Willingness to Bear the Costs of Preventative Public Health Measures

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ABSTRACT

We take advantage of a 2003 general-population choice-experiment survey of U.S. residents designed to determine people's willingness to bear the costs of public policies to reduce illnesses and avoid premature deaths in their communities. We re-estimate earlier models, omitting all respondent-specific individual characteristics and adding new county-level data on a variety of contextual variables circa 2003. Then we transfer our re-estimated model to the context of the 2020-21 COVID-19 pandemic, substituting 2020-era levels of the contextual variables, including county-level household incomes and unemployment rates. We calculate the model's implied values of what would have been people's ex-ante willingness to pay (WTP) to avoid numbers of generic cases and deaths equal to the actual monthly totals of cases and deaths during March 2020 to April 2021, by county and month, for the conterminous U.S. states. Our estimated aggregate WTP across the U.S. adult population from March 2020 to April 2021 is about 3 trillion dollars. These estimates are a lower bound because the original choice scenarios pertained to non-infectious illnesses and accidents, rather than pandemic illness. Our models reveal that WTP for public health policies to reduce illness and avert deaths is greater for people from counties with higher proportions of adults in labor force and counties with a higher proportion of Blacks residents. People from counties with higher income and higher health access also tend to have higher WTP to reduce the risks to public health. If preferences over public health programs, conditional on context, remained relatively stable over time, our findings may be relevant for predicting contemporary willingness to bear the costs of public health measures, either retrospectively for the current pandemic, or prospectively for future pandemics.

1 Introduction

Many policies and regulations are intended to protect human life and health. In the context of the current global pandemic, given the externalities associated with infectious disease, public health policies are essential. To analyze the benefits and costs of public health measures, policymakers must take into account the level of (and heterogeneity in) people's willingness to bear the costs of appropriate public health measures.

It is challenging to monetize the social benefit from costly policies to protect human life and health. Economists typically use a measure called the Value of a Statistical Life (VSL) to quantify society's willingness to bear the costs of small reduction in mortality risks for a large number of people. VSL can be interpreted as a marginal rate of substitution between individual private mortality risk and money. Mathematically, VSL is the marginal utility of a small reduction in mortality risk divided by the marginal utility of a small change in income. In 2006, for example, the U.S. Environmental Protection Agency (EPA) estimated that people in the U.S. are willing to pay about $7,000,000 for one "statistical" life. This number means, for example, people are willing to pay about $70, on average, to reduce the probability of death by 1/100,000 for 100,000 people.[1]

For the COVID-19 pandemic, Echazu and Nocetti (2020) calculate society's overall willingness to pay for morbidity and mortality risk reductions. They estimate that the aggregate social WTP for a sizeable reduction in infection risk during a pandemic may be on the order of $3T to $7T. This dramatic estimate for WTP (for all statistical lives "lost") for risk reduction during an *infectious* pandemic likely reflects the fact that people are willing to pay not just for a reduction in their own risk of illness and death, but also to permit reductions in the stringency of pandemic restrictions. Cameron (2010) points out that VSL, as a "one-size-

[1] EPA's estimates of the value of a mortality risk reduction were reviewed in a white paper called "Valuing Mortality Risk Reduction in Environmental Policy" included 33 studies between 1988 to 2009. See line 694 in this white paper.

fits-all" measure, can hinder our ability to understand distributional effects of risk-reducing policies or interventions. A single VSL—where the majority of estimates of the VSL are derived from labor-market studies where the risk in question is sudden death in an industrial workplace accident—may also fail to reflect the particular features of COVID-19 as a specific health threat. Likewise, the populations for which wage-risk VSLs are typically estimated (prime-aged white male workers in hazardous occupations) may be a poor approximation to the characteristics of the populations most seriously affected by COVID-19.

