48 · D91

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## 1 Introduction

Many problems surrounding externalities, such as excessive pollution, overfishing or traffic congestion, have relatively straightforward remedies that most economists embrace—price the externality-generating activity and people will change their behavior accordingly. Often, however, the public does not support policies based on these remedies as much as economists would predict (or like), even when these policies seem to be in the public's interest. As a consequence, local and national governments have struggled to implement welfare-improving policies and wonder what determines the acceptability of them. This paper investigates how the effectiveness and personal experience of a policy trial as well as individuals' worldviews and beliefs influence the acceptability of a welfare-enhancing policy in a laboratory experiment.

While the problem of lack of acceptability applies to many incentive-based policies, from carbon pricing (e.g., Carattini et al. 2018) to economic instruments for agricultural groundwater use (e.g., Figureau et al. 2015), we focus here on the acceptability of congestion pricing. Traffic congestion and its impacts have been a growing problem in most urban centers around the world. In the United States, for example, 8.8 billion hours were lost in 2017 from the additional travel time due to congestion and 3.3 billion gallons of fuel were wasted, according to the 2019 Urban Mobility Report (Schrank et al. 2019). By optimizing road use and making people pay the true social cost of their traveling, congestion pricing is argued to be an efficient tool to tackle the congestion problem and lessen its societal costs. Moreover, most academic economists agree that revenue-neutral congestion charges "would make citizens on average better off."[1] Theoretical models demonstrating the potential impact of congestion pricing on efficient road use date back to Pigou (1920), and since then the welfare impacts and incidence of pricing policies have been studied extensively (Small and Verhoef 2007).[2]

While congestion pricing works in theory, there have been relatively few applications (Mahendra et al. 2012; Hall 2018). Urban congestion pricing has been successfully implemented and accepted in Stockholm, London, Singapore, Rome, and Milan (Börjesson et al. 2012), and as of 2019 is planned for Manhattan to start in 2021,[3] but implementation has failed in places such as Hong Kong, Edinburgh, Manchester, San Francisco, and previously in Manhattan (Ison and Rye 2005; Anas

[1] Congestion Pricing. January 11, 2012. The Initiative on Global Markets. Chicago Booth School of Business. http://www.igmchicago.org/surveys/congestion-pricing. Accessed January 29, 2019.

[2] However, Pigou (1937) already recognized that the practical difficulty of determining the correct tax or congestion price would be "extraordinarily great. The data necessary for scientific decision are almost wholly lacking" (p. 42). Note also the debate between Pigou and Knight (see Knight 1924), as summarized and clarified in Salant and Seegert (2018), about whether the government or the private sector should set a toll. Salant and Seegert (2018) show theoretically that Pigou's claim that government, not private toll-setters, can always achieve efficiency by imposing road-specific tolls is correct.

[3] Laurel Wamsley, "New York Is Set To Be First U.S. City To Impose Congestion Pricing," NPR, National Public Radio, Inc, April 2, 2019, https://www.npr.org/2019/04/02/709243878/new-york-is-set-to-be-first-u-s-city-to-impose-congestion-pricing (accessed June 2, 2019).

and Lindsey 2011).[4] The congestion pricing literature argues that the lack of public acceptability prevails as the main barrier to implementation.

Two related factors seem to play a major role in undermining acceptability of congestion pricing and other incentive-based policies: First, while overall society gains from these policies, some segments of society might actually lose; based on a basic theoretical model and empirical studies, Fullerton (2011) provides an overview of who gains and loses from the introduction of an incentive-based policy (carbon pricing in his case) that results in a potential Pareto improvement overall. Second, even if all segments of society might gain from a policy, some groups might gain more than others, which could appeal to fairness considerations. For example, Light (2009) argues theoretically that congestion pricing helps those with high and low values of time more than those with intermediate values.

Another factor impacting acceptability of a policy is the uncertainty about the effects a proposed policy will have. Fernandez and Rodrik (1991) and De Borger and Proost (2012) explain that the reluctance to implementing efficiency-improving policies that are advocated by economists may stem from a bias toward the status quo stemming from individuals' uncertainties of the policy's impacts. De Borger and Proost (2012) provide a model on how the presence of uncertainty is responsible for the evolution of public attitudes in places where congestion pricing was introduced like Stockholm and London. Using a simple majority voting model that employs two types of uncertainty (the idiosyncratic individual uncertainty about the exact cost of car use and the political uncertainty on the use of collected revenues), they demonstrate that because of individual uncertainty, a majority of drivers that are ex ante against road pricing may ex post be in favor after a policy trial removes individual uncertainty. This ex post majority favorability would suggest that policymakers might want to consider experimental trials against the political will of the majority of their constituents.

But how individuals inform their beliefs and attitudes when assessing these two types of uncertainties may go beyond self-interest and fairness motives (even after a policy trial when uncertainty is removed). Peoples' worldviews and beliefs, as well as psychological responses towards the introduction of congestion pricing, may also explain acceptability or the lack thereof (Schade and Baum 2007), and in the absence of more specific information on the specific costs and benefits of a proposed policy they may choose to rely on easily available heuristics. The cultural cognition thesis is particularly appropriate for our setting: The individualism-communitarianism dimension differentiates people with "attitudes toward social orderings that expect individuals to secure their own well-being without assistance or interference from society" from "those that assign society the obligation to secure collective welfare and the power to override competing individual interests" (Kahan et al. 2011) with clear implications for general attitudes towards Pigouvian taxation. The hierarchy-egalitarianism dimension holds equally clear implications for attitudes towards policies with (in-)equitable implications for payoffs. Cherry et al. (2017) find a consistent and strong impact of worldviews on support for efficiency-enhancing

[4] See Gu et al. (2018) for an overview of congestion pricing schemes.

policies: "people with different worldviews exhibit substantially different levels of policy aversion—by more than 25% points in some cases."

To examine effectiveness and acceptability of congestion pricing, we pose three research questions: (1) Does congestion pricing work even with heterogeneity of users and potential losers from a toll? (2) Does experience and the resulting removal of the policy's uncertainties from a policy trial influence acceptability? And (3) Do individual attributes impact the acceptability of tolls and does this acceptability evolve when an individual becomes accustomed to the problem and policy?

We address these questions using a laboratory experiment. Understanding why congestion pricing was accepted in some places but not in others by observing both the performance and acceptability of congestion pricing at an individual level in the real world would be ideal. But such data collection would be too costly and almost impossible to implement. Alternatively, we turn to experimental economics. Falk and Heckman (2009) argue that laboratory experiments complement other empirical methods and data sources in the social sciences. Laboratory experiments allow for a low financial and political cost alternative. They provide a controlled environment in which researchers can test competing theories or evaluate the impacts of alternative policies on participant behavior.

Previous laboratory experiments in the transportation economics literature have examined travel decisions (e.g., departure time, route choice, or mode choice) and how congestion pricing, information disclosure, and a new link in a transportation system affect user travel behavior.[5] To our knowledge, however, no previous laboratory congestion experiments incorporate voting or measures of public acceptability. The most relevant laboratory congestion experiments on congestion pricing use two-route networks to investigate the Pigou-Knight-Downs paradox, which states that improvements in a road network might not improve traffic congestion. Anderson et al. (2008) and Hartman (2012) investigate the effects of an efficient toll and information disclosure of past entrants and do find similar results regarding the effect of information and that the toll has its intended effects. Hartman (2006, 2007) also examines travel behavior when individuals have either *real* or assigned heterogeneous time preferences; Hartman (2007) compares the outcomes from the same toll when heterogeneous users have different assigned value-of-time distributions (no, low, or high heterogeneity). However, the outcomes were not compared to the behavior of the same assigned heterogeneous individuals for when no toll existed in the network. Our experiment is the first to compare route-choice behavior with and without a toll of heterogeneous individuals with assigned values of time.

