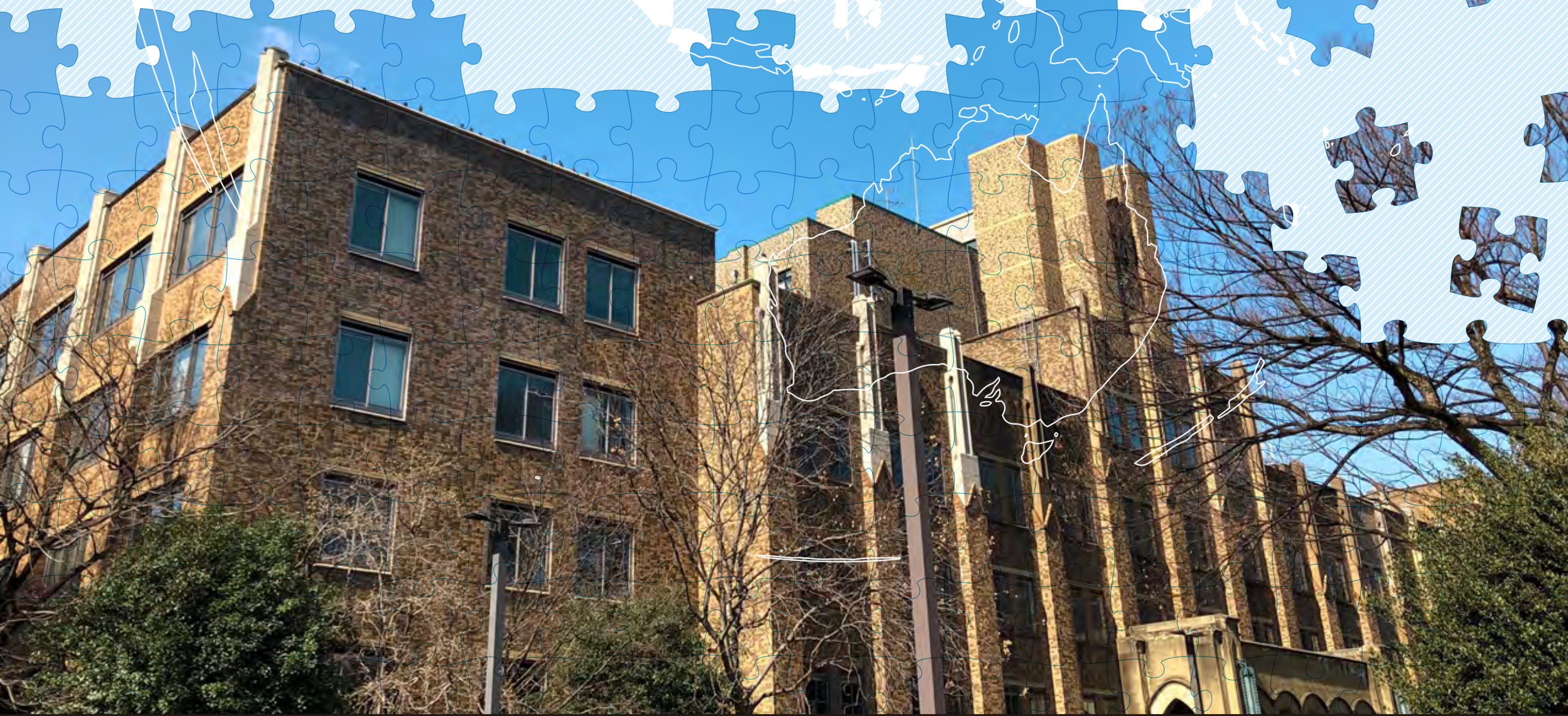
CSRDA
Center for Social Research and Data Archives, Institute of Social Science, The University of Tokyo

SUSTAINABLE DEVELOPMENT GOALS

CSRDA supports the Sustainable Development Goals

CSRDA Discussion Paper

Persistent Mind: The Effects of Information Provision on Policy Preferences



No. 5

Date Feb. 2021

SDGs
1 NO POVERTY
3 GOOD HEALTH AND WELL-BEING
10 REDUCED INEQUALITIES

Name
Keisuke Kawata, Masaki Nakabayashi

Persistent Mind:

The Effects of Information Provision on Policy Preferences*

Keisuke Kawata† Masaki Nakabayashi‡

January 23, 2021

Abstract

In a democracy, information exchanges are assumed to affect relative policy preferences and those preferences assumed to persist over periods of legislative policymaking. We implemented an online panel survey with a randomized conjoint preferences within a multi-attribute public policy space. The policy space consisted of spending on education, infrastructure, health insurance, pensions, and welfare programs for poor individuals as well as fiscal retrenchment. Providing information on the poverty rate in the first wave directed respondents' preferences toward support for welfare programs by either increasing or reallocating the budget. The effects persisted for one year and depended little on respondents' backgrounds, such as education and income characteristics, or political positions, including preferences on the size of government.

Keywords Persistent information treatment effects; multidimensional policy space; income redistribution; randomized conjoint experiment.

JEL classification c odes. P16; H53; D72.

*This research was funded by JSPS Grant-in-Aid KAKENHI JP18H03630.
†Institute of Social Science, The University of Tokyo. E-mail: keisukekawata@iss.u-tokyo.ac.jp
‡Institute of Social Science, The University of Tokyo. E-mail: mn@iss.u-tokyo.ac.jp

1 Introduction

A nation is established as a shared policy space is formed over time. A shared policy space is defined by a nation's constitution, a sort of "wish list" that covers all of citizens' preferences as dimensions of the policy space. Once the policy space is drawn in the constitution, citizens debate the allocation of resources to each dimension. This involves determining the spending shares for the wish-list elements or the direction of the policy vector given the budget constraint. To raise spending in one category, it must be reduced in others. In a democracy, the direction, if often not the scalar (the size of government), of the policy vector is discussed and set on a daily basis.

In discussing legislation on the policy direction, citizens exchange relevant information about each dimension. Once an agreement is reached, legislation moves forward. Legislation is a commitment device, given the tendency of habituation if preferences do not necessarily change. Once citizens make up their minds, they can discuss the policy direction again and advance further legislation.

The first requirement in the policymaking discussion process is that citizens seek to affect each other's preferred direction of the policy vector by providing each other with information. The second is that throughout the legislation process, the effects of information provision must persist for a certain period of time. Even if citizens become inactive in the process, their preferences might not change. Then, legislation serves to remind citizens to implement the agreed policy vector.

In this study, we test whether an information treatment related to a critical issue persists for one year through an online panel experiment. Assuming that "there is no free lunch" in the policy space, we measure the effects of information treatment on the direction of the preferred policy vector. To this end, we adopt a randomized conjoint experimental design to define a policy space. In the experiment, we set up a public policy space. We take income inequality as our critical issue and provide information about the relative poverty rate in our information treatment.

The issue on which we focus is directly related to experiments on citizen views on income redistribution. Building a dataset on the US, UK, France, Italy, and Sweden, Alesina, Stantcheva and Teso (2018) found that information on pessimistic prospects for social mobility raised support for income redistribution among left-wing people and that the effect was consistent one week later. Using a US dataset, Kuziemko, Norton, Saez and Stantcheva (2015) showed that information provision led to substantial updates of perceptions of income inequality but hardly affected support for income transfers except through estate taxes, which are paid by a small minority only. Meanwhile, using the same US survey service, Becker (2020) showed that a focus on inequality of opportunity rather than outcomes raised support for redistribution among Americans and that the effects persisted.

One factor that makes interpretation of the different results from overlapping sample countries difficult is that these works measured the information treatment effects on support for income redistribution unidimensionally. Income redistribution can be financed either through reallocation of spending on other public policies or through tax increases. While the former alternative does not change the size of government, the latter does. Unidimensional measurement cannot identify which scenario respondents are considering and thus what their preferences on extending the size of government are.

To generalize a framework measuring the effects of information provision on policy preferences, we use a randomized conjoint design to estimate the effects of an information treatment on the preferred public policy direction as a relative policy expenditure preference in comparison to alternative public policies and fiscal retrenchment. By allowing the respondent to reallocate expenses across alternative public policies and to shrink or enlarge the size of government, we can identify the information treatment effects on the policy direction in a policy space delineated by income redistribution and the size of government.

One possible advantage of our design is that it could capture multidimensional effects on preferences in the policy space rather than degenerated unidimensional estimates. Another is that our framing is close to practices in functional democracies. The policy direction is often discussed and set through the democratic process, given the tax revenue for each fiscal year.

Often, constitutional states assume that the agreed direction of the policy vector is time consistent for a certain period, usually one fiscal year. Even if citizens become less active in advocating for their preferences over this period, they allow the state to carry on in the direction that they believe is right. Therefore, we set up an experimental design where the tax increase is given and focus on the direction of the preferred policy vector in the public policy space. The public policy space consists of the dimensions of education, national health insurance, the national basic pension plan, infrastructure, welfare programs for poor individuals, and fiscal retrenchment. Respondents are asked about the relative importance of each element within the preferred policy vectors.

We find that information provision about the poverty rate in Japan in the first wave raises relative support for welfare programs for poor people, and the direction of support for welfare programs does not change in the second and third waves conducted over the next year. We also show that the information treatment effects depend little on background characteristics such as own income, party support, or preference on the size of government and that the effects only slightly rely on updates of prior perceptions about poverty. Regarding the direction of spending of already raised taxes, information exchanges affect it, and the effects persist for a certain period of time.