The research described in this paper constitutes an exercise in "benefits function transfer" (Smith et al., 2002), where the "study sample" is an existing survey-based choice experiment fielded to more that 1400 respondents in a representative probability sample of households in counties across the U.S. in 2003 (Bosworth et al., 2009). The goal in that original study was to determine the social benefits from public health policies to reduce illness and deaths from different types of health threats in the respondent's community. For the current benefits transfer task, the "policy samples" consist of the populations of all counties across the U.S. during the 2020-21 COVID-19 pandemic.

Benefits transfer has been widely use to in environmental economics to supply information for benefit-cost analyses to support policy decisions when a new study is not affordable or when no time is available to conduct a thorough new study (Richardson et al., 2015). Benefits *function* transfer exercises can involve study and policy samples at different point in time where conditions may be different. For example, Price et al. (2017) evaluate the temporal stability of willingness-to-pay values from two identical stated preference surveys undertaken in 2004 and 2012. The surveys were designed to capture the trade-offs between (a) risk reductions for two health endpoints related to tap water, and (b) monetary costs. Across these two time periods, their study found no significant differences in real-valued WTP, or in the structure of heterogeneous preferences.[2]

[2]Benefit function transfers maybe be derived from just one study, or they may combine the results for

In the broader environmental benefits literature, it is also a common practice to estimate a benefits function for one country, and to attempt to transfer this benefits function to another country. These efforts can be challenging, however, because there are often cultural differences between countries (especially between developed and developing countries) that can call into question whether the preferences estimated in one country should be *expected* to hold in another country (Ready and Navrud, 2006; Brander et al., 2007; Lindhjelm and Navrud, 2008). In this paper, fortunately, we seek to transfer a benefits function only between two different time periods in the U.S. This requires only that we assume that U.S. preferences over public health policies and net incomes be relatively stable across time, after controlling for changes over time in the variables that systematically affect these preferences. It also requires the assumption that *cross-sectional* differences among U.S. counties in 2003 have similar effects on public health policy preferences as do changes over time in the characteristics of these U.S. counties.

Instead of using a single one-size-fits-all VSL, our research estimates people's WTP for public health policies that reduce both illnesses and deaths, in light of both the relevant cost and the expected duration of such policies. Furthermore, rather than focusing on *private* WTP to reduce an individual's personal mortality risk, we emphasize a specifically *public* program, where people are asked their WTP for reduction in the risk of illness and deaths in their broader community. In our current analysis, we interpret *counties* as communities. Although counties are not the smallest geographic regions we might use, they are the most appropriate administrative units in the context of the original survey. During a public health crisis like the COVID-19 pandemic, data on cases and deaths are also commonly reported at the county level.

Assessing people's willingness to pay for community-level public health policies is essential for public health policymakers for four reasons. First, people from the same community

several related studies to "triangulate" the conditions for which a new benefits estimate is needed.

often have more in common than do people from different communities, in terms of sociodemographics, ethnicities, economic status, and health characteristics. To the extent this is true, community characteristics may systematically affect individuals' preferences for public health policies. Second, during an infectious pandemic like COVID-19, people's behaviors and actions are intimately related to the health and well-being of *others* who live in the same community. Third, pandemic policies have often been tailored to conditions in specific counties as authorities attempt to allocate public health resources more efficiently. Fourth, many communities struggle with specific types of health risks systematically. For example, Lincoln et al. (2014) find that Black communities tend to suffer more from obesity and depression than do White communities. Yancy (2020) finds that during COVID-19, infection rates within Black-dominated communities have sometimes been three times higher than that in a White-dominated communities. Even more strikingly, the COVID-19 death rate for Black communities has been as much as six times higher than in White communities. With more-refined knowledge about their population's willingness to bear the costs of community-level health policies, county-level decision makers can implement public health measures with greater confidence that their strategies will deliver positive net social benefits for their constituents.