Recent experimental papers on public acceptability of Pigouvian policies have examined factors that contribute to the (un)acceptability of Pigouvian policies. Cherry et al. (2014) find that experience of a trial run of a Pigouvian tax increases the acceptability of the tax and that the positive experience can overcome

[5] For example, Seale et al. (2005), Hartman (2007), Ziegelmeyer et al. (2008), Selten et al. (2007), Anderson et al. (2008), Denant-Boemont and Hammiche (2009), Morgan et al. (2009), Hartman (2012), Dechenaux et al. (2014), Rey et al. (2016), Wijayaratna et al. (2017). Dixit et al. (2017) reviews field and lab experiments in transportation research.

misperception and biases.[6] Kallbekken et al. (2011) observe that a lack of understanding of the workings and effects of a Pigouvian tax instrument does not influence the opposition of such policies. The authors also find an aversion to Pigouvian taxes: a substantial subset of subjects oppose taxes that can increase individual and social welfare. By challenging the behavioral notion that people act solely on their monetary self-interest, this result reveals a barrier in implementing potentially efficient policies. Cherry et al. (2017) observe a strong correlation between individuals' worldviews based on Kahan's cultural cognition framework and their acceptance of different Pigouvian instruments. While in their paper all participants are materially equally impacted by the implementation of a policy, our research contributes by examining personal attributes that may affect acceptability as well as have a context where a policy either creates all 'winners' or both 'winners' and 'losers' with unequal outcomes. Worldviews might play a different role in our case, if people feel differently about government policies with distributional effects (this paper) or without distributional effects (Cherry et al. 2017).[7]

Our experiment employs a congestion game, in which individuals with heterogeneous "time preferences," induced by the experimenters, choose between two routes. One route is shorter but congestible, and the other route has a longer but constant travel time. Subjects vote three times—before they experience the game, after they experience it without tolls and again after they experience it with tolls—on whether the last stage of the experiment should have a toll. This novel design allows us to address the two main research questions 2 and 3 above: The votes provide a measure of the evolution of the acceptability of the toll by first obtaining an initial preference of tolls given exogenous characteristics (including individual cultural worldviews that are elicited in a post-experiment survey), and then any changes in attitudes from being accustomed to the congestion problem and the congestion pricing policy.

To test additionally whether the answers to the two main research questions are sensitive to inequality and efficiency concerns and to information about relative positions, we vary two factors between different groups of subjects in a $2 \times 2$ design: (a) toll revenues are either recycled 100% (which makes every subject better off with the introduction of the toll, albeit at different levels) or 40% (which makes only some subjects better off with the toll, even though overall the sum of individual payoffs increases in equilibrium), and (b) after the policy trial subjects either know only how much the policy affected their costs in absolute and percentage terms or they additionally know their group-ranked position by viewing how much the policy affected the costs of the other group members.

We find that, as expected, without a toll the congestible route is overused. Once a congestion toll is implemented it initially does not work well, but after a few

[6] This finding is consistent with survey responses reported in Swanson and Hampton (2013) who observed that focus group participants changed their attitudes towards congestion pricing significantly after receiving information on congestion problems, the purpose of congestion pricing and the states of transportation funding.

[7] Because of the distributional effects, it would be interesting to explore the role of social preferences, but herein the interest was motivated by the literature considering behavioral influences of cultural worldviews.

periods the toll leads to improved coordination and higher efficiency—not only does the number of commuters converge to the efficient level but subjects also sort efficiently; the subjects with high values of time take the shorter, congestible route and pay the toll, while the subjects with a low value of time take the longer, free route but receive parts of the toll revenues. Approval of the toll is at its highest level, particularly among subjects that gain from the toll, when subjects have experienced the congestion problem and the toll. Interestingly, in the last vote monetary earnings have a stronger effect on votes than worldviews. Our findings offer two main contributions to the behavioral literature. First, we introduce an experimental design for voting experiments that controls for experience across multiple rounds of voting. Second, we provide evidence on the behavioral influences of cultural worldviews in voting experiments with heterogeneity in payoffs and equilibrium outcomes.

The following sections provide an explanation of the theoretical two-route congestion model used in the experiment (Sect. 2) and the design of the experiment (Sect. 3). Section 4 discusses the empirical results, and the paper concludes with Sect. 5.

## 2 Theoretical set-up

We employ a two-route congestion model where six agents have the option of taking one of two routes (A or B) to get them to their destination (similar models have been developed by, for example, Anderson et al. 2008).[8] The total cost incurred by each individual to reach their destination is a function of the amount of time spent en route and their value of time. Table 1 presents the possible travel time outcomes: Total travel time for Route B is always equal to 12 min, while total time traveling on the congestible Route A is a function of the number of users who take Route A, and it varies from 5 min if only one person uses Route A to 10 min if all six do. With 10 smaller than 12, no user has an incentive to enter Route B without a toll, and there is no coordination problem about who should take Route A in equilibrium.

The per-minute cost of time varies across individuals. The six individuals are split into users with high values of time (12, 11, and 10 "tokens" per minute, with tokens as the monetary unit used in the experiment) and users with low values of time (4, 3, and 2 tokens per minute). Figure 1 illustrates the two-route problem by showing the monetized marginal time savings and marginal external costs for each Route A entrant for heterogeneous users with values of times from 12 to 2 in descending order.[9] Note the time externality—equal to the marginal social cost since there

[8] The general-form model is presented in the electronic supplementary material; here we present the specific numerical form that we use in the experiment.

[9] To interpret the curves, consider as illustration two individuals, the users with the second-highest and fifth-highest values of time: if the user with time value 11 enters Route A as the second person (after the person with time value 12), she will save herself 6 min by doing so, which translates into a marginal private benefit of $11 \times 6 = 66$ tokens. But she also increases person 1's travel time by 1 min and travel cost by 12 tokens, the external cost. If the user with time value 3 enters as the fifth person, he will save himself 3 min for a marginal private benefit of nine tokens, but his presence on Route A instead of B costs now the other four users of Route A 4 min and $12 + 11 + 10 + 4 = 37$ tokens.

are no marginal private costs—increases for each additional user entering Route A. Users are assumed not to internalize this externality. Therefore all six users will use Route A since they will gain positive marginal private benefits by decreasing their travel times compared to taking Route B. To incentivize users in the system to make socially optimal decisions, a toll should satisfy $50 \geq toll > 16$, ignoring any cost adjustments users may make from revenue redistribution.[10]

Consider the intuition for the possible travel outcomes detailed in Table 1. Without a toll, Route B is always inferior to Route A for each individual, so all six users will use Route A creating a total travel time of 10 min for each user, or 60 total minutes—the Nash equilibrium for the game without tolls (usually referred to as the "user equilibrium" in the transportation literature). If the objective were to minimize total travel time, then the theoretical social optimum would be that four people use Route A and two use Route B ($4 \times 8 + 2 \times 12 = 56$ total minutes). However, with the experiment's given values of time for the six participants, the travel-cost-minimizing level, or social optimum, calls for the three high-value users to use Route A and the three low-value users to use Route B. The predicted user equilibrium results in a total social travel time cost of 420 tokens, while the cost at the social optimum, where travel costs are minimized, is 339 tokens (57 total minutes), a 19.3% improvement.

In this two-route network with heterogeneous users, an efficient toll reduces total group costs but makes some users worse off if revenues are not redistributed. The level of the toll and type of revenue redistribution can compensate some or all of the low-value-of-time users' losses from taking the longer route, Route B, with a higher level of redistribution making more commuters better off. As described in the next section, we chose a 21-token toll and manipulated the level of lump-sum redistribution (100% or 40%) to obtain the desired welfare effects for addressing the objectives of this study. Note that even without any revenue redistribution, the travel cost savings from the three highest-value users paying the 21-token toll exceed the increased travel costs by the low-value-of-time Route B users (even when the toll is subtracted) resulting in a socially superior outcome than the user equilibrium without a toll (402 versus 420 tokens).

In summary, the basic numerical design resembles a real-world congestion situation: Each agent making individually optimal route choices results in a socially suboptimal level of congestion, the hallmark of a Prisoner's Dilemma. Not all individuals are better off at the social optimum; but since the social optimum is a "potential Pareto improvement" over the laissez-faire situation without government interventions, policies with redistribution schemes exist that can incentivize each individual to act socially optimally *and* to be better off. In the next section about the experimental design, we will present the timeline of the decisions and present details on how the policy is supposed to work.

[10] See Hartman (2012) for a theoretical derivation of marginal external costs in a similar framework.