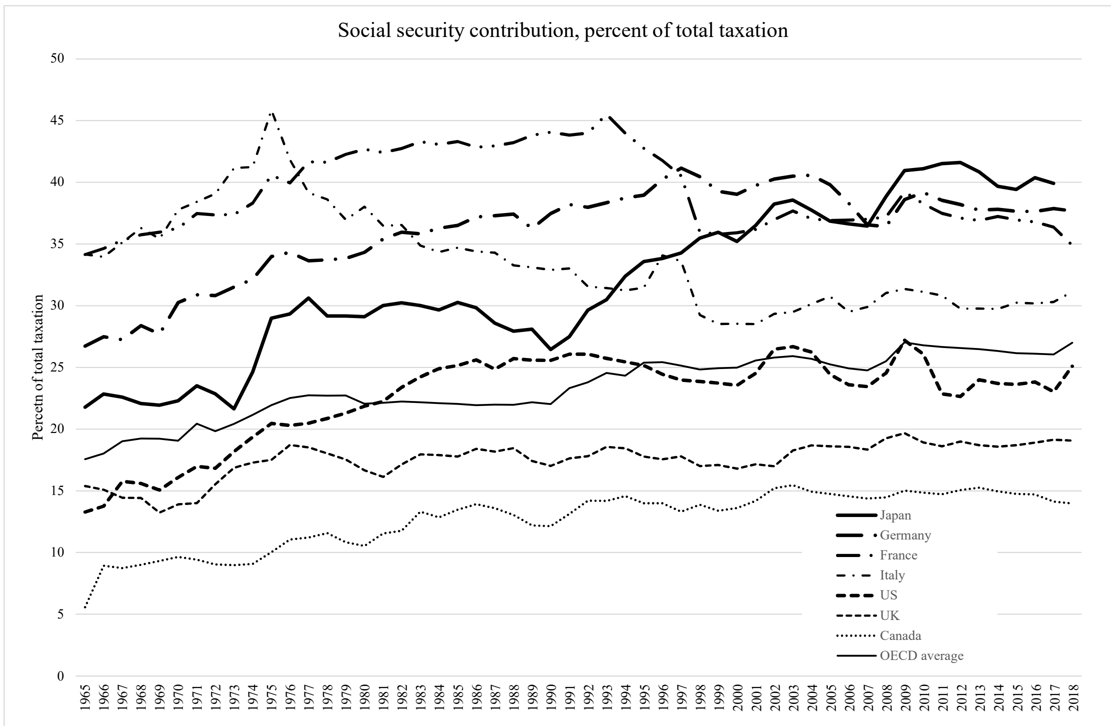
The remainder of the paper is organized as follows. Section 2 describes the Japanese context of income inequality and fiscal conditions. Section 3 describes our experimental design. A randomized conjoint experimental design reduces the cognitive burden on respondents, and a large number of respondents helps mitigate possible experimental design errors. We implemented a randomized conjoint experimental design with 15,000 respondents. This allows us to retain sufficiently large redundancy. Section 4 presents our identification strategy. Section 5 reports our results. Section 6 concludes the paper.

2 An urgent issue

Rapid aging over the last three decades has pushed Japan to extend its public medical and pension insurance. Increases in social security contributions have mainly financed this spending.[1] This rise has led to Japan joining a group of large welfare states, among them continental European nations. In terms of the share of social security contributions in Japan's total tax revenue, it has been the highest among the major advanced economies since the mid-2000s (Figure 1).

[1] According to the OECD, "Social security contributions are compulsory payments paid to the general government that confer entitlement to receive a (contingent) future social benefit," and they include "unemployment insurance benefits and supplements, accident, injury and sickness benefits, old-age, disability and survivors' pensions, family allowances, reimbursements for medical and hospital expenses or provision of hospital or medical services" (OECD (`https://data.oecd.org/`; last accessed July 20, 2020).

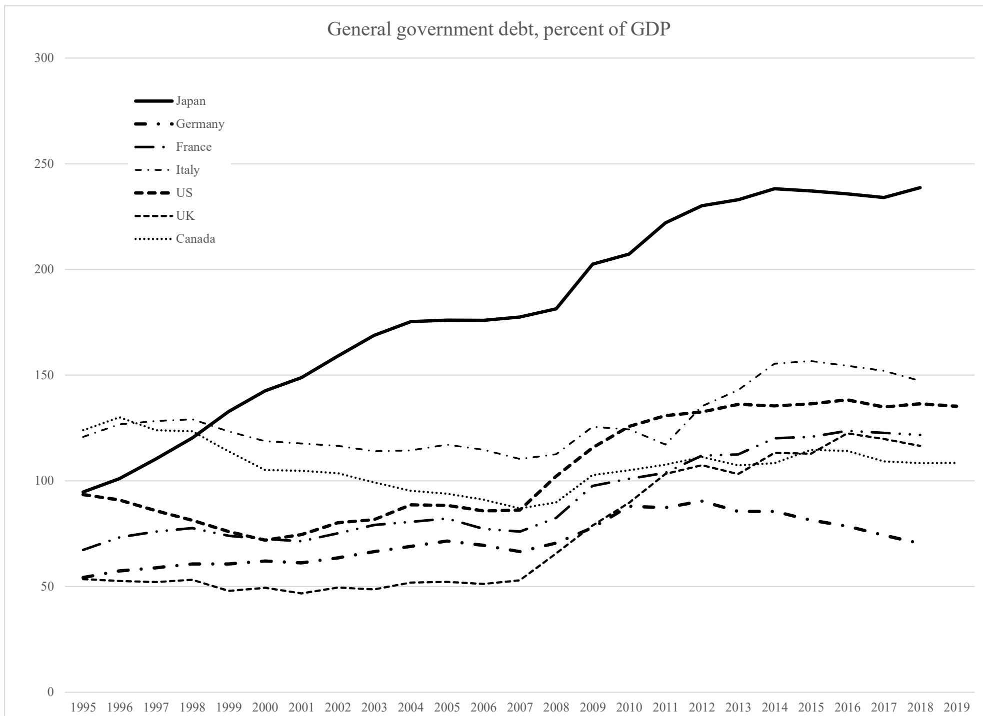
Figure 1: Social security contributions, percent of total tax revenue.



Source: OECD (`https://data.oecd.org/`; last accessed July 20, 2020).

However, to cope with its population aging, Japan has also financed medical and pension insurance through debt. Its general government debt over gross domestic product deviated from the levels of other major advanced economies in the late 1990s and soared to higher than 200 percent (Figure 2). Given these circumstances, Japan raised the consumption tax (value added tax) rate from 8 percent to 10 percent in October 2019.

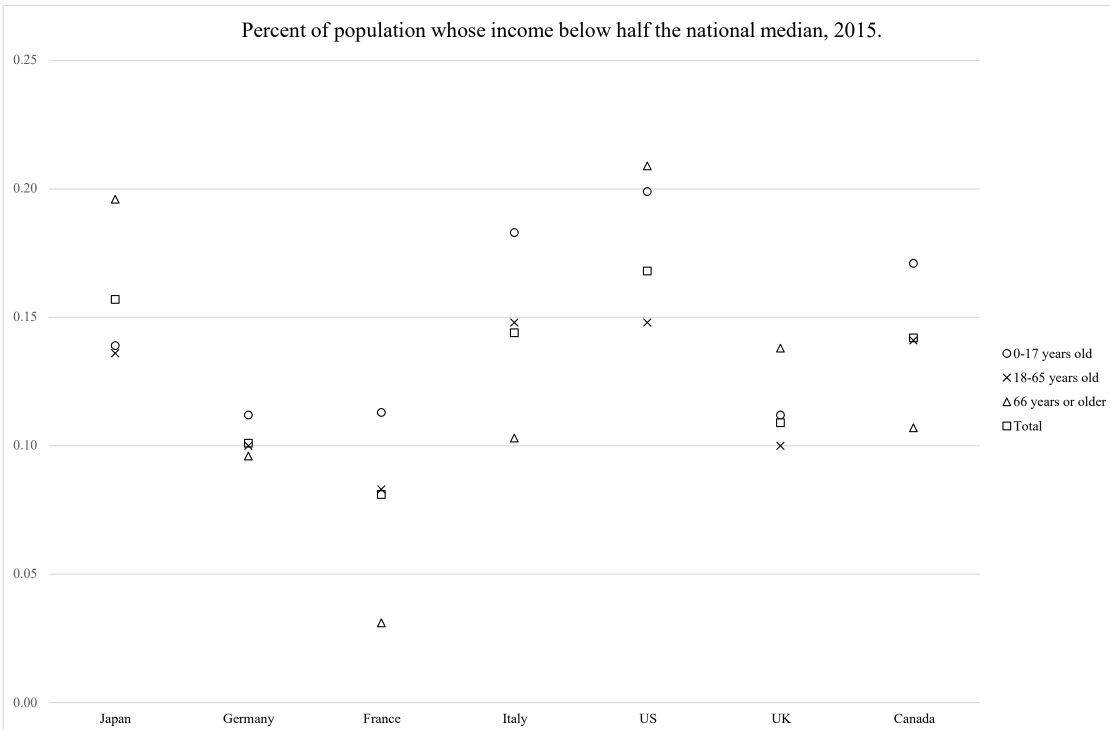
Figure 2: General government debt, percent of gross domestic product.



Source: OECD (`https://data.oecd.org/`; last accessed July 20, 2020).

The rapid growth in public medical and pension spending, however, has not delivered an equal society. While Japan has considered itself an equal society since the drastic income deconcentration that occurred during the Second World War (Moriguchi and Saez (2008)), this self-impression has been questioned, particularly since the 1990s (Chiavacci (2008); Hommerich and Kikkawa (2019); and Kanbayashi (2019)). Its relative poverty rate as of the mid-2010s is the highest after the US among seven major advanced economies (Figure 3).

Figure 3: Poverty rate, percent of total population, 2015.



Source: OECD (`https://data.oecd.org/`; last accessed July 20, 2020).

Poverty is a fact confronting Japan. Mandatory spending for medical and pension insurance to cope with demographic change have already financially pressed Japan. An inevitable question is now whether to raise taxes to spend on addressing poverty. In our randomized conjoint design, we focus on this question by randomizing spending on welfare programs for poor individuals alongside spending on other social security programs such as pension and medical insurance, public investment in infrastructure, and government bond redemption to reduce outstanding debt.

3 Experimental design

3.1 Survey respondents

We sent out our questionnaire to 15,000 respondents through a survey company, Rakuten Insight, in each wave. If a participant did not respond to our survey in two consecutive waves, we replaced her with a new one. Our sample is representative of the Japanese population. Detailed information about the respondents treated by Rakuten Insight is available on its website.[2]

3.2 Background characteristics of respondents

We carried out panel surveys to collect respondents' background information. The questions were on basic demographic characteristics, occupation, education, political preference, fiscal policy, and values in a broader context.

The questions on demography cover gender, age, prefecture of residence, marital status, number of children, and residential status (whether the respondent lives with parents, parents-in-law, or neither). These conditions might affect respondents' welfare policy preferences.