In this research, we re-analyze some high-quality stated-preference choice-experiment survey data from an original 2003 study reported in Bosworth et al. (2009) that reveals people's preferences for randomized public policies that benefit community-level health.[3] To permit out-of-sample forecasting, our re-analysis substitutes county-level explanatory variables for the individual-specific variables that were largely relied-upon to explain respondents' choices in the original study. We collect new data on county-level policy contexts with the requirement that measures for all these county-level variables be available for both (a) the 2003

[3]The 2003 survey was one of four surveys funded by research grants from the U.S. EPA and the National Science Foundation, and was fielded using Knowledge Networks, the leading research-quality representative consumer panel available in the U.S. at the time.

context and (b) the contemporary context of the 2020-21 pandemic. We need to control for differences, both across counties and between 2003 and 2020-21, in each county's mix of socio-demographic characteristics, incomes, political affiliations, health status, and access to medical care. If people's preferences for policies to reduce risks to public health have remained sufficiently stable between 2003 and 2020-2021, after controlling for shifts in all of these explanatory variables, lessons from our 2003 survey can illuminate people's likely policy preferences today. While we cannot identify a premium for infectious diseases, it will be helpful at least to understand what people would be willing to give up simply to avert illnesses and premature deaths at the scale of the current pandemic.

We first estimate a latent class model and discern three classes of preferences. Within each class, people's preferences are driven by different combinations of policy attributes and community characteristics. There is evidence of considerable heterogeneity. Next, we use LASSO methods to help select the most important observable determinants of heterogeneity in support for public health policies using our 2003 data. Then, based on the updated community-level characteristics in counties across the U.S. in 2020-21, we use the fitted model to predict overall WTP for policies to reduce monthly generic cases and deaths on a scale commensurate with county-level casualties from the COVID-19 pandemic. For example, we find that people from Black-dominated counties have a higher WTP for public health policies in these pandemic times than those from White-dominated counties. Residents of counties that have populations which are younger or more highly educated have lower WTP for public health interventions to reduce illnesses and deaths on a scale such as COVID-19 risks, compared to those who live in counties with older and less-educated populations.

Stated preference methods, such as those employed for this paper, are used frequently to quantify preferences in health economics, health technology assessment, risk-benefit analysis, and health services research (Mühlbacher and Johnson, 2016). A few contemporary survey-based discrete choice experiments have sought to understand public perceptions of COVID-

19 pandemic interventions and to identify preference classes across individuals. (Rees-Jones et al., 2020) conduct a survey of 2,516 Americans concerning their preferences for both short- and long-term expansion to governmental-provided healthcare and unemployment insurance programs. That study finds that preferences for such programs are positively affected by the county's COVID-19 deaths, unemployment caused by COVID-19, and how respondents perceive the consequences of COVID-19. Chorus et al. (2020) use survey-based choice experiments to infer people's preferences from the trade-offs they are willing to make among policy effects, including health-related effects, impacts on the economy, education, and personal income. They find that "the average citizen, to avoid one fatality directly or indirectly related to COVID-19, is willing to accept a lasting lag in the educational performance of 18 children, or a lasting (>3 years) and substantial (>15%) reduction in net income of 77 households."

In an earlier, pre-COVID context, Cook et al. (2018) use a survey in Singapore regarding the trade-offs between risks of infectious diseases and the inconvenience of government interventions to prevent outbreaks of infectious disease. They find that respondents preferred more-intense interventions and preferred scenarios with fewer deaths and lower taxes. Li et al. (2020) use a survey-based choice experiment in three U.S. states and empirically quantify "willingness to stay home." They find broad support for statewide mask mandates. Their estimate of WTP to reduce new positive cases is large, and demographic and socioeconomic factors are the main drivers of the heterogeneity in individuals' willingness to stay home. Reed et al. (2020) also use a survey-based choice experiment in the U.S. to quantify Americans' acceptance of COVID-19 infection risks from lifting public health restrictions earlier and to reduce economic impact of the pandemic.[4]

Other recent papers focus on factors that affect people's responses to COVID-19. Cat-

[4]They find four classes of people among all respondents: "risk-minimizers", "waiters", "recovery-supporters", and "openers". Political affiliation, race, household income, and employment status were all associated with class membership.

tapan et al. (2020) find that the need for community engagement is pressing in a pandemic crisis. Engagement is essential to ensure that policy-making is built on equity, access, and inclusion. Adeel et al. (2020) find that the sub-national policies of U.S. states and Canadian provinces are more important than the national-level policies in each country.