**Table 1** Possible travel time outcomes

| Number of people using Route A | Total travel time (in minutes) | |
|---|---|---|
| | Route A | Route B |
| 1 | 5 | 12 |
| 2 | 6 | 12 |
| 3 | 7 | 12 |
| 4 | 8 | 12 |
| 5 | 9 | 12 |
| 6 | 10 | 12 |

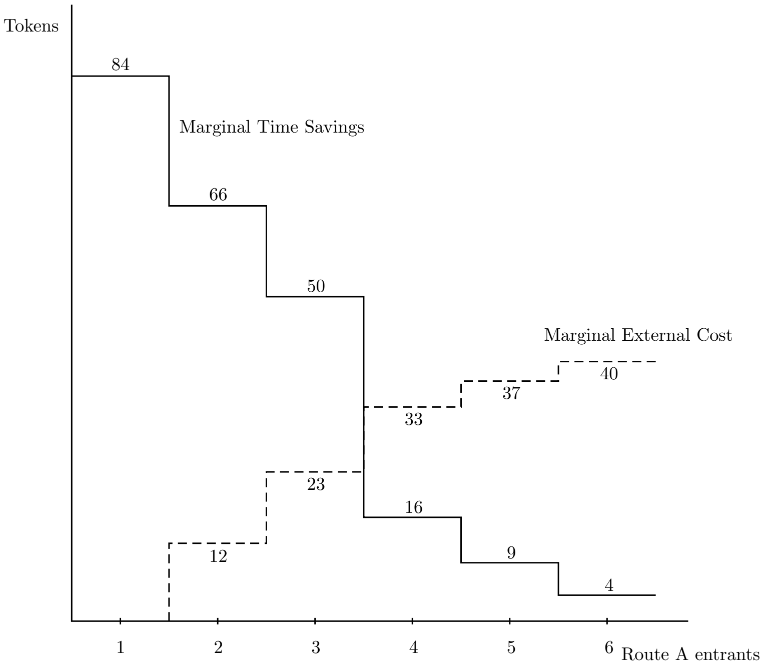


**Fig. 1** Graphical representation of marginal time savings and marginal external costs for Route A entrants

## 3 Experimental design

To answer the three research questions, we designed an environment in which we can examine both route-choice decisions and voting behavior. Subjects are assigned to groups of six for the entire experiment, and each subject makes a total of 33 decisions—30 route choices and 3 votes. Table 2 summarizes the timeline of the experiment. Subjects participate in three ten-period stages in which they make route-choice decisions. Stage 1 does not have a toll, while a 21-token toll exists in each period of Stage 2 for those users using Route A. It is up to the group of six to determine whether there will be a toll in the periods of Stage 3. Before the final vote, subjects receive feedback that compares their cost performance between Stage 1 and Stage 2. At the end of the experiment, one of the three stages is randomly chosen to determine the subjects' monetary payoffs.

Consider first the differences between having a toll or not having a toll. Table 3 reports values of time, endowments,[11] theoretically predicted costs and net earnings without the toll and the welfare effects of the toll by individual values of time and redistribution rates (100% or 40% of the toll revenues are paid back lump-sum to the group members). Welfare impacts, in parentheses, are the differences in costs and net earnings when comparing the Nash equilibria with and without the 21-token toll. Note that without a toll, equilibrium earnings are the same for all individuals. Note also that welfare impacts of the toll are non-linear, which is consistent with previous literature. For example, within a two-route model, Light (2009) shows that those who are indifferent or near indifferent between the priced and the free route are among those that will be made worse off from a toll; the potentially better off groups are those with values of time at the high and low ends of the value-of-time distribution. That is, individuals with the highest values of time have the most to gain from the faster speeds on the toll route while those with the lowest values of time that take the slower route are less harmed by the toll and can be potentially made better off after any revenue recycling.

Table 3 suggests that self-interested individuals should always vote for the toll when there is 100% redistribution since everyone gains in equilibrium (a Pareto improvement), while in treatments with 40% redistribution, the individuals with a value of 3 and 4 tokens per minute should always vote against the toll, even though the overall effect on the entire group is positive (a potential Pareto improvement).[12] The level of the toll and the redistribution rates were selected because of their specific welfare effects as seen in Table 3 and to observe how sensitive individuals are to them.

As seen in Table 2, participants are given a chance to vote three times to determine what happens in Stage 3. The vote elicits an individual's acceptability of a toll before experiencing the congestion problem, after experiencing the congestion problem, and finally after experiencing the toll. The first vote tries to gauge an individual's preference of a Pigouvian tax in the context of a transportation problem before experiencing the problem or its policy. The design after Stage 1 then closely follows the individual uncertainty modeled in Fernandez and Rodrik (1991) and De Borger and Proost (2012). It is also related to Stockholm's 2006 experience, where

[11] Endowments were privately provided to the subjects and not common knowledge, and the language in the experiment focuses on (adjusted) cost reductions rather than changes in earnings, since most of the real-world discussion of congestion pricing is about the reduction in costs (i.e., the increased time savings) and not on the increase in consumer surplus or earnings.

[12] Of course, the statement "should vote for the toll" assumes that voters recognize that they are better off in the new equilibrium even though the direct effect of the toll might seem to be negative. This is not a trivial assumption, as Dal Bó et al. (2017) observe in their voting experiment that "voters may systematically err when assessing potential changes in policy by underappreciating how new policies lead to new equilibrium behavior."

**Table 2** Summary of experiment

| Vote 1 | Stage 1 | Vote 2 | Stage 2 | *feedback* | Vote 3 | Stage 3 |
|---|---|---|---|---|---|---|
| | 10 Periods<br>*No Toll* | | 10 Periods<br>*Toll* | | | 10 Periods<br>*Toll or no toll* |

a referendum on congestion pricing was conducted after a six-month trial (Winslott-Hiselius et al. 2009; Börjesson et al. 2012); our design's second vote is the equivalent to the pre-trial polls, while our third vote resembles the after-trial referendum.

A group's voting outcomes are not revealed until after the third vote is cast. At that time, the experimenter has a volunteer roll a die to determine which of the three votes count for all groups in the session.[13] Each vote is potentially binding, which provides an incentive-compatible measure of how an individual feels about the toll. Since there are groups of six, a volunteer is asked to pull from a deck of cards to determine what the tiebreaker would be if any group in the session has a 3-to-3 tie for the chosen vote. The design mitigates any endogeneity concerns for how an individual performs in Stages 1 and 2. Stage 3 and its ten route-choice decisions exist primarily to make the votes consequential. The two main research questions 2 and 3 can be addressed by examining the three votes.

In addition, the experiment employs a 2 × 2 design, with two between-subject treatment variables that are being used to provide a sensitivity analysis for the results to the two main research questions (each of the four treatment conditions had 8 independent groups of 6 subjects, with a total of 192 subjects participating in the experiment). The first treatment variable varies the welfare impacts of the toll. There exist two settings: one where all participants are better off and are all "winners" with the toll (100% toll revenue redistribution) and another where only a fraction of the toll revenues are redistributed so all payoffs are uniformly scaled down, which results in having "winners" and "losers" of the toll (40% toll revenue redistribution).

The second treatment variable varies the level of information feedback subjects see after Stage 2 prior to the third vote (see Table 2). In all sessions, individuals receive feedback about their own average total costs of Stages 1 and 2 and the percentage change in costs between the two stages—but in one set of sessions subjects see additionally each group member's cost differences in a group-ranked table, so that they are able to compare the effect of the policy on themselves and on everybody else. The motivation for including this information treatment variable is to examine whether the main results would hold even when subjects could see that others had lower (or higher) cost changes. We know from a plethora of laboratory experiments that inequality aversion can impact individual behavior; in particular, Nishi et al. (2015) have found that making wealth (and wealth differences) visible abets the persistence of (experimentally induced) inequality.

[13] Similarly, a session's binding stage is also chosen randomly from among all three stages and after survey questions have been answered.