Questions on occupation include whether the respondent works, whether she is employed or self-employed, and if she is employed, whether it is full- or part-time employment and regular or non-regular work; also included are the job title, size of the

[2] https://insight.rakuten.co.jp/download/PanelProfile_EN.pdf and https://insight.rakuten.co.jp/download/PanelCharacteristicSurveyEN.pdf.

employer. Regarding income, we asked own annual income, and own household's annual income. Klor and Shayo (2010) and Maurice, Rouaix and Willinger (2013) showed that own income might affect preferences for redistribution. Our design incorporates this possibility.

Regarding educational backgrounds, we asked about the highest degree attained.

Regarding political preference, we asked whether the respondent supports a specific party, and if so, which party, degree of satisfaction with the current political situation, degree of support for the current administration's economic and political policies, and subjective perception of how right-leaning she was. Kuziemko et al. (2015) and Alesina et al. (2018) found that political position might be a factor in the effects of an information treatment on support for income redistribution. Esarey, Salmon and Barrilleaux (2012), Clark and D'Ambrosio (2015), and Kerschbamer and Müller (2020) also found a relationship between political position and baseline support for income redistribution. Our survey about party support and preference on the size of government addresses this possibility.

We also asked the respondent whether she agrees with collective self-defense and whether she believes the current constitution of 1946 should be amended. The government of Japan and the ruling Liberal Democratic Party long held that the 1946 constitution of Japan restricted the right of collective self-defense. However, in 2016, the cabinet, led by then prime minister Shintaro Abe, who was still in power during our survey in 2018 to 2019, changed the government's interpretation of the constitution and announced that the constitution allows the country's self-defense forces to exercise the right of collective defense. Thus, the question is related to the next one on a possible constitutional amendment. Whether the constitution should be changed is informative about the respondent's political position in Japan.

To provide broader context, we asked which individual or public interests the respondent prioritizes. We labeled respondents who prioritized “individual interests” over “national interests” as “individualist.” Also, we asked preference on the size of government.

Additionally, we asked about the respondent’s subjective perception of her own social class. Fernández-Albertos and Kuo (2018) showed that perception of own relative income might affect preferences on redistribution. Our setting addresses this issue.

The surveyed background characteristics are summarized in Table 1.

Table 1: Primary characteristics surveyed as background.

Category	Characteristics
Demography	· gender/age/prefecture of residence
	· educational background
	· marital status/number of children
	· whether living with parents or parents-in-law
Occupation	· working status
	> employed or self-employed
	> regular or non-regular/job title/size of the employer
Income	· own income/own household’s income
Political preference	· party support
	· subjective perception of how right-leaning
	· satisfaction with the current political situation
	· whether agreeing with current administration’s policies
	· whether agreeing with collective self-defense
	· whether agreeing with constitutional amendment

Table 1: Primary characteristics surveyed as background.

Values	· which prioritizing national or individual interests
	· size of government
Class-consciousness	· subjective perception of own social class

Let $\boldsymbol{X}_i$ denote a vector of all the background characteristics of respondent i surveyed in period 1 as described above. If we detect observable heterogeneity in the effects of the information treatment, we then evaluate whether specific characteristics drive the heterogeneity. Then, we further analyze the background characteristics that at least partly modify information treatment effects.

3.3 Randomized conjoint design

An advantage of using a randomized conjoint experimental design to decompose respondents' multidimensional preferences is that it imposes a much lighter cognitive burden on respondents than other survey methods such as vignettes and hence yields a higher quantity and quality of responses (Hainmueller, Hangartner and Yamamoto (2015) and Bansak, Hainmueller, Hopkins and Yamamoto (2018)). Primarily due to this virtue, randomized conjoint experimental designs have become widely used to identify multidimensional preferences in a broad range of social medical sciences pursuing policy implications; in this design, respondents are presented with alternative packages whose attributes are randomly assigned and hence statistically independent of one another (Lusk and Norwood (2005); Lusk, Fields and Prevatt (2008); Norwood and Lusk (2011); Hainmueller, Hopkins and Yamamoto (2014); Boyle, Stover, Tiwana and Zhylyevskyy (2015); Seanehia, Treibich, Holmberg, Müller-Nordhorn, Casin, Raude and Mueller (2017); Gallego and Marx (2017); Fukuda, Isdwiyani, Kawata and Yoshida (2018); Setiawan, Kaneko and Kawata (2019); Sydavong, Goto, Kawata, Kaneko and Ichihashi (2019); Leeper, Hobolt and Tilley (2020); Kreps, Prasad, Brownstein, Hswen, Garibaldi, Zhang and Kriner (2020); Sun, Wagner, Ji, Huang, Zikmund-Fisher, Boulton, Ren and Prosser (2020); Motta (2021)).

Another derivative advantage of randomized conjoint experimental design lies in its ability to pin down which attributes of the sample are homogeneous and which are heterogeneous. This feature of the randomized conjoint experimental design fits our purpose.

Our design assumes that the consumption tax rate is raised from 8 percent to 10 percent. Then, our conjoint experiment randomly assigns 0, 5, 10, 15, or 20 percent of the revenue from an increase in consumption tax to (a) "welfare (minimum wages, unemployment benefits, public housing for low-income earners, etc.)," (b) "pensions," (c) "health insurance," (d) investment in "infrastructure (roads, running water, airports, etc.)," and (e) "education (subsidies for tuition, expansion of nursery schools, etc.)," as described in Table 2. If any residual exists after summing all the percentages, it is allocated to redemption of government bonds.

Table 2: Attributes and attribute levels for hypothetical public policies.

Policy attributes	level	Policy attributes	level	Policy attributes	level
Welfare programs	0%	Pensions	0%	Health insurance	0%
	5%		5%		5%
	10%		10%		10%
	15%		15%		15%
	20%		20%		20%
Education	0%	Infrastructure	0%	Residual is to	
	5%		5%	redeem debts	
	10%		10%		
	15%		15%		
	20%		20%		

Let $\boldsymbol{A}_j$ denote a five-dimensional policy package vector that includes a to e and $\boldsymbol{A}_{-j}$ denote an alternative policy package vector. In each round of the conjoint experiment, each respondent is requested to choose her preference between the randomly generated $\boldsymbol{A}_j$ and $\boldsymbol{A}_{-j}$ packages. Any residual is allocated to government debt redemption. Thus, by requesting that each respondent indicate whether she prefers the five-dimensional $\boldsymbol{A}_j$ or the five-dimensional $\boldsymbol{A}_{-j}$, we track the respondent's preferences on the six-dimensional policy package vectors of $\boldsymbol{A}_j$ and $\boldsymbol{A}_{-j}$, with fiscal retrenchment as the residual.

Under the Japanese social security system, the national pension plan and national health insurance are universal insurance policies covering all adult residents in Japan. The beneficiaries of the increased subsidies to pensions and health insurance from the raised consumption tax are not limited to poor individuals but include all residents. Thus, only spending for (a) welfare directly aims to transfer income from rich to poor individuals.

For instance, for respondent i in round r in wave t, package $\boldsymbol{A}_j^{i,r,t}$ might assign 10 percent to (a), 5 percent to (b), 5 percent to (c), 20 percent to (d), 20 percent to (e), and 40 percent to redemption of government bonds. Another package $\boldsymbol{A}_{-j}^{i,r,t}$ might assign 5 percent to (a), 10 percent to (b), 15 percent to (c), 0 percent to (d), 10 percent to (e), and 60 percent to redemption of government bonds. Thus, each package is a menu of how much of the increased tax revenue should be spent on what programs rather than government debt reduction. Respondent i is requested to choose which of $\boldsymbol{A}_j^{i,r,t}$ and $\boldsymbol{A}_{-j}^{i,r,t}$ she prefers to the other in round r. Let us consider the outcome of the choice, $Y_{i,j,r,t}\left(\boldsymbol{A}_j^{i,r,t}, \boldsymbol{A}_{-j}^{i,r,t}\right)$, which takes one if and only if a policy package $\boldsymbol{A}_j^{i,r,t}$ is preferred to $\boldsymbol{A}_{-j}^{i,r,t}$ such that

$$Y_{i,j,r,t}\left(\boldsymbol{A}_j^{i,r,t}, \boldsymbol{A}_{-j}^{i,r,t}\right) = \begin{cases} 1 & \text{if} \quad \boldsymbol{A}_j^{i,r,t} \succ_i \boldsymbol{A}_{-j}^{i,r,t}, \\ 0 & \text{if} \quad \boldsymbol{A}_j^{i,r,t} \prec_i \boldsymbol{A}_{-j}^{i,r,t}. \end{cases} \tag{1}$$

We request that respondents perform a task to choose one preferred policy package between two alternatives generated by this randomized conjoint design for 5 rounds for each respondent in each wave. Thus, we observe $\boldsymbol{A}_j^{i,r,t}$, $\boldsymbol{A}_{-j}^{i,r,t}$, $\boldsymbol{X}_i$, and $Y_{i,r,t}\left(\boldsymbol{A}_j^{i,r,t}, \boldsymbol{A}_{-j}^{i,r,t}\right)$ for respondent $i = 1, \ldots, 15,000$ in round $r = 1, \ldots, 5$ in period $t = 1, 2, 3$. Therefore, we observe 10 pairs of $\boldsymbol{X}_i$ and either $\boldsymbol{A}_j^{i,r,t}$, which corresponds to $Y_{i,r,t} = 1$, or $\boldsymbol{A}_{-j}^{i,r,t}$, which corresponds to $Y_{i,r,t} = 0$, for each respondent i in period t. We call a response of i in round r in period t on policy package j an observation.

3.4 Information treatment

In each wave, to measure respondents' expectations about Japan's poverty rate, we asked them to estimate how many of Japan's total households are in poverty and how many single-parent households are in poverty. The same question was asked in all three waves from November 2018 to October 2019.

In the first wave, in November 2018, we provided the treatment group with information about Japan's poverty rate based on a survey by the Ministry of Health, Labour and Welfare of the government of Japan in 2015. The ministry survey indicates that 16 percent of total households and 51 percent of single-parent households were in poverty as of 2015.[3] We had the treatment group view the information in two share graphs. The control group did not view them.

In the second wave in March 2019 and the third wave in October 2019, we did not provide any information. Instead, we again asked the respondents to estimate the poverty rates of total households and of single-parent households.

Therefore, along with the randomized conjoint experiments described above, we investigated 1) how long an update of prior expectations about the poverty rate after the information treatment persisted and 2) whether any impact of the information treatment on policy preference persisted. Our experiment was designed to identify whether the intervention effects through information provision persisted, whether the update of perceptions through the intervention supported these effects, and whether the information treatment effects and perception updates triggered by the treatment were associated with each other.