Some studies focus on the benefit-cost analysis of restrictive public health policies during COVID-19. For example, Viscusi (2020) applies a standard Value of a Statistical Life (VSL) to monetize COVID-19 deaths for the first half of 2020 and produces a U.S. mortality cost estimate of $1.4 trillion. Miles et al. (2020) conduct a benefit-cost analysis of U.K. public health policies during COVID and find that the costs of continuing severe restrictions are large compared to benefits. Dorantes et al. (2020) use county-level data on COVID-19 mortality and infections, as well as the county-level information on the adoption of non-pharmaceutical interventions (NPI) and find that NPIs slowed infection rates in counties where the healthcare system might otherwise have been overwhelmed by the pandemic. They also suggest that political ideology might have limited the effectiveness of those measures in Republican-dominated counties.

2 Data

2.1 The original 2003 survey

Our survey from 2003 was originally employed in an analysis that takes advantage of the characteristics of individual survey respondents to explain their policy preferences in that 2003 context. The original analysis described is in Bosworth et al. (2009). The 2003 survey produced 1,466 completed responses, and was designed specifically to elicit individuals' willingness to pay for *publicly* provided health policies.[5] Each respondent faces a choice between either of two different health policies and the status quo. For example, Policy A might be

[5] See Johnston et al. (2017) for an inventory of current best practices in SP research.

described as reducing air pollutants that cause heart disease; and Policy B might reduce pesticides in foods that cause adult leukemia. The status quo "Neither Policy" option would involve no change in community health risks, but also no cost to the respondents' household. Each policy is also described in terms of a set of attributes that includes cases and premature deaths prevented in this community, duration of the policy, and the cost of the policy. The randomized illness labels include respiratory disease, cancer, leukemia, colon/bladder cancer, asthma, lung cancer, heart disease, heart attack, and stroke. See Appendix Figure A1 for one instance of the randomized choice sets used in the survey.

The original survey was fielded in June of 2003 and was distributed to members of a premium nationally representative consumer panel (Knowledge Networks) that produced a representative sample of respondents from counties throughout the conterminous U.S. The essentially national scope of the survey captured extensive geographic variation in sociodemographics, voting patterns, health status, and access to medical care. Figure A2 maps the geographic distribution of our 1,466 respondents.

The main policy attributes described in each policy choice task include monthly cost, policy duration, the size of the affected population, illnesses avoided and premature deaths averted. Our basic model allows for "status quo" effects, i.e., a discrete mass of utility, positive or negative, associated with the "Neither Policy" option, regardless of the specified attributes of either of the the two public health policies under consideration. Importantly, each policy choice was followed by a "self-interest" question about the degree to which the respondent or their family would personally benefit from that particular public health policy. Briefly, the relevant policy attributes for the present study were:

- **Affected population in thousands:** Across respondents, but not within a respondent's version of the survey, the original survey varies the size of the population affected by the policy. While it would have been ideal to describe this population as that of the respondent's own county, the anonymity of the survey prevented the tailoring of policy options specifically to match each respondents' county of residence. We asserted, about each pair of policies, that these two policies will be implemented for the "X thousand people living around you." We randomized X (among 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20 (2-3% in each case), 30 (4%), and 50, 100, 500, and 1,000 (8-15% each).