**Table 3** Predicted per-period individual welfare effects from the toll

| | | Effect on costs | | | | Effect on earnings | | | |
|---|---|---|---|---|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Value of time | Endowment[a] | Cost w/o toll | Cost w/ toll (No redist.) | Cost w/ toll (40% redist.) | Cost w/ toll (100% redist.) | Earnings w/o toll | Earnings w/ toll (No redist.) | Earnings w/ toll (40% redist.) | Earnings w/ toll (100% redist.) |
| 12 | 145 | 120 | 105 | 100.8 | 94.5 | 25 | 40 | 44.2 | 50.5 |
| | | | | (−16%) | (−21.3%) | | | (+76.8%) | (+102%) |
| 11 | 135 | 110 | 98 | 93.8 | 87.5 | 25 | 37 | 41.2 | 47.5 |
| | | | | (−14.7%) | (−20.5%) | | | (+64.8%) | (+90%) |
| 10 | 125 | 100 | 91 | 86.8 | 80.5 | 25 | 34 | 38.2 | 44.5 |
| | | | | (−13.2%) | (−19.5%) | | | (+52.8%) | (+78%) |
| 4 | 65 | 40 | 48 | 43.8 | 37.5 | 25 | 17 | 21.2 | 27.5 |
| | | | | (+9.5%) | (−6.3%) | | | (−15.2%) | (+10%) |
| 3 | 55 | 30 | 36 | 31.8 | 25.5 | 25 | 19 | 23.2 | 29.5 |
| | | | | (+6%) | (−15%) | | | (−7.2%) | (+18%) |
| 2 | 45 | 20 | 24 | 19.8 | 13.5 | 25 | 21 | 25.2 | 31.5 |
| | | | | (−1.0%) | (−32.5%) | | | (+0.8%) | (+26%) |
| Group Total | | 420 | 402 | 376.8 | 339 | 150 | 168 | 193.2 | 231 |
| | | | | (−10.3%) | (−19.3%) | | | (+28.8%) | (+54%) |

[a]Participants are unaware of the endowment values of other individuals in their group

The experiment was programmed and conducted with the software z-Tree (Fischbacher 2007). Subjects are given and read aloud the instructions that also include practice questions, which emphasize the possible outcomes of route-choice decisions and the congestion problem. We reduce the risk of anchoring by not having any question show a positive (or negative) individual welfare impact from the toll.[14] At the beginning of the experiment, individuals know their endowment, their value of time, and how their value of time compared to the values of other group members. Subjects also know that these values do not change throughout the entire experiment.

In each period of a stage, subjects are asked which route to take: Route A or Route B. Before each decision, subjects are provided the possible time outcomes listed in Table 1 as well as their private travel costs without toll, and, if applicable, the level of the toll and redistribution rate. After a decision is made, subjects receive feedback on which route they took, the number of Route A users, their travel time, and their travel costs for that period, and, in periods with a toll, the period's toll revenue generated, their share of toll revenue, and adjusted travel costs after redistribution. In each period, subjects have the option to see their history of previous route-choice decisions and number of Route A entrants.[15] Following the findings in Anderson et al. (2008) and Selten et al. (2007) that information feedback reduces variation around the equilibrium, we wanted to provide the best chance to create stable equilibria with and without a toll (i.e., generate similar experiences) so to allow comparable observations of individual attitudes toward a toll across all subject groups.

Subjects participate in three referendum votes, which elicit the acceptability of tolling before and after being accustomed to the congestion problem and the implementation of a toll. The first vote occurs after the instructions are read and subjects are given their endowed values. The congestion problem that occurs when an additional person uses Route A is objectively explained as well as shown in the instructions' practice problems. The instructions state that the toll is set at a level that "optimizes the use of Route A."[16] The redistribution rate is also stated in the instructions.

At the time of Vote 1 subjects know the level of the toll as well as their endowed values—their value of time and where their value of time ranks within their the group of six. They have all the information available to calculate how the toll will impact their earnings, but they have not experienced the actual problem nor the potential solution. Their votes at that point are based more on their general preferences about a toll. Subjects, however, have experienced the problem and the impact

[14] A copy of the instructions for the 100% revenue redistribution treatment is provided in the electronic supplementary material.

[15] See the electronic supplementary material for z-Tree screenshots of the referendum vote, the per-period feedback and history screens, and the information feedback treatment provided before the final vote. A screenshot of the route-choice decision environment can be found in the experiment instructions located in the electronic supplementary material.

[16] "Optimize traffic at free-flowing speeds" was language used for explaining the toll policy goals of California 91 Express Lanes in Orange County. The Orange County Transportation Authority, https://www.91expresslanes.com/toll-policies/. Accessed February 8, 2019.

of the policy at the time of Votes 2 and 3, respectively. Since the group's voting outcomes are not revealed until after the final vote, each vote discloses an individual's opinion independent of the favorability of the other group members. The experiment is designed to ensure that the voting decisions of other individuals have no influence on any individual's voting behavior.

## 4 Results

192 undergraduates from Colorado State University participated in the experiment, yielding 32 group observations in 30 periods and 6336 total individual experimental observations including 576 voting observations (192 for each of the three votes). A session lasted about 75 min, and the average compensation was $18.74 with a range of $11.75 to $30.25. One token in the experiment equals $0.06. Eight groups of six subjects participated in each of the four treatments. Each session consisted of at least two groups who stayed the same over the entire 30 periods ("partner" design), and subjects did not know which other session participants were in their group. The average age was 19.3 with 93 females (48%) participating. At the end of the experiment, all subjects answered a survey that elicited demographic information and beliefs on several dimensions.

### 4.1 Does congestion pricing work?

While the focus of our study is on the factors that drive voting behavior, we first examine whether congestion pricing worked and subjects behaved as anticipated. Albeit others have observed the success of congestion pricing in the lab before us (e.g., Hartman 2012), we need to examine its efficacy since a) our theoretical model predicts non-linear effects and even potential losers from the toll, which is in contrast to theoretical predictions in other experimental papers on congestion pricing, and b) if the toll does not work as predicted then the voting behavior is more difficult to interpret, and the two other research questions are basically mute.

The theoretical model predicts that, without the toll, all six individuals enter Route A since, as was seen in Table 1, the highest travel time possible when using Route A (10 min) is still less than the (fixed) travel time when using Route B (12 min). The toll should minimize total travel costs by reducing the number of Route A entrants to the three highest values of time users (users with values of 10, 11, and 12 tokens per minute) and by incentivizing the low-value users to use Route B to minimize their total costs.

The route-choice decisions are displayed in Table 4, which reports the average number of Route A entrants, total travel time, total travel costs after revenue redistribution, and an efficiency index for the three 10-period stages. Average number of Route A entrants and efficiency index by period for periods 1-20 are also visualized in Figs. 2 and 3, respectively.[17] Figure 2 displays the number of Route A entrants separated by value of time (high versus low value, as defined in the previous paragraph) and, for periods 11–20, by redistribution treatment.[18]

We measure efficiency by using an index that normalizes travel costs to 1 (when costs are minimized at the socially optimal level) and 0 (for costs at the Nash or user equilibrium without tolls). The index is then calculated as

$$\textit{Efficiency Index} = \frac{\textit{Costs at User Equilibrium} - \textit{Observed Costs}}{\textit{Costs at User Equilibrium} - \textit{Costs at Social Optimum}} \tag{1}$$

where costs at user equilibrium and costs at social optimum are 420 and 339 tokens, respectively (see bottom row of Table 3). The average efficiency indices for periods 1–20, separated by redistribution treatment, are depicted in Fig. 3.

Note a third line in periods 11–20. Because in the 40% redistribution treatment the lowest possible travel cost is actually 376.8 tokens (instead of 339; see Table 3) since not all revenue is recycled, an unadjusted Efficiency Index's upper bound is 0.533 instead of 1. In addition, we also present an adjusted Efficiency Index that accounts for this "leaky bucket" by using 376.8 and not 339 tokens as the cost-minimizing baseline so that the maximum for the adjusted index is 1 again.

Table 4 and Figs. 2 and 3 suggest that the toll works relatively well, particularly from period 15 onward. The average number of Route A entrants in Stage 1 without a toll is 5.6, close to the predicted equilibrium of six, and there is no significant difference between high- and low-value users. The reported Wilcoxon tests show that the toll in Stage 2 significantly reduced the number of Route A entrants ($p < 0.001$). In Stage 2 the average number of entrants is 3.6, and also note that in Stage 3 those groups that self-selected to have a toll have an average of 3.5 entrants.[19]

This reduction in the number of Route A entrants improves group outcomes in terms of travel time and cost, and it increases efficiency. Average total travel time and cost both decrease significantly from around 59 min and 413 tokens in Stage 1 to 57 min and 388 tokens, respectively, in Stage 2. The Efficiency Index goes up from 0.056 to 0.636 (0.731 for groups with tolls in Stage 3) when 100% of the revenues are redistributed. In the treatment with 40% redistribution the unadjusted Efficiency Index increases only from 0.122 to 0.164 between Stage 1 and Stage 2, due to toll revenues leaving the system; the increase in the adjusted

[17] We left out the respective lines for periods 21–30 since those periods did not have any impact on votes anymore.