[3]The estimate of the relative poverty rate followed the standard defined by the Organisation of Economic Co-operation and Development (`https://www.mhlw.go.jp/toukei/list/dl/20-21-h28_rev2.pdf`; last accessed November 28, 2020).

4 Identification strategy

4.1 Individual information treatment effect

We estimate heterogeneous treatment effects in the potential outcomes framework (Imbens and Rubin (2015), 18–19, Wager and Athey (2018), and Athey and Imbens (2019)). Thus, by comparing one potential outcome with the information treatment and one without it, we identify the difference as the causal effect of the information treatment.

Let us consider an experiment where half of the respondents receive the information treatment and the other half receive the control treatment in period 1. Let W_i denote the information treatment indicator, which takes value one if respondent i has received the information treatment and zero if i received the control treatment. After receiving the information or control treatment, respondents are asked about their preferences on hypothetical policy packages generated by our randomized conjoint design. Each policy package is characterized by its attributes $\boldsymbol{A} = [A_1, ..., A_L]$, where A_l is a level of the lth attribute. In our case, A_l takes 0, 5, 10, 15, or 20 percent for $l = 1, ..., 5$, which refer to policy a to policy e described above, and the residual is assumed to be spent on government debt repayment.

Consider a potential outcome for respondent i, $Y_i\left(\boldsymbol{A}_j, \boldsymbol{A}_{-j}|W_i\right)$ given information treatment status W_i, where $\boldsymbol{A}_j$ and $\boldsymbol{A}_{-j}$ are alternative policy packages as described above, $\boldsymbol{X}_i$ denotes the vector of background characteristics of surveyed respondent i as described above, and

$$Y_{i,j}\left(\boldsymbol{A}_j, \boldsymbol{A}_{-j}|W_i\right) = \begin{cases} 1 & \text{if} \quad \boldsymbol{A}_j \succ_i \boldsymbol{A}_{-j}, \\ 0 & \text{if} \quad \boldsymbol{A}_j \prec_i \boldsymbol{A}_{-j}. \end{cases} \tag{2}$$

We randomly assign the information treatment and hence satisfy the unconfoundedness assumption,

$$W_i \perp\!\!\!\perp \left[Y_i\left(\boldsymbol{A}_j, \boldsymbol{A}_{-j}|W_i=0\right), Y_i\left(\boldsymbol{A}_j, \boldsymbol{A}_{-j}|W_i=1\right)\right] \big| \boldsymbol{X}_i.$$

Then, let us define the individual information treatment effect for respondent i in period t as

$$\tau_{i,t}(\boldsymbol{A}_j, \boldsymbol{A}_{-j}) = Y_{i,t}(\boldsymbol{A}_j, \boldsymbol{A}_{-j}|W_i=1) - Y_{i,t}(\boldsymbol{A}_j, \boldsymbol{A}_{-j}|W_i=0), \tag{3}$$

which captures the information treatment effects on respondent i's preference over policy packages $\boldsymbol{A}_j$ and $\boldsymbol{A}_{-j}$ in period t.

4.2 Average marginal component effect

We first review policy preference by estimating the average marginal component effect (AMCE) for each policy (Hainmueller et al. (2014)) such that

$$E\left[Y_{i,j}|a_{j,l}=a_1, W_i=w\right] - E\left[Y_{j,i}|a_{j,l}=a_0, W_i=w\right], \tag{4}$$

where $a_{j,l}$ is the lth attribute of policy j, $w \in \{0,1\}$, and

$$Y_{i,j} = \begin{cases} 1 & \text{if respondent } i \text{ supports policy } j, \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

Then, we assess the overall information treatment effect by estimating the distribution of conditional information effects in period t, defined as

$$E\left[\tau\left(W_i\right)\right] = E\left[Y_{i,j,t}|W_i=1,t\right] - E\left[Y_{i,j}|W_i=0,t\right]. \tag{6}$$

4.3 Group average treatment effects and classification analysis

Since respondent i receives either the information or the control treatment and we observe only one outcome, we cannot directly estimate the individual treatment effect $\tau_{i,t}$. Moreover, we have information about background characteristics $\boldsymbol{X}_i$ and policy attributes $\boldsymbol{A}_j$ and $\boldsymbol{A}_{-j}$. Thus, we first predict individual treatment effects $\tilde{\tau}_i$ as a function of $\boldsymbol{X}_i$, $\boldsymbol{A}_j$ and $\boldsymbol{A}_{-j}$, employing the causal forest algorithm (Wager and Athey (2018) and Athey, Tibshirani and Wager (2019)), and second sort the observations described in section 3, depending on the degree of predicted individual treatment effects, to estimate the sorted group average marginal treatment effects (GATES) (Chernozhukov, Demirer, Duflo and Fernández-Val (2018)).

We implement the information treatment in period 1 and investigate whether the related updates persist in periods 2 and 3. Thus, the GATES are defined as

$$E\left[\tau_{i,1}(\boldsymbol{A}_j, \boldsymbol{A}_{-j}, \boldsymbol{X}_i)|G_k\right], \tag{7}$$

where $G_k = \{\tilde{\tau}_{i,1} \in [g_k, g_{k+1})\}$ is an indicator of group membership and $\tilde{\tau}_{i,1}$ is a predicted individual treatment effect in period 1.

We next sort the observations into groups G_1, G_2, and G_3 based on the degree of $\tilde{\tau}_{i,1}$ in the highest tertile, second tertile, and lowest tertile and take an average of the treatment effects of each group. Note that we sort groups not by $|\tilde{\tau}_{i,1}|$ but by $\tilde{\tau}_{i,1}$. In sum, our algorithm to estimate the GATES is as follows:

1. Predict the individual information treatment effects on preferences over policy packages $\tilde{\tau}_{i,1}$ as a function of policy attributes $\boldsymbol{A}_j$ and $\boldsymbol{A}_{-j}$ and a vector of background characteristics $\boldsymbol{X}_i$. The causal forest algorithm is employed for prediction.

2. Decompose the combination of policy and background characteristics of the sample

into three groups, depending on the policies' $\tilde{\tau}_{i,1}$: the highest tertile of $\tilde{\tau}_{i,1}$ into Group 1 (G_1), the second tertile into Group 2 (G_2), and the third tertile into Group 3 (G_3).

3. Estimate the GATES in each group.

Then, we estimate the average characteristics of the most and least (or adversely) affected units through classification analysis (CLAN) (Chernozhukov et al. (2018)). In our sample, support for policies with $\tilde{\tau}_{i,1}$ in the highest tertile and sorted into Group 1 (G_1) was positively affected by the information treatment, support for policies with $\tilde{\tau}_{i,1}$ in the second tertile and sorted into Group 2 (G_2) was the least affected, and support for policies with $\tilde{\tau}_{i,1}$ in the lowest tertile and sorted into Group 3 (G_3) was negatively affected.

Out of the positively affected group of attributes (G_1), the least affected group (G_2), and the most negatively affected group (G_3), we focus on the average characteristics of the most and negatively affected groups, G_1 and G_3. Thus, we estimate the following estimands,

$$E\left[Z|G_1\right] - E\left[Z|G_3\right], \tag{8}$$

where Z is an element of the policy attribute vector $\boldsymbol{A}$ or background characteristics vector $\boldsymbol{X}_i$. Calculating the expected values of either element $\boldsymbol{A}$ or $\boldsymbol{X}$ in the group of observations classified as the most positively affected by the information treatment and those of observations classified as the most adversely affected and taking a difference between them, we estimate which element of $\boldsymbol{A}$ is more preferred or which element of $\boldsymbol{X}$ is more likely to be a characteristic among the observations classified in the most positively affected group in comparison to those in the most adversely affected group.

5 Results

5.1 Descriptive statistics of the background survey

Out of the 15,000 respondents that we surveyed, 9,000 responded to the survey in all three periods. We show descriptive statistics of the background survey for the basic variables of these 9,000 respondents, for whom we analyze the persistence of the information treatment effects. The values are from period 1. Table 3 presents the statistics for demography, employment, and education.

Table 3: Demography, employment, and education.

variable	mean	sd
age	52.33	15.16
female	0.47	0.50
married	0.65	0.48
number of children	2.22	1.12
work status: employed or self-employed	0.62	0.49
education: high school or less	0.02	0.14
education: college or higher	0.50	0.50

Table 4 presents the distribution of party support. The Liberal Democratic Party (LDP) has been Japan's ruling party in most periods since its creation in 1955. The Constitutional Democratic Party is the largest opposition party, which pursues the extension of welfare programs and is further left than the LDP. The Komeito is backed by the Soka Gakkai, a new religion that branched off from a Buddhist sect. It has been part of a governing coalition with the LDP since 2012. Other parties include ones on both the left, such as the Japanese Communist Party, and the right.

Table 4: Party support.