- **Policy duration:** Each prospective policy to reduce public health risks was described as a commitment to pay the cost of the policy for a specified time period.
- **Total illnesses avoided and deaths averted:** Over the specified time horizon, each policy is described as being expected to result in a specific number of cases avoided and a specific number of premature deaths averted. Preliminary models revealed that WTP for these public health policies is not simply linear in these policy attributes. Instead, people appear to derive diminishing marginal utility from additional avoided illnesses or averted premature deaths. Likewise, preferences are nonlinear in the policy's duration and in the size of the affected population.[6]
- **Status quo (or conversely, "Any policy") effects:** Respondents are allowed to choose "Neither policy" in every choice set, if they do not like either of the offered policies. Best practices in choice modeling include making an allowance for a status-quo effect. Equivalently, we use an indicator that equals one for "any policy (regardless of its effectiveness or duration)" and zero for the "Neither policy" alternative.
- **Monthly cost to your household:** Each prospective policy was associated with a specified private household cost, expressed both per month and annually, with a reminder of the duration of the commitment.

Given that we need a model that can be transferred to the 2020-21 COVID-19 context, we must forgo the use of any of the available individual-specific variables that were collected by the 2003 survey for those respondents. In place of these individual-specific variables, we recruit new county-level variables that are both available and consistently measured both close to the time of the original 2003 survey and likewise close to the time of the current pandemic.

Most of our 1,466 respondents made five policy choices each. For our estimating sample, then, the 14,466 non-status-quo policies described in our choice experiments have randomized levels of each attribute, with the attribute levels in each case designed to span a wide range of possible policy choice scenarios, fortunately the original design spans the potentially relevant

[6]For the models in this paper, we employ logarithmic or shifted logarithmic transformations for these variables, since these functions seem best to explain people's choices.

ranges of attributes for the 2020-21 pandemic. The arbitrary randomized distribution of the program design attributes used in the 2003 survey is summarized in Table 1.

Table 1: Descriptive statistics, public health policy design variables, choice experiments posed within the 2003 estimating sample

	mean	sd
Pop. affected/county pop.	2.706	8.341
Duration of policy (months)	167.9	116.6
Baseline illnesses	1004.7	2334.5
Number of illnesses avoided	606.9	13854.
Baseline deaths	96.16	472.0
Number of deaths avoided	102.1	467.9
Policies	14466	

2.2 County-level sociodemographic and contextual heterogeneity

Respondents to the original survey considered an aggregate of 7,233 choice sets. The randomized design of the choice experiments permits the estimation of a set of homogeneous preferences without any risk of the omitted variables bias. In this paper, however, we seek to identify important dimensions of preference heterogeneity. We permit policy preferences to vary systematically with the characteristics of the community-of-residence (county) for each respondent. Models with adequate preference heterogeneity allow us to predict changes in demand for public health policies, over time, in response to changes in sociodemographics, political ideologies, and healthcare access.[7] The cross-sectional variation in the original sample can be exploited to accomodate differences in the composition of county populations across the 17-year interval between the 2003 study period and the 2020-21 policy period.

[7]See data source in Table B6 in Appendix.

3 Estimating specification

We specify indirect utility as linear in net income. This is a common practice and is expedient because this functional form allows the individual's own household income level to drop out of the utility difference that drives the model. This leaves only the policy cost as a dollar-denominated measure that can be used to calculate the marginal rates of substitution that can be interpreted as marginal willingnesses to pay for avoided illnesses and avoided premature deaths.[8]

Preliminary exploration of the data has revealed that people tend to experience diminishing marginal utility from illnesses prevented and premature deaths averted. Given that microeconomic theory does not guide the functional form of utility beyond an expectation of diminishing marginal utility, we generalize our additively separable shifted-logarithmic form to a more flexible translog-type specification that is quadratic in these shifted log transformations, by including the square of each logged variable and the interaction between these logged terms, as well as a translog-type specification for the changes in the numbers of illnesses and deaths associated with policy A.[9]

$$\begin{aligned}
V_i^A &= \alpha\left(Y_i - c_i^A\right) \\
&\quad + \beta_1 log\left(\Delta illnesses^A + 1\right) + \beta_2 log\left(\Delta illnesses^A + 1\right)^2 \\
&\quad + \beta_3 log\left(\Delta deaths^A + 1\right) + \beta_4 log\left(\Delta deaths^A + 1\right)^2 \\
&\quad + \beta_5\left[log\left(\Delta illnesses^A + 1\right) log\left(\Delta deaths^A + 1\right)\right] + \beta_6(0) + \epsilon^A
\end{aligned} \tag{1}$$

[8]This description of the model assumes a basic familiarity with utility-theoretic conditional logit choice models.