[18] We conducted a conditional analysis, which confirms the visual inspection of Fig. 2 low-value subjects are significantly more likely (in all cases $p < 0.01$) to use Route A in period intervals 1–5, 6–10 and 11–15 compared to periods 16–20, and in the 100% redistribution treatment compared to the 40% treatment. For high-value users, however, only Route A use in periods 11–15 is significantly different from Route A use in periods 16–20.

[19] Table B.1 in the electronic supplementary material presents the average number of Route A entrants by value of time and redistribution rate. The equilibrium predictions for the periods with tolls call for only the three high-value users to enter A. The data indicate that in Stage 2 about 85–95% of high-value users and 16–46% of low-value users enter Route A. In groups with toll in Stage 3, the respective ranges are 92–99% and 13–38%.

**Table 4** Summary of group performance across stages[a]

| | No Toll (Stage 1) | Toll (Stage 2) | No Toll (Stage 3) | Toll (Stage 3) |
|---|---|---|---|---|
| Route A entrants (out of 6) | 5.6 | 3.6*** | 5.9 | 3.5 |
| Travel Time ("minutes") | 59.0 | 57.0*** | 59.7 | 56.7 |
| Travel Costs (tokens) | 412.8 | 387.6*** | 418.6 | 378.5 |
| *Efficiency Index* | | | | |
| 40% | 0.122 | 0.164 | 0.016 | 0.328 |
| 40% adjusted[b] | | 0.308** | | 0.615 |
| 100% | 0.056 | 0.636*** | 0.019 | 0.731 |
| Observations | 32 | 32 | 8 | 24 |

[a]*Wilcoxon rank-sum tests: ***, **, *, represent statistical differences at the 1%, 5% and 10% level, respectively, in the group comparisons between Stage 1 and Stage 2.*

[b]*Values represent the adjusted efficiency index for 40% redistribution that accounts for 376.8 and not 339 as the cost-minimizing outcome*

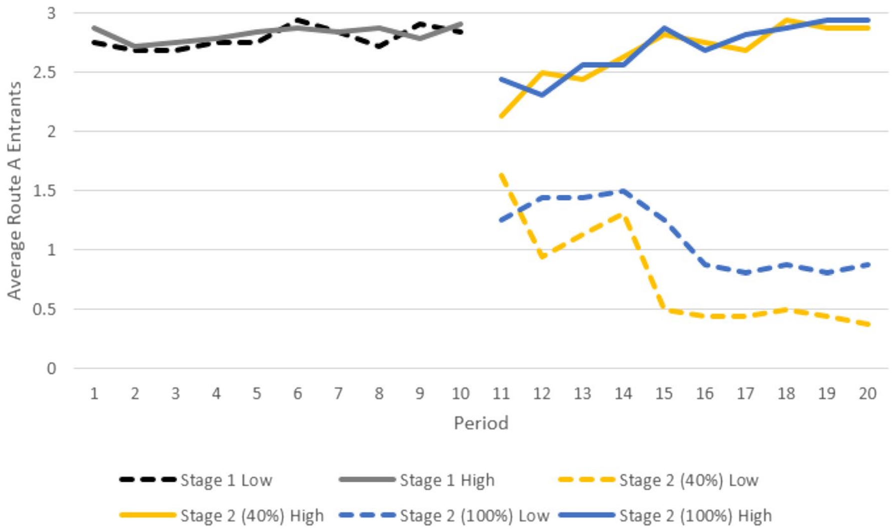


**Fig. 2** Average Route A entrants by value of time grouping

Efficiency Index to 0.308 indicates that the groups are improving their performance once the loss in revenues is accounted for.

As Figs. 2 and 3 suggest, the efficiency gains are more distinctive when experiential learning is accounted for. Table 5 presents the efficiency indices for periods 1–20 broken up in five-period intervals. Efficiency is going down from the first to the second half in Stage 1 of the 40% treatment, presumably because subjects learn that it is in everybody's personal interest to take Route A, while efficiency in both treatments increases from the first to the second half in Stage 2

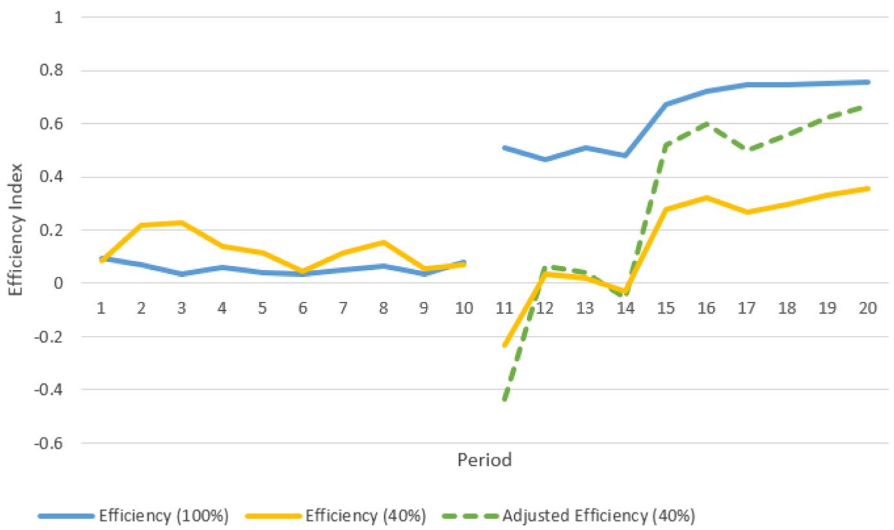


**Fig. 3** Average efficiency index by redistribution treatment

**Table 5** Efficiency index by five-period intervals for the first two stages

| Efficiency index | No toll (Stage 1) | | Toll (Stage 2) | |
|---|---|---|---|---|
| | Periods 1–5 | Periods 6–10 | Periods 11–15 | Periods 16–20 |
| 40% | 0.157 | 0.088 | 0.014 | 0.314 |
| 40% adjusted | | | 0.027 | 0.589 |
| 100% | 0.059 | 0.053 | 0.527 | 0.744 |

when not only the number of Route A users goes down, but also the "right" (i.e., high-value) users take Route A, while low-value users take Route B more often.

We conclude with the answer to Research Question 1:

*Result 1: The toll mitigates congestion and improves group outcomes in the lab by adequately reducing Route A entrants to those users with the highest value of time.*

While the efficiency gain is not as large as predicted when averaged over all ten periods, subjects clearly learn their best choices—in the second half of Stage 2, coordination and efficiency is much improved compared to the second half of Stage 1. These improvements across both redistribution rates could affect users' acceptability, measured in votes, after experiencing the network with and without the toll. We next turn to the question whether experience, be it positive or negative, with the toll has an impact on voters' acceptability, as expressed in "yes" votes in the third referendum. In Sect. 4.2 we will examine this question using descriptive statistics, and in Sect. 4.3 we will present a regression analysis.

### 4.2 Does experience and the resulting removal of the policy's uncertainties from a policy trial influence acceptability?

Subjects participate in three referendum votes; the votes elicit the acceptability of a toll before and after subjects are accustomed to the congestion problem and implementation of a toll.

Column 3 of Table 6 reports the predicted change in costs by redistribution rates (column 1) and individual values of time (column 2). If subjects were given perfect information about the equilibrium effects of the toll on their costs (and thus their earnings), profit-maximizing individuals in the 100% redistribution treatment should unanimously vote for the toll while the individuals in the 40% redistribution treatment with the value of times of 3 and 4 tokens per minute should be opposed to the toll (in equilibrium the toll decreases the costs for subjects with a value of 2 tokens per minute by only 1% so these subjects should basically be indifferent between the two equilibria with and without toll).