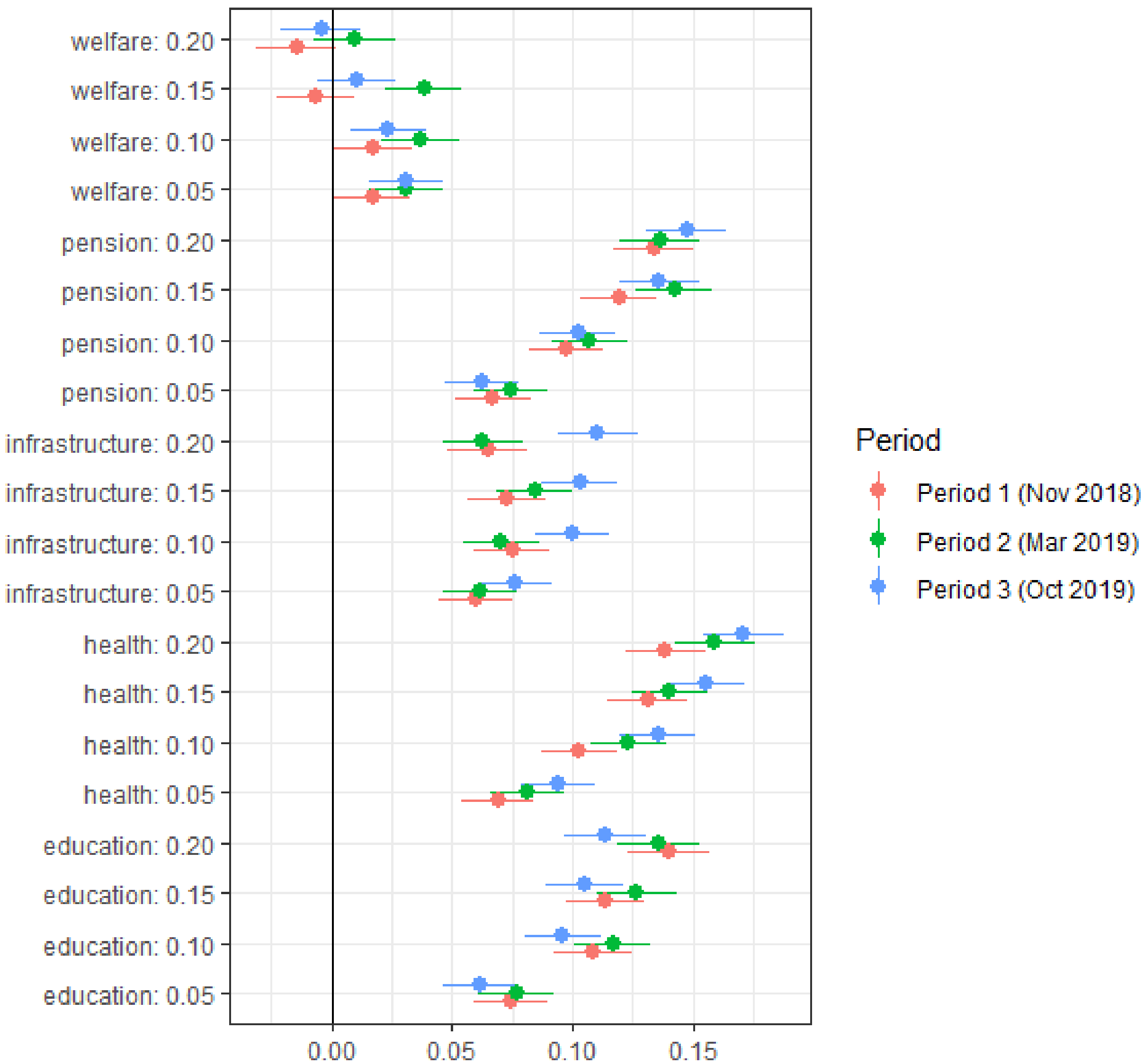
variable	mean	sd
Liberal Democratic Party	0.25	0.43
Constitutional Democratic Party	0.09	0.28
Komeito	0.02	0.14
other parties	0.09	0.29
independent	0.55	0.50

5.2 Average marginal component effect

We first report the average marginal component effect and 95 percent confidence intervals without the information treatment in Figure 4. The dependent variable is the probability that policy package $\boldsymbol{A}_j$ is preferred to policy package $\boldsymbol{A}_{-j}$. As described above, each policy package is composed of an allocation of the tax revenue from the raised value-added tax to (a) welfare, (b) pensions, (c) health, (d) infrastructure, and (e) education policies, and any residue is assumed to be spent on repayment of government debt. Thus, the independent variables denote spending of 0 to 20 percent of the raised consumption tax revenue on each policy instead of austerity. We take the weighted average over the background characteristics vector $\boldsymbol{X_i}$ surveyed in period 1. Periods 1, 2, and 3 denote our survey timings of November 2018, March 2019, and October 2019, respectively.

Figure 4: Average marginal component effects

.



First, respondents preferred spending on public health insurance and the national basic pension over spending on education and welfare for poor individuals in all three periods. The priority given to national health insurance and the national pension plan is widely shared.

Second, the probabilities of support for pension spending, public health care spending, and education spending monotonically increased with the share of expenditure in all three periods. For these three categories, respondents' attitude toward spending was "the more, the better."

Third, the probability of supporting infrastructure spending monotonically increased with the share of spending only in period 3. The probability fell below 15 percent in periods 1 and 2.

Fourth, in all three periods, support for welfare spending was nonmonotonic. Support was increasing in spending shares from 0 percent to 5 percent but was mixed for shares between 5 percent and 15 percent and decreasing in shares beyond 15 percent.

5.3 Group average marginal effects

Here, we classify the observations into three groups according to support for the five policies and respondents' background characteristics. We observe the effects of the information treatment in relation to each attribute level for each policy, and we bundle the policies into Groups 1 to 3, depending on the degree of information treatment effects on policy preferences. Then, we estimate the GATES defined as equation (7). The result is shown in Figure 5.

Figure 5: Group average treatment effects.

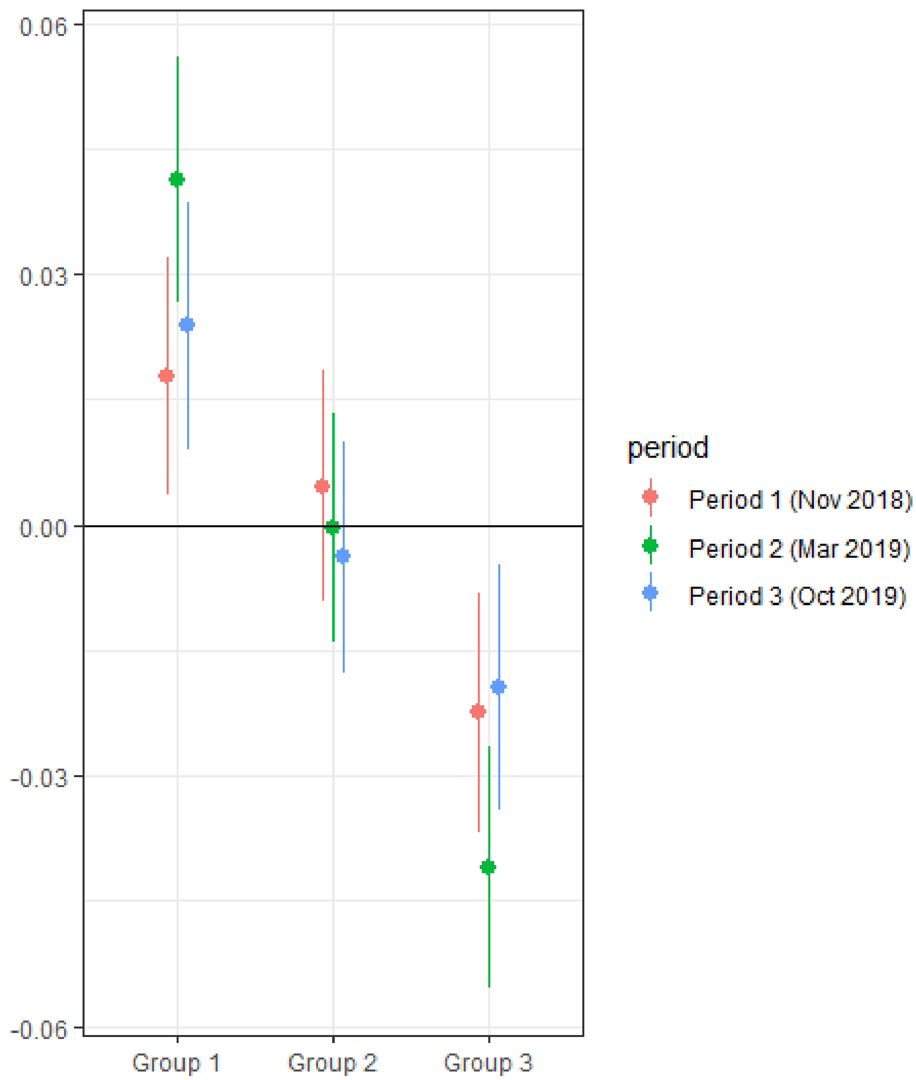


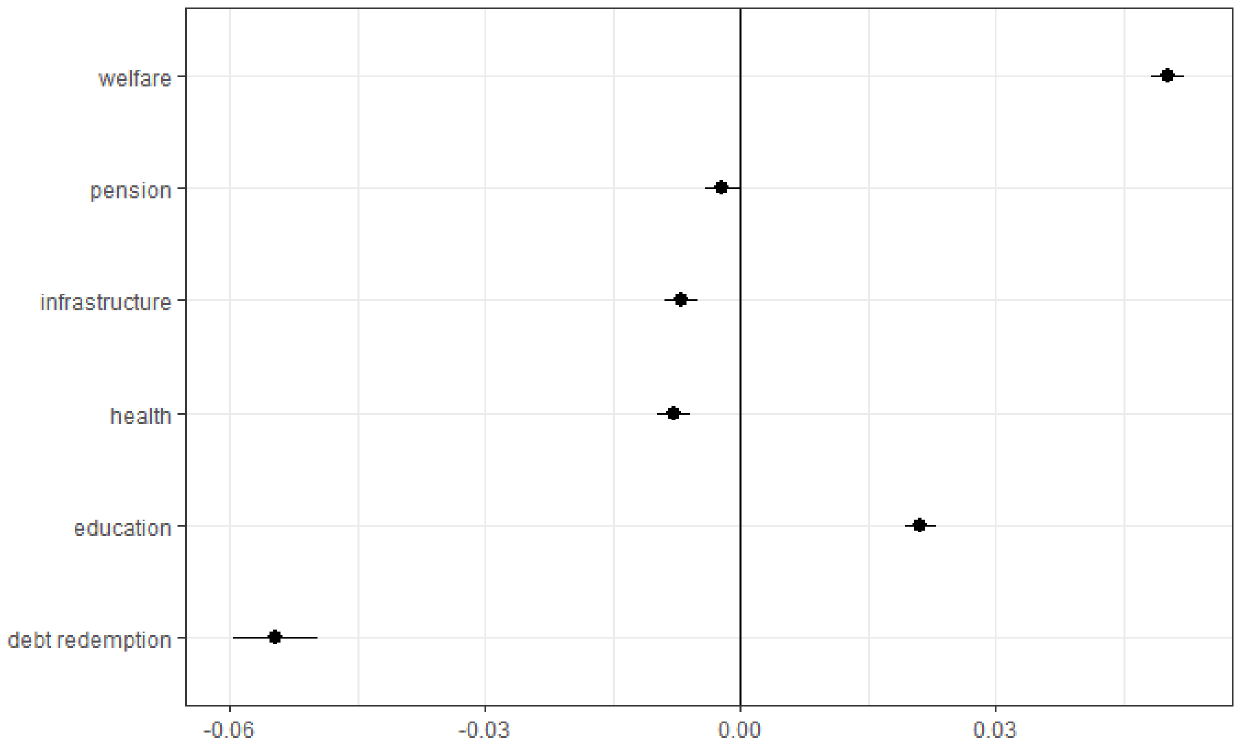
Figure 5.3 demonstrates that the effects of the information treatment on policy preference were astonishingly persistent over the three waves from November 2018 to March 2019 and October 2019. The policy packages that were more preferred conditional on background characteristics in the first period due to the information treatment continued to be preferred in the second and third periods. Support for policy packages

conditional on respondents' background characteristics that were least responsive to the information treatment barely changed in the second and third waves. The policy packages conditional on background characteristics that lost support due to the information treatment did not regain support in the second and third periods. The effects were not only consistent but also so persistent that they never attenuated for one year.

5.4 Classification analysis

The GATES analysis demonstrates considerable heterogeneity across attributes. Thus, in a CLAN, we investigate possibly different levels of support between the respondents in Group 1, whose support was most positively affected by the information treatment, and those in Group 3, whose support was most adversely affected by the information treatment, by means of equation (8).

Figure 6: Classification analysis: Policy attributes.

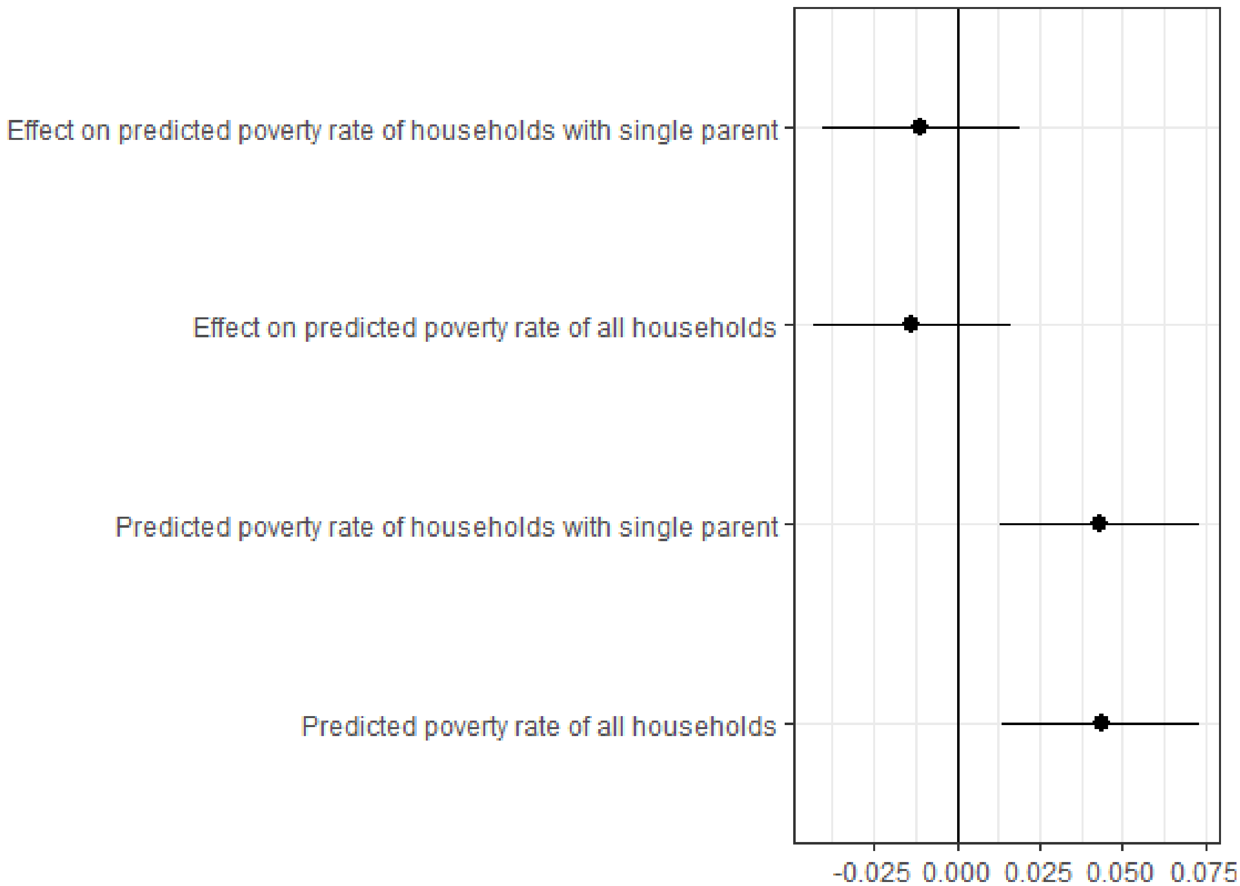


The horizontal axis of Figure 6 is the difference in the values estimated by equation (8) and thus the difference in average support for each policy between the observations classified in Group 1 and those in Group 3. Figure 6 demonstrates that the difference in average support among those in Group 1 and those in Group 3 is particularly large for welfare programs for poor individuals. A negative value for a policy means that average support for the policy is smaller among the observations classified in Group 1 than among those in Group 3. Thus, the highly negative value for debt redemption means that the observations classified in Group 1, on average, preferred to finance a rise in spending on welfare programs by reducing government debt redemption. Slightly negative values for infrastructure and health indicate that the observations classified in Group 1 also included those preferring to finance a rise in spending on welfare programs by reducing expenditures on infrastructure and subsidies for national health insurance.

Thus, focusing on the direction of the policy vector in the multidimensional policy space, we identify two approaches to financing welfare programs: through an increase in total spending and through a decrease in spending on other public policies. Respondents who displayed increased support for welfare included those who came to prefer a larger government through a reduction in government debt redemption and those who came to prefer reallocation of revenue from other public policy components such as infrastructure and national health. This is a finding that unidimensional approaches such as those of Kuziemko et al. (2015) and Becker (2020) did not identify.

Next, we identify how much the rise in support for welfare for poor individuals depended on the perception of Japan's relative poverty rate and how the information treatment affected the perception of poverty rates. As the lower two rows show, the observations classified in Group 1 are more likely to perceive higher poverty rates than those classified in Group 3. However, the information treatment barely affected this perception. The upper two rows in Figure 7 show the classification analysis of the change in perceptions of poverty rates before and after the information treatment. They show that the information treatment effects on the perception of the poverty rate were hardly different for observations classified in Groups 1 and 3. Thus, the information treatment effects on support for welfare programs are unlikely to have occurred through updates of perceptions of the poverty rate.

Figure 7: Classification analysis: Information treatment effects on predictions of the poverty rate.



We next investigate the effects of political and other background characteristics by using equation (8). Figure 8 shows that the observations classified into Group 1 on average had a higher self-perception of respondents' social status. While those in Group 1 were more likely to be older, we do not see substantial differences in educational background and gender between those in Groups 1 and 3.

Figure 8: Classification analysis: Educational backgrounds.

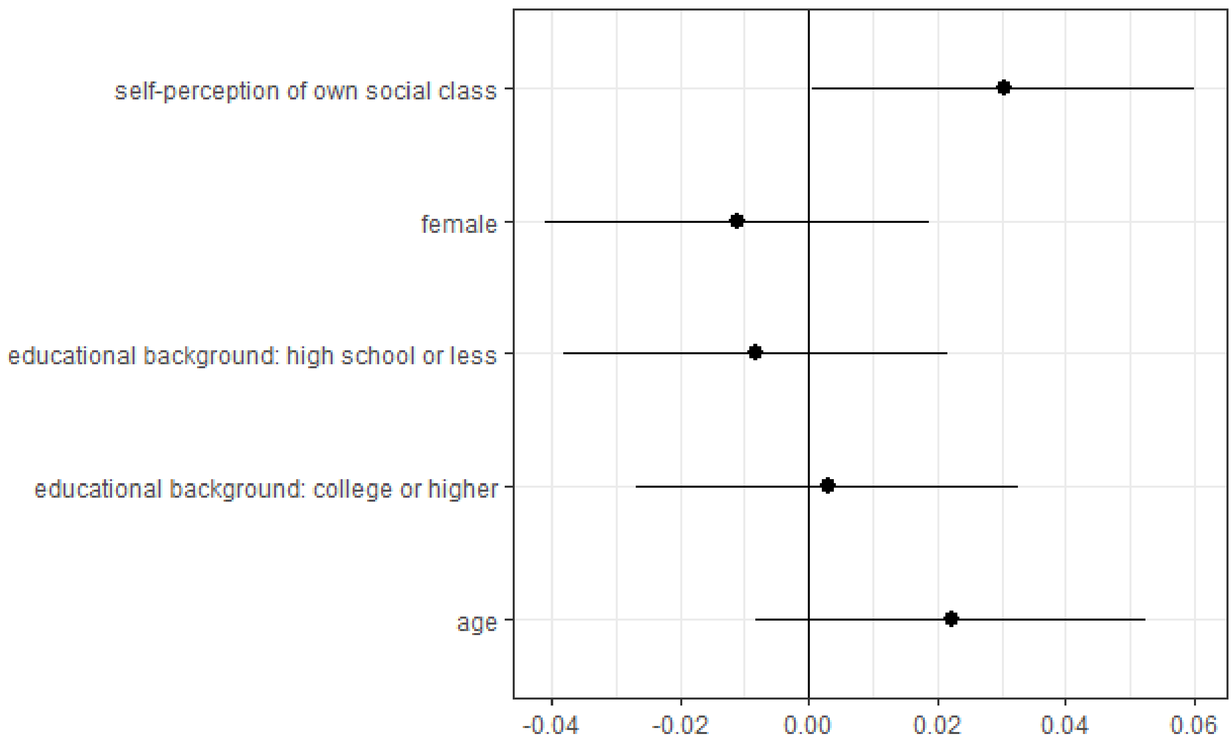
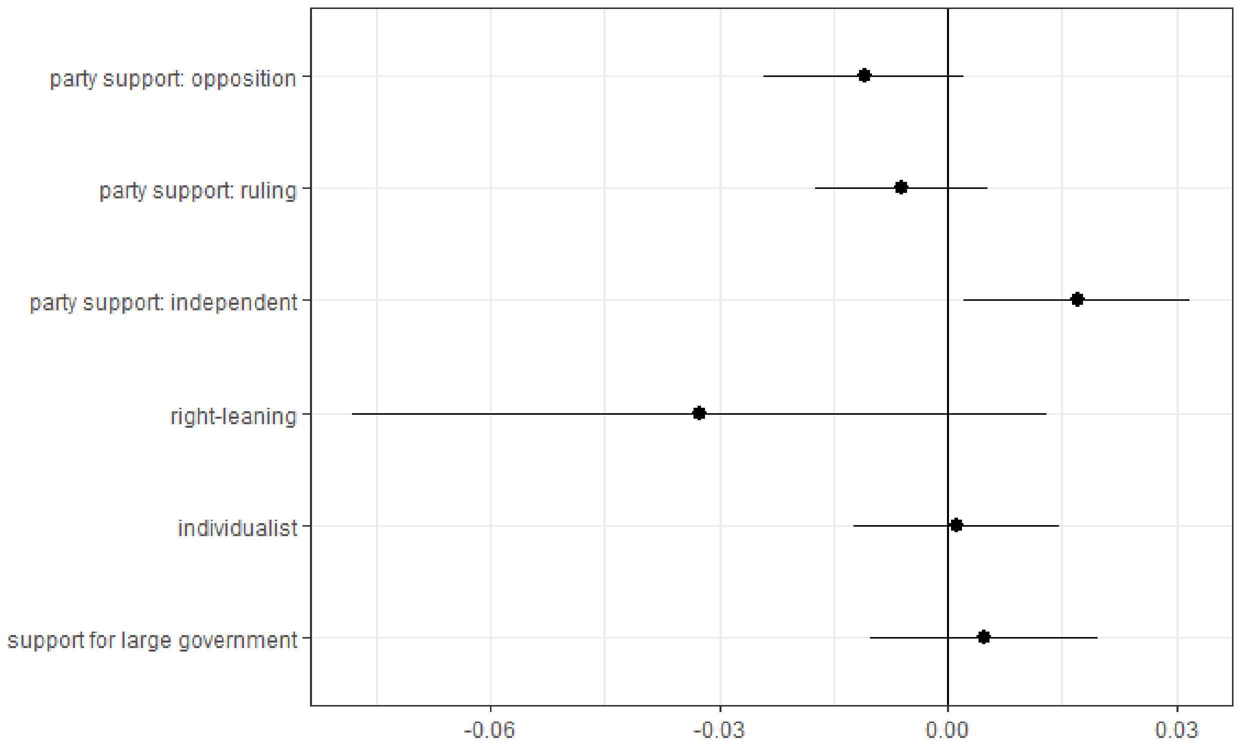