Column 5 of Table 6 reports the percentage of "yes" votes in the first referendum.[20] There appears to be no noticeable pattern on voting sensitivity to redistribution rate and an individual's value of time. For example, individuals in the 40% treatment are not less likely to vote for the toll (58.3%) compared to individuals in the 100% treatment (49%).[21] And only 37.5% of both, the individuals with the lowest and highest values of time (2 and 12 tokens per minute, respectively), who would in relative terms gain the most from a toll in the 100% redistribution treatment (cost decreases of 32.5% and 21.3%, respectively), voted in favor of the toll. Clearly, and probably not surprisingly, votes are not impacted by predicted changes in costs in the first referendum when subjects had not experienced the congestion problem and the policy. We will return to the question what did then impact those first votes in Sect. 4.3.

The second and third votes help measure the evolution of an individual's acceptability after experiencing the congestion problem and after experiencing a toll that mitigates the congestion problem. Column 6 in Table 6 shows that favorability of the toll does not change significantly after Stage 1, even for those individuals in the 40% redistribution treatment that are predicted to be made worse off once the toll is introduced. Across all treatments, the increase in "yes" votes from 53.6% in the first vote to 61.5% in the second vote is not statistically significant according to a two-sample proportions test ($p = 0.122$). The overall increase in "yes" votes from vote 1 (53.6%) to vote 3 (65.1%) is significant ($p = 0.023$), as are the increases in the 100% treatment from votes 1 and 2 to 3 (both $p < 0.001$) and the decrease in the 40% treatment from vote 2 to vote 3 ($p = 0.041$).

The third vote captures the acceptability of the toll after users are accustomed to the problem with and without the toll and with disclosure on objective measures on how the toll affected costs. First, consider the 100% redistribution treatment where

[20] Note that there was no significant difference in voting behavior across the different information treatments, so we pool the data here.

[21] A two-tailed t-test yields a $p$ value of 0.195.

in equilibrium everybody should be better off (i.e., have a lower cost) with a toll, albeit at different levels; Column 4 in Table 6 confirms that indeed on average each time-value group in that treatment is better off. The percentages of "yes" votes in column 7 of Table 6 indicate that this relative success of the toll in lowering travel costs impacts acceptability substantially. The majority of voters in each group with 100% redistribution voted overwhelmingly in favor of the toll (between 75% and 88%, with an overall 80.2% yes-votes).

The situation in the 40% redistribution treatment is more subtle—subjects in the three high-value groups should still be better off with the toll (and are, even though not as much as predicted), while the toll makes all low-value subjects worse off, even the lowest-value subjects, who in equilibrium were predicted to have a one-percent decrease in costs.[22] This too is reflected in the votes: approval of the votes is on average between 62.5 and 93.5% for the high-value subjects, but only 12.5–37.5% for the low-value subjects.

These percentages suggest that experience matters. Group averages can, of course, be deceiving; we will test the hypothesis that lower costs (and therefore higher earnings) due to the toll make it more likely to vote in favor of a toll more rigorously in Sect. 4.3. For now, note that the bivariate correlation coefficient between Vote 3 and Actual Percentage Change in Costs, which is − 0.50 and highly significant ($p < 0.001$) and compare it to the same correlation coefficients for Vote 1 and 2 (0.14 and 0.13). The answer to Research Question 2 can be summarized as

*Result 2: The experience and accustomation of the congestion problem with and without the toll and a trial's removal of uncertainty of the policy's effects influences attitudes; monetary self-interest appears to be a major determinant on the opinion of the toll, for both, those made better off by the toll and those made worse by it.*

The full experience of being accustomed to and obtaining an objective measure of the congestion problem with and without the toll appears to matter; however, not all individuals voted in their monetary self-interest. The third research question then asks, when controlling for accustomation and nature of the experience, whether individual attributes and worldviews are correlated with voting behavior as well.

### 4.3 Do individual attributes impact the acceptability of tolls and does this acceptability evolve when an individual becomes accustomed to the problem and policy?

The results in the previous section suggest that subjects increasingly voted in their monetary self-interest as they experienced the actual effects of the toll, with only a minority maintaining their opposition to congestion pricing. The continued opposition may be explained by non-monetary factors. In this section we attempt to identify which factors help determine how individuals vote and how the impact of these factors evolve over time. We also investigate what factors affect individuals'

[22] Note that this statement even holds in periods 16–20 compared to 6–10, where the average earnings for the lowest-value subjects were 24.9 tokens in periods 6-10 compared to 23.6 in periods 16–20 ($p$ value 0.014).

**Table 6** Approval percentages by predicted outcomes by individual's value of time

| (1)<br>Redistribution rate | (2)<br>Value of time | (3)<br>Predicted change in costs (%) | (4)<br>Average actual % change in costs (%) | (5)<br>Vote 1 (%) | (6)<br>Vote 2 (%) | (7)<br>Vote 3 (%) |
|---|---|---|---|---|---|---|
| 40% | 12 | −16.0 | −5.5 | 56.3 | 68.8 | 81.5 |
| | 11 | −14.7 | −4.6 | 66.8 | 62.5 | 62.5 |
| | 10 | −13.2 | −3.6 | 62.5 | 62.5 | 93.8 |
| | 4 | 9.5 | 15.1 | 56.3 | 66.8 | 12.5 |
| | 3 | 6 | 10.9 | 50 | 56.3 | 13 |
| | 2 | −1 | 13.6 | 56.3 | 68.8 | 37.5 |
| 100% | 12 | −21.3 | −11.7 | 37.5 | 75 | 81.3 |
| | 11 | −20.5 | −12.2 | 56.3 | 50 | 81.3 |
| | 10 | −19.5 | −9.2 | 62.5 | 75 | 81.3 |
| | 4 | −6.3 | −5.5 | 50 | 62.5 | 75 |
| | 3 | −15.0 | −8.1 | 50 | 43.8 | 75 |
| | 2 | −32.5 | −29.6 | 37.5 | 43.8 | 87.5 |
| 40% | – | −10.3 | 4.3 | 58.3 | 64.6 | 50 |
| 100% | – | −19.3 | −12.7 | 49 | 58.3 | 80.2 |
| All | – | −14.8 | −4.2 | 53.6 | 61.5 | 65.1 |

inclinations to switch their votes from the second to the third referendum once they experienced the effect of the toll.

Recent work has turned to the cultural theory of risk (Douglas and Wildavsky 1983) to investigate the role of individual cultural worldviews on perceptions of social issue and policy (Cherry et al. 2017, 2019; Kahan et al. 2011). A person's worldview is the socially constructed orientation that dictates how she interprets and interacts with reality, and the theory asserts that worldviews, in addition to economic interests and cognitive biases, can influence perceptions and actions around social and environmental risks and policies. It follows that voting behavior over policies that manage risk and uncertainty may be sensitive to worldviews as they relate to government intervention, inequality, and redistribution. Recent studies have provided supporting evidence in voting experiments (e.g., Cherry et al. 2017, 2019). We contribute to this literature by considering the role of individual cultural worldviews on voting in our setting with uncertainty about the toll's effects.

To measure individual cultural worldviews, we follow previous studies and administer a post-experiment questionnaire to elicit beliefs. Developed by Kahan et al. (2011), the instrument is used to measure individual worldviews across two dimensions: individualism-communitarianism and hierarchy-egalitarianism using six statements to measure each dimension.[23] People with an individualistic orientation expect individuals to "fend for themselves and therefore tend to be competitive"

[23] The statements are reported in the electronic supplementary material.

(and are likely to oppose governmental intervention of any type), whereas those with a communitarian orientation assume individuals interact frequently in “a wide range of activities” so that they “depend on one another” (Kahan et al. 2011)—making them more likely to express support for social institutions, including government intervention. People with a hierarchical orientation “expect resources, opportunities, respect and the like to be ‘distributed on the basis of explicit public social classifications’”, whereas those with an egalitarian orientation support “an egalitarian state of affairs in which no one is prevented from participating in any social role because he or she is the wrong sex, or is too old, or does not have the right family connections”, making them more likely to support changes that redistribute resources in an equitable manner.

Table 7 reports the averages of the worldviews, which correspond to scores reported in previous studies.[24] Figure 4 provides a scatterplot of the two worldview scores for each individual and shows that subjects tended to hold more individualistic views while being relatively diverse with views of hierarchy. Following the literature (e.g., Kahan et al. 2011, 2012; Cherry et al. 2017), we classify subjects according to their scores across both worldview dimensions. Subjects that score above the median in both dimensions are defined as Hierarchical-Individualist (upper right quadrant), while those that score below the median in both dimensions are defined as Egalitarian-Communitarian (lower left quadrant). Similarly, subjects that fall in the upper left quadrant and lower right quadrant are defined as Hierarchical-Communitarian and Egalitarian-Individualist, respectively.

To consider whether individual worldviews affect voting behavior, we estimate the following linear probability model that defines the probability of voting for congestion pricing as a function of payoff factors and individual worldviews:

$$\begin{aligned} Y_{ij} = &\beta_1 PredAbsChgEarn_i + \beta_2 Redist40 * PredAbsChgEarn_i + \\ &\beta_3 GroupInfo * PredAbsChgEarn_i + \beta_4 Stage1OthersCongest_i + \\ &\beta_5 Stage2OthersCongest_i + \beta_6 Hierarchical\text{-}Individualist_i + \\ &\beta_7 Hierarchical\text{-}Communitarian_i + \beta_8 Egalitarian\text{-}Individualist_i + \\ &\alpha + \epsilon_{ij} \end{aligned} \tag{2}$$

where $Y_{ij}$ is a binary variable that indicates whether the $i^{th}$ subject voted yes in referendum j (=1 if yes; =0 otherwise); $PredAbsChgEarn_i$ is the predicted change in equilibrium earnings with and without a toll (see columns 7 vs. 8 in Table 3)[25,26], $PredAbsChgEarn * Redist40_i$ is an interaction term that controls for the efficiency

[24] The averages for Hierarchy (17.5) and Individualism (23.2) are comparable to those in Cherry et al. (2017) (19.2 and 23.3, respectively). Cronbach’s alpha for Hierarchy (0.83) and Individualism (0.71) are similar to those reported in Kahan et al. (2011) (0.87 and 0.81, respectively).

[25] We use predicted instead of actual changes in earnings for three reasons: (a) actual changes are not available for votes 1 and 2; (b) actual changes may be correlated with individual voting tendencies; and (c) actual earnings is not as precisely defined because it varies across periods between votes, particularly in Stage 2.

[26] Regressions with predicted changes in costs instead of earnings yielded similar results.

**Table 7** Summary of individualism and hierarchy worldview scores

| | Average | Standard deviation | Range | Percentiles 25% | 50% | 75% | Cronbach's alpha |
|---|---|---|---|---|---|---|---|
| Individualism (6–36) higher value implies more individualistic | 23.22 | 4.81 | 13–36 | 20 | 23 | 26.5 | 0.71 |
| Hierarchy (6–36) higher value implies more hierarchical | 17.45 | 6.65 | 6–36 | 12 | 17 | 21.5 | 0.83 |

loss for subject $i$ (with $Redist40_i = 1$ for the "leaky bucket" treatment with only 40% of toll revenues recycled); $PredAbsChgEarn * GroupInfo_i$ is an interaction term that controls for the impact of providing participants information about the earnings of other subjects within their group (with $GroupInfo_i = 1$ for subjects in the treatment where they can observe how their cost changes compared to others in their group); $Stage1OthersCongest_i$ and $Stage2OthersCongest_i$ captures how many of the other group members selected Route A in the periods 1–10 and 11–20; three dummy variables signify the worldview category of subject $i$ (defined in the previous paragraph, with Egalitarian-Communitarian as omitted variable in the regressions); and $\alpha$ is the estimated intercept and $\epsilon_{ij}$ is the well-behaved error term. For clarity, we estimate equation 2 for each vote separately.

Results for the three voting models are reported in Table 8.[27] We find evidence that worldviews matter in the early votes but not in the final vote. In the first vote, estimates indicate that subjects with egalitarian-individualistic views are more likely to support the toll than subjects with egalitarian-communitarian views. In the second vote, subjects with both hierachical-communitarian and hierarchical-individualistic views are less likely to support the toll than those with egalitarian-communitarian views. In vote three, however, worldviews do not significantly explain voting behavior. The story differs for factors that impact payoffs. Estimates provide evidence that monetary incentives do not matter in early votes but they do matter in the final vote. Predicted changes in earnings and their interaction with the redistribution treatment variable both have no significant influence on support in the first and second votes, but they have significant effects in the third vote, with the expected signs—predicted changes are positively correlated with the likelihood to vote, while the 40% redistribution treatment (interacted with the changes in earnings) is negatively correlated with the likelihood to vote. The results suggest that with uncertainty about the impact of the incentives, subjects rely on heuristics such as worldviews. But the

[27] Note that 28 of the 192 subjects were excluded from the regressions since their worldviews scores were exactly at the median of one or both dimensions. We additionally conducted regressions with all 192 subjects, where we categorized the median worldviews in the higher or in the lower category, with similar results.

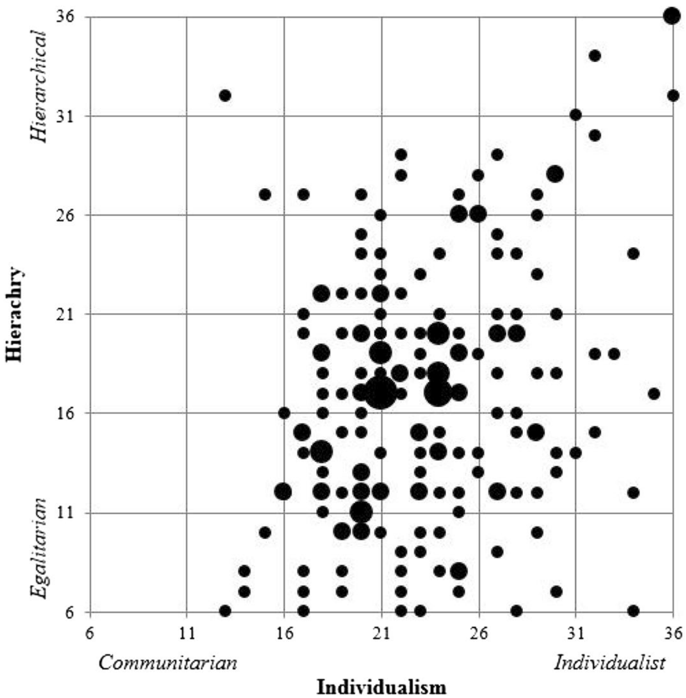


**Fig. 4** Scatterplot of Kahan et al. (2011) worldview scores. Note: Densities of individuals (small mark = 1 subject, largest mark = 5 subjects)

influence of worldviews gives way to monetary incentives as the uncertainty dissolves and people gain more experience with the toll.

The first three models are static models of voting. To capture the effect of experience with the policy more explicitly, we extend the analysis by considering how people change votes across the second and third referenda, those two referenda before and after subjects experienced the congestion toll. First consider Table 9, which overviews how many subjects followed which voting pattern in the three referenda. The first row shows the frequencies and percentages for all 192 voters; the other four rows for subjects according to their worldview quadrants. Note that 118 subjects (104 with well-defined worldviews) voted "yes" in the second referendum (sum of columns 1–2 & 7–8), while 74 (60) voted "no" (sum of columns 3–6).