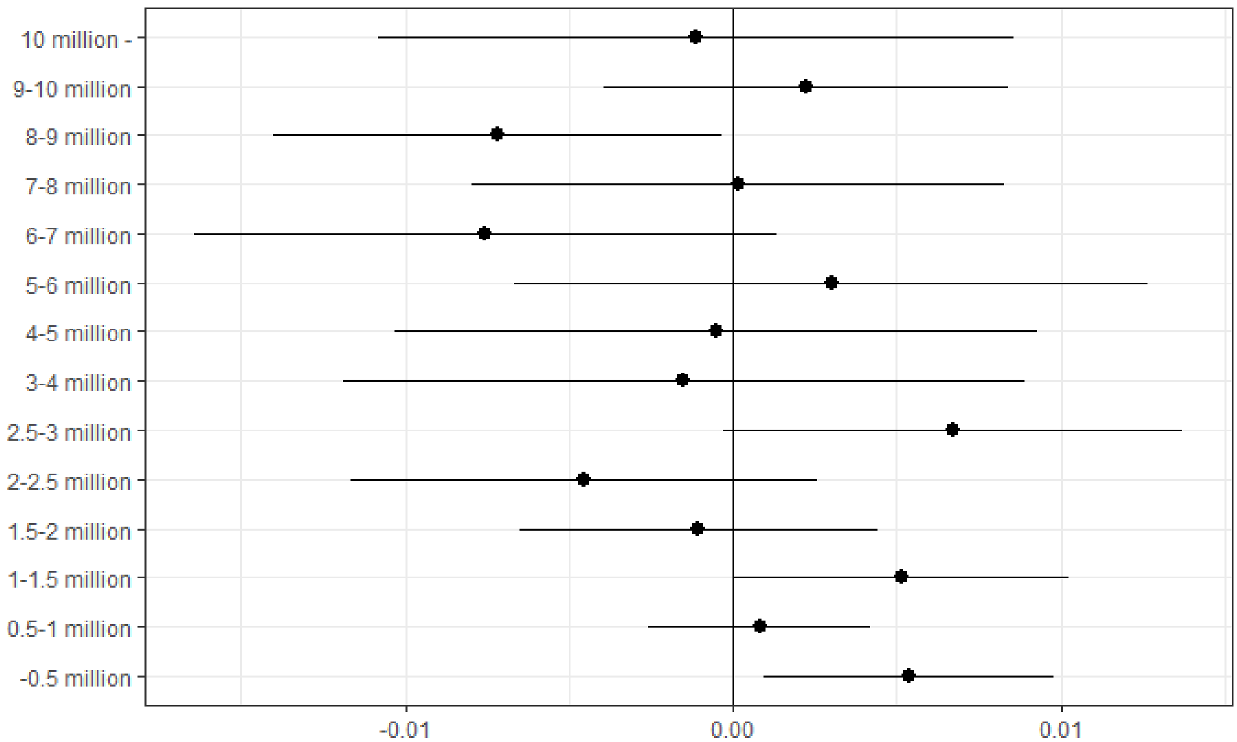
Figure 9 shows that the observations classified in Group 3, which were adversely affected by the information treatment, are more likely to consider themselves right-leaning. However, on other measures of political positions, those classified in Groups 1 and 3 did not show significant differences. Thus, neither individualism nor support for large government or for conservative ruling parties differed between Groups 1 and 3. While those in Group 1 were slightly more likely to be independent regarding party support, they were also less likely to be supporters of opposition parties that included left-wing parties. We cannot detect a consistent relationship between the information treatment effects and political positions.

Figure 9: Classification analysis: Political characteristics.



While Figure 8 shows that the observations classified in Group 1 were more likely to have a higher self-perception of social status, the effects of respondents' self-perceived social status are not necessarily consistent with those of their income. Figure 10 shows that the effects of respondents' household income level are quite weak and not monotonic. We cannot find any positively or negatively consistent relationship between household income levels and being classified into Group 1 or Group 3. Thus, the information treatment effects were not monotonic over own household income levels.

Figure 10: Classification analysis: Household income.



6 Conclusion

We suggested a more generalized design to measure the effects of information provision on public policy preferences than the unidimensional approaches such as those of Kuziemko et al. (2015), Alesina et al. (2018), and Becker (2020). The setting enabled us to find that the effects of an information treatment on preferences over policy direction were not sensitive to respondents' political position, party support or preference on the size of government and that the effects persisted for one year. Furthermore, we revealed how respondents wanted to finance the increase in relative support for welfare programs.

They preferred to finance welfare programs by cutting spending on government debt repayment, investment in infrastructure, or national health insurance, as presented in Figure 6. Respondents who displayed increased support for income redistribution did not necessarily want to have a larger government. In some cases, they preferred to reallocate spending on other public policies toward welfare. Such a change in policy direction was only detectable because of our multidimensional approach.

Moreover, we found that the respondents who were most affected by the information treatment tended to predict higher poverty rates, as seen in Figure 7. However, the marginal rise in respondents' estimation of the poverty rate due to the information treatment was mostly indifferent between the respondents who were the most affected by the information treatment and those who were adversely affected, as is also presented in Figure 7. Regarding the two possible channels of the treatment effect, "update" or "persuade," our results on the persistent treatment effects are consistent with the latter channel.

Our results are also related to mixed results in the growing literature of experimental interventions in energy and environmental economics. Surveying previous works, Brandon, Ferraro, List, D., Price and Rundhammer (2017) summarized that information treatment effects may persist for one to six months but attenuate rapidly. Ferraro, Miranda and Price (2011), Ferraro and Miranda (2013), Ferraro and Price (2013), and Bernedo and Price (2013) demonstrated that provision of norm-based message impacts on recipients' preference over water saving. Thus, the information treatment effects that might last but attenuate rapidly is a consensus of previous experiments. Allcott and Rogers (2014) described the attenuation of the intervention effects in energy saving as "action and backsliding." We tend to habituate and get inactive over issues we once considered urgent. Indeed, Ito (2015) and Ito, Ida and Tanaka (2018) showed that pecuniary incentives for energy saving helps energy saving actions last. Money helps prevent people from backsliding. Meanwhile, Costa and Gerard (forthcoming) reports significant hysteresis of consumers' behavior after intervention. Our results indicate that such persistent but attenuating effects on actions might be explained by persistent effects of intervention's persuasion on consumers' policy preferences but their attenuating actions due to habituation. Focusing exclusively on effects of intervention on preferences might help decompose the mixed results.

At the same time, we acknowledge limitations of our results. First, our design does not identify how much our results depend on Japanese society's specific characteristics and how much on the multidimensional policy space design. Further applications and analyses of multidimensional approaches are left for future research.

Additionally, our results suggest the effects of information exchange. Similar effects may arise regardless of whether the exchanged information is correct. Indeed, Nyhan and Reifler (2010) showed that impacts of deception might also persist through the entrenchment of perceptions affected by fake news. This might cause further divisions rather than integration among citizens. However, the quality of media is beyond the scope of our design.

References

Alesina, Alberto, Stefanie Stantcheva, and Edoardo Teso (2018) "Intergenerational mobility and preferences for redistribution," *The American Economic Review*, 108 (2), 521–54, 10.1257/aer.20162015.

Allcott, Hunt and Todd Rogers (2014) "The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation," *The American*

Economic Review, 104 (10), 3003–3037, 10.1257/aer.104.10.3003.

Athey, Susan and Guido W. Imbens (2019) "Machine Learning Methods That Economists Should Know About," *Annual Review of Economics*, 11 (1), 685–725, 10.1146/annurev-economics-080217-053433.

Athey, Susan, Julie Tibshirani, and Stefan Wager (2019) "Generalized random forests," *Annals of Statistics*, 47 (2), 1148–1178, 10.1214/18-AOS1709.

Bansak, Kirk, Jens Hainmueller, Daniel J. Hopkins, and Teppei Yamamoto (2018) "The number of choice tasks and survey satisficing in conjoint experiments," *Political Analysis*, 26 (1), 112—119, 10.1017/pan.2017.40.