We now modify the specification of Eq. 2 to estimate the likelihood that subjects in each group switched votes between referenda two and three, and estimate models separately according to how they voted in the second referendum. Model 4 estimates the likelihood of voting "no" in referendum three conditional on voting "yes" in referendum two (i.e., Y=1 if subject switched votes from "no" to "yes"; Y=0 if subject voted "no" consistently). Similarly, Model 5 estimates the likelihood of voting "yes" in referendum three conditional on voting "no" in referendum two (i.e., Y=1 if subject switch votes from "yes" to "no"; Y=0 if subject voted "yes" consistently). In

**Table 8** Regression results

| VARIABLES | (1)<br>Yes in<br>Vote 1 | (2)<br>Yes in<br>Vote 2 | (3)<br>Yes in<br>Vote 3 | (4)<br>Yes to No<br>Vote 2 to 3 | (5)<br>No to Yes<br>Vote 2 to 3 |
|---|---|---|---|---|---|
| *Payoff Factors* | | | | | |
| PredAbsChgEarn | −0.0069 | 0.0384 | 0.102*** | −0.136** | 0.0619* |
| | (0.0245) | (0.0317) | (0.0385) | (0.0640) | (0.0370) |
| Redist40 × PredAbsChgEarn | 0.0221 | 0.00835 | −0.0543* | 0.117*** | −0.00171 |
| | (0.0245) | (0.0190) | (0.0327) | (0.0451) | (0.0342) |
| Groupinfo × PredAbsChgEarn | −0.0011 | 0.0158 | −0.0162 | 0.0184 | −0.0395 |
| | (0.0247) | (0.0186) | (0.0245) | (0.0302) | (0.0381) |
| Stage1OthersCongest | | −0.236 | 0.523* | 0.465 | 1.634** |
| | | (0.369) | (0.303) | (0.667) | (0.792) |
| Stage2OthersCongest | | | −0.188 | 0.825* | 0.411 |
| | | | (0.358) | (0.497) | (0.469) |
| *Worldviews* | | | | | |
| Hierarchical-Individualist | 0.149 | −0.371** | 0.316 | −0.143 | 0.611 |
| | (0.225) | (0.167) | (0.467) | (0.536) | (0.521) |
| Hierarchical-Communitarian | 0.0893 | −0.720*** | 0.123 | −0.468 | −0.106 |
| | (0.247) | (0.223) | (0.246) | (0.497) | (0.364) |
| Egalitarian-Individualist | 0.675* | −0.077 | 0.378 | −0.107 | 1.253 |
| | (0.358) | (0.231) | (0.365) | (0.423) | (0.765) |
| Constant | −0.155 | 1.302 | −2.150 | −4.543 | −9.067** |
| | (0.286) | (1.710) | (1.967) | (3.956) | (3.541) |
| Observations | 164 | 164 | 164 | 104 | 60 |

Robust standard errors in parentheses

***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$

short, this analysis helps us answer the question which factors impact voters' likelihood to switch their votes once they had experience with the toll.

Model 4 results indicate that stronger monetary incentives (higher predicted changes in earnings and a higher redistribution factor) decreases the likelihood of switching votes from "yes" to "no". In addition, a higher number of others congesting (which could be indicative of the toll not working as expected) is positively correlated with a switch to a "no"-vote. The estimates offer no evidence that worldviews have a significant role in subjects changing votes. Similarly, results for Model 5 suggest that monetary incentives (predicted changes in monetary earnings), not worldviews, explain the switching of votes from "no" to "yes".[28]

Overall, the estimates provide evidence for

[28] The main conclusions are robust to a model change, with a dummy variable *LowValue* (= 0 for time values 12, 11 and 10, and =1 for time values 4, 3 and 2) in place of the variable *PredAbsChgEarn*.

**Table 9** Distribution of voting patterns

| | Voting sequence (Y=Yes; N=No) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | YYY | YYN | YNY | YNN | NNN | NNY | NYN | NYY | %/(freq.) |
| All | 0.281 | 0.125 | 0.073 | 0.057 | 0.089 | 0.167 | 0.078 | 0.130 | 1.0 |
| | (54) | (24) | (14) | (11) | (17) | (32) | (15) | (25) | (192) |
| Hierarchical-Individualist | 0.3 | 0.1 | 0.06 | 0.04 | 0.04 | 0.26 | 0.08 | 0.12 | 1.0 |
| | (15) | (5) | (3) | (2) | (2) | (13) | (4) | (6) | (50) |
| Egalitarian-Communitarian | 0.283 | 0.130 | 0.022 | 0.022 | 0.109 | 0.109 | 0.130 | 0.196 | 1.0 |
| | (13) | (6) | (1) | (1) | (5) | (5) | (6) | (9) | (46) |
| Hierarchical-Communitarian | 0.270 | 0.054 | 0.081 | 0.081 | 0.135 | 0.216 | 0.054 | 0.108 | 1.0 |
| | (10) | (2) | (3) | (3) | (5) | (8) | (2) | (4) | (37) |
| Egalitarian-Individualist | 0.355 | 0.194 | 0.129 | 0.032 | 0 | 0.129 | 0.032 | 0.129 | 1.0 |
| | (11) | (6) | (4) | (1) | (0) | (4) | (1) | (4) | (31) |
| Well-defined Worldviews | 0.299 | 0.116 | 0.067 | 0.043 | 0.073 | 0.183 | 0.079 | 0.140 | 1.0 |
| | (49) | (19) | (11) | (7) | (12) | (30) | (13) | (23) | (164) |

*Result 3: Worldviews can shape individual support for congestion pricing when people have little experience with the consequences on congestion and earnings (vote 1 and 2). However, with experience (vote 3), support is driven by the impact of the congestion pricing on earnings.*

This result differs from the results in Cherry et al. (2017) who find that the influence of worldviews on support persisted even with experience. The discrepancy may be due to the redistribution feature of the toll in this study, which had different impacts on subjects. In contrast, the tax in Cherry et al. (2017) had uniform effects on homogeneous group members.

## 5 Conclusion

We use a laboratory experiment to examine the effectiveness of a welfare-improving policy in an environment where *ex ante* the individual and societal effects of this policy are uncertain and where *ex post* some participants actually lose despite the overall gain in efficiency. Inspecting how votes on implementation of this policy evolve over time as subjects gain more experience with the externality problem and its solution, we also test whether the acceptability of the policy is impacted by subjects' cultural worldviews and by the success of the policy. As case study we use a congestion problem and congestion pricing.

We find that the policy does decrease congestion even though the success does not happen immediately after implementation of the policy. In the first two referenda, when subjects have not experienced the policy yet, support for the policy is independent from the gains or losses the policy has on payoffs, and instead support is influenced by subjects' worldviews. In the third referendum, however, after subjects experienced the effect of the policy, it is the impact on payoffs that matter and not individual worldviews.

These experimental results seem to be consistent with real-world scenarios involving externalities and the introduction of incentive-based mechanisms (i.e., trials). Incentive-based mechanisms, such as using congestion pricing to manage traffic congestion, create fairness and equity concerns and the effects of such Pigouvian-like policies are uncertain and are not well understood by the public. Fernandez and Rodrik (1991) and De Borger and Proost (2012) explain that the reluctance to implementing efficiency-improving policies that are advocated by economists may stem from a bias toward the status quo stemming from individuals' uncertainties of the policy's impacts. These concerns can explain the widespread reluctance of using such incentive-based mechanisms, and why policymakers may have to go against the majority of their constituents to implement socially efficient policies. However, the experience of a six-month trial of congestion pricing in Stockholm revealed that public opinions can change. The initially reluctant Stockholmers ended up passing a referendum to keep the congestion pricing permanent after experiencing the policy (Winslott-Hiselius et al. 2009; Börjesson et al. 2012). Stockholm's experience using a policy trial and an element of uncertainty modeled in De Borger and Proost (2012) are reproduced here in a laboratory setting to observe how beliefs, accustomation, and the nature of the experience explain the evolution of acceptability in a controlled environment. Similar to the Winslott-Hiselius et al. (2009) survey analysis of Stockholm's experience, our results showed that the personal experience from a trial period changed acceptability and that trials can be effective in implementing initially unattractive incentive-based and efficiency-improving environmental policy measures. The results also support the Anas and Lindsey (2011) recommendation that it is best to hold a referendum once a trial has been implemented. Our experiment can help explain why congestion pricing policies have become successful in some places but not others by demonstrating that peoples' initial biases and judgments about a policy's potential costs and benefits can evolve after a policy's potential benefits become salient and widespread only after careful implementation. The success of the Stockholm experience is at least partly due to the length of the trial period; our experiment suggests that a lengthy trial period is warranted since even in our basic set-up the policy did not have the anticipated effects until the second half of Stage 2.

Our paper makes a contribution to the thriving experimental economics literature on the effect of experience in uncertainty situations. Our findings suggest that a substantial set of subjects rely on their worldviews as heuristic when they are uncertain about the effects of experimenter-induced policies. Because our novel voting mechanism provides each subject with the same policy experience at the time of each vote, we can observe how preferences evolve with experience and how tangible financial incentives replace worldviews as main decision criterion for most subjects. This suggests that the role of (lengthy) policy trials is as important in experiments as it is in the real world.

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