Becker, Bastian (2020) "Mind the income gaps? Experimental evidence of information's lasting effect on redistributive preferences," *Social Justice Research*, 33 (2), 137–194, 10.1007/s11211-019-00343-7.

Bernedo, Ferraro-Paul J., Marí and Michael Price (2013) "The persistent impacts of norm-based messaging and their implications for water conservatism," *Journal of Consumer Policy*, 37 (3), 437–452.

Boyle, Glenn, Roger Stover, Amrit Tiwana, and Oleksandr Zhylyevskyy (2015) "The impact of deposit insurance on depositor behavior during a crisis: A conjoint analysis approach," *Journal of Financial Intermediation*, 24 (4), 590– 601, https://doi.org/10.1016/j.jfi.2015.02.001.

Brandon, Alec, Paul Ferraro, John A. List, Metcalfe Robert D., Michael K. Price, and Florian Rundhammer (2017) "Do the effects of social nudges persist? Theory and evidence from 38 natural field experiments," Nationa Bureau of Economic Research Working Paper 23277.

Chernozhukov, Victor, Mert Demirer, Esther Duflo, and Iván Fernández-Val (2018) "Generic Machine Learning Inference on Heterogenous Treatment Effects in Randomized Experiments," Working Paper 24678, National Bureau of Economic Research, 10.3386/w24678.

Chiavacci, David (2008) "From class struggle to general middle-class society to divided society: Societal models of inequality in postwar Japan," *Social Science Japan Journal*, 11 (1), 5–27, 10.1093/ssjj/jyn022.

Clark, Andrew and Conchita D'Ambrosio (2015) "Attitudes to income inequality: Experimental and survey evidence," *Handbook of Income Distribution*, 2, 1147–1208, 10.1016/B978-0-444-59428-0.00014-X.

Costa, Francisco and François Gerard (forthcoming) "Hysteresis and the welfare effect of corrective policies: Theory and evidence from an energy-saving program," *Journal of Political Economy*, forthcoming, `https://www.dropbox.com/s/79jirpmitp4p0p7/Costa_Gerard_2020_paper.pdf?dl=0`.

Esarey, Justin, Tim Salmon, and Charles Barrilleaux (2012) "Social insurance and income redistribution in a laboratory experiment," *Political Research Quarterly*, 65 (3), 685–698, 10.1177/1065912911411096.

Fernández-Albertos, José and Alexander Kuo (2018) "Income perception, information, and progressive taxation: Evidence from a survey experiment," *Political Science Research and Methods*, 6 (1), 83 – 110, 10.1017/psrm.2015.73.

Ferraro, Paul J., Juan Jose Miranda, and Michael K. Price (2011) "The persistence of treatment effects with norm-based policy instruments: Evidence from a randomized environmental policy experiment," *The American Economic Review*, 101 (3), 318–22, 10.1257/aer.101.3.318.

Ferraro, Paul J. and Juan José Miranda (2013) "Heterogeneous treatment effects and mechanisms in information-based environmental policies: Evidence from a large-scale field experiment," *Resource and Energy Economics*, 35 (3), 356–379, https://doi.org/10.1016/j.reseneeco.2013.04.001.

Ferraro, Paul J. and Michael K. Price (2013) "Using nonpecuniary strategies to influence behavior: Evidence from a large-scale field experiment," *Review of Economics & Statistics*, 95 (1), 64–73, `http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=86185659&lang=ja&site=ehost-live`.

Fukuda, Katsufumi, Rofiq Isdwiyani, Keisuke Kawata, and Yuichiro Yoshida (2018) "Measuring the impact of modern waste collection and processing service attributes on residents' acceptance of waste separation policy using a randomised conjoint field experiment in Yogyakarta Province, Indonesia," *Waste Management & Research*, 36 (9), 841–848, 10.1177/0734242X18793939.

Gallego, Aina and Paul Marx (2017) "Multi-dimensional preferences for labour market reforms: A conjoint experiment," *Journal of European Public Policy*, 24 (7), 1027–1047, 10.1080/13501763.2016.1170191.

Hainmueller, Jens, Dominik Hangartner, and Teppei Yamamoto (2015) "Validating vignette and conjoint survey experiments against real-world behavior," *Proceedings of the National Academy of Sciences*, 112 (8), 2395–2400, 10.1073/pnas.1416587112.

Hainmueller, Jens, Daniel J. Hopkins, and Teppei Yamamoto (2014) "Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments," *Political Analysis*, 22 (1), 1— 30, 10.1093/pan/mpt024.

Hommerich, Carola and Toru Kikkawa (2019) "Movement behind the scenes: The quiet transformation of status identification in Japan," *Social Science Japan Journal*, 22 (1), 11–24, 10.1093/ssjj/jyy041.

Imbens, Guido W. and Donald B. Rubin (2015) *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction*, Cambridge: Cambridge University Press.

Ito, Koichiro (2015) "Asymmetric incentives in subsidies: Evidence from a large-scale electricity rebate program," *American Economic Journal: Economic Policy*, 7 (3), 209–237, 10.1257/pol.20130397.

Ito, Koichiro, Takanori Ida, and Makoto Tanaka (2018) "Moral Suasion and Economic Incentives: Field Experimental Evidence from Energy Demand," *American Economic Journal: Economic Policy*, 10 (1), 240–267, 10.1257/pol.20160093.

Kanbayashi, Hiroshi (2019) "The changing images of Japan's social stratification: The other side of the 'quiet transformation'," *Social Science Japan Journal*, 22 (1), 45–63, 10.1093/ssjj/jyy048.

Kerschbamer, Rudolf and Daniel Müller (2020) "Social preferences and political attitudes: An online experiment on a large heterogeneous sample," *Journal of Public Economics*, 182, 104076, https://doi.org/10.1016/j.jpubeco.2019.104076.

Klor, Esteban F. and Moses Shayo (2010) "Social identity and preferences over redistribution," *Journal of Public Economics*, 94 (3), 269 – 278, https://doi.org/10.1016/j.jpubeco.2009.12.003.

Kreps, Sarah, Sandip Prasad, John S. Brownstein, Yulin Hswen, Brian T. Garibaldi, Baobao Zhang, and Douglas L. Kriner (2020) "Factors associated with US adults' likelihood of accepting COVID-19 vfaaccination," *JAMA Network Open*, 3 (10), e2025594–e2025594, 10.1001/jamanetworkopen.2020.25594.

Kuziemko, Ilyana, Michael I. Norton, Emmanuel Saez, and Stefanie Stantcheva (2015) "How elastic are preferences for redistribution? Evidence from randomized survey experiments," *The American Economic Review*, 105 (4), 1478–1508, 10.1257/aer.20130360.

Leeper, Thomas J., Sara B. Hobolt, and James Tilley (2020) "Measuring subgroup preferences in conjoint experiments," *Political Analysis*, 28 (2), 207–– 221, 10.1017/pan.2019.30.

Lusk, Jayson L., Deacue Fields, and Walt Prevatt (2008) "An incentive compatible conjoint ranking mechanism," *American Journal of Agricultural Economics*, 90 (2), 487–498, `http://www.jstor.org/stable/30139599`.

Lusk, Jayson L. and F. Bailey Norwood (2005) "Effect of experimental design on choice-based conjoint valuation estimates," *American Journal of Agricultural Economics*, 87 (3), 771–785, `http://www.jstor.org/stable/3697912`.

Maurice, Jonathan, Agathe Rouaix, and Marc Willinger (2013) "Income redistribution and public good provision: An experiment," *International Economic Review*, 54 (3), 957–975, 10.1111/iere.12024.

Moriguchi, Chiaki and Emmanuel Saez (2008) "The evolution of income concentration in Japan, 1886–2005," *The Review of Economics and Statistics*, 90 (4), 713–734.

Motta, Matt (2021) "Can a COVID-19 vaccine live up to Americans' expectations? A conjoint analysis of how vaccine characteristics influence vaccination intentions," *Social Science & Medicine*, 113642, https://doi.org/10.1016/j.socscimed.2020.113642.

Norwood, F. Bailey and Jayson L. Lusk (2011) "A calibrated auction-conjoint valuation method: Valuing pork and eggs produced under differing animal welfare conditions," *Journal of Environmental Economics and Management*, 62 (1), 80–94, https://doi.org/10.1016/j.jeem.2011.04.001.

Nyhan, Brendan and Jason Reifler (2010) "When corrections fail: The persistence of political misperceptions," *Political Behavior*, 32 (2), 303–330, http://www.jstor.org/stable/40587320.

Seanehia, Joy, Carole Treibich, Christine Holmberg, Jacqueline Müller-Nordhorn, Valerie Casin, Jocelyn Raude, and Judith E. Mueller (2017) "Quantifying population preferences around vaccination against severe but rare diseases: A conjoint analysis among French university students, 2016," *Vaccine*, 35 (20), 2676 – 2684, https://doi.org/10.1016/j.vaccine.2017.03.086.

Setiawan, Rulli Pratiwi, Shinji Kaneko, and Keisuke Kawata (2019) "Impacts of pecuniary and non-pecuniary information on pro-environmental behavior: A household waste collection and disposal program in Surabaya city," *Waste Management*, 89, 322–335, https://doi.org/10.1016/j.wasman.2019.04.015.

Sun, Xiaodong, Abram L. Wagner, Jiahui Ji, Zhuoying Huang, Brian J. Zikmund-Fisher, Matthew L. Boulton, Jia Ren, and Lisa A. Prosser (2020) “A conjoint analysis of stated vaccine preferences in Shanghai, China,” *Vaccine*, 38 (6), 1520 – 1525, https://doi.org/10.1016/j.vaccine.2019.11.062.

Sydavong, Thiptaiya, Daisaku Goto, Keisuke Kawata, Shinji Kaneko, and Masaru Ichihashi (2019) “Potential demand for voluntary community-based health insurance improvement in rural Lao People’s Democratic Republic: A randomized conjoint experiment,” *PLos One*, 14 (1), e0210355 1–21, https://dx.doi.org/10.1371/journal.pone.0210355.

Wager, Stefan and Susan Athey (2018) “Estimation and inference of heterogeneous treatment effects using random forests,” *Journal of the American Statistical Association*, 113 (523), 1228–1242, 10.1080/01621459.2017.1319839.