[9]A shifted logarithmic transformation adds one to the argument of the log function, ensuring that the function takes a value of zero when the argument is zero. An alternative to our specification in equation (1 where utility is expressed in terms of *reductions* in illnesses and deaths (which should be "goods") would be to use *absolute* illnesses and deaths, with and without each policy (which would imply that each attribute was a "bad", likely to confer a negative marginal utility).

where β_6 is the lump of utility associated with the status quo alternative, which involves no policy. For Policy A in equation (1), of course, there is no status-quo utility increment/decrement.[10] Under the status quo alternative, in the absence of the policy, there will be no cost, but also no changes in the baseline numbers of illnesses or deaths, so that indirect utility will be determined simply by the individual's income and any utility associated with the status quo:

$$V_i^N = \alpha\left(Y_i\right) + \beta_6(1) + \epsilon^N \tag{2}$$

Thus, in a pairwise choice between just Policy A and No Policy (N), the utility-*difference* will depend on the cost of the policy, the expected cases of illness avoided, and the expected number of premature deaths averted under the chosen policy:

$$\begin{aligned} V_i^A - V_i^N = {} & \alpha\left(-c_i^A\right) \\ & + \beta_1 log\left(\Delta illnesses^A + 1\right) + \beta_2\left[log\left(\Delta illnesses^A + 1\right)\right]^2 \\ & + \beta_3 log\left(\Delta deaths^A + 1\right) + \beta_4\left[log\left(\Delta deaths^A + 1\right)\right]^2 \\ & + \beta_5\left[log\left(\Delta illnesses^A + 1\right) \times log\left(\Delta deaths^A + 1\right)\right] \\ & + \beta_6(-1) + \left(\epsilon^A - \epsilon^N\right) \end{aligned} \tag{3}$$

Note that if baseline levels of illness or death are to affect utility within this particular framework, they need to be interacted with the changes in the numbers of illnesses and deaths under each policy. To limit the complexity of the specification, we will allow baseline illnesses to shift only the marginal utility of reductions in the number of illnesses, and allow baseline deaths to shift only the marginal utility of reductions in the number of deaths. We also allow the baseline marginal utility parameters in the equation (3) to vary with

[10] If the interaction term in equation (1 does not have a statistically significant coefficient, the level curves of the indirect utility function would to be circular, rather than elliptical.

selected sociodemographic variables for each respondent's county. The coefficients on these interactions capture the extent to which these county-level variables affect the underlying preference parameters $\beta_1, ..., \beta_6$. As is typical, we assume that the marginal utility of net income is approximately constant.[11]

4 Results

4.1 Identifying important dimensions of heterogeneity: LASSO Estimation

Table **??** provides parameter estimates for a set of three increasingly complex specification. After employing our shifted log transformations, Model 1 in Table **??** is even simpler than equation (3), being linear and additively separable. Model 2 is a homogeneous-preferences model that is consistent with equation (3), involving some key interactions between the basic attributes. Model 3 permits preferences to vary systematically with the characteristics of each respondent's county (circa the 2003 time period). To identify the subset of more-important sources of systematic heterogeneity in policy preferences across counties, we force the basic attributes into the model. We then interact each of the basic with all of the available county-level data and subject just these interaction terms to LASSO variable selection.

Table 2: LASSO results

	(1) Parsim.	(2) Homog.	(3) Double Lasso
Preferred alternative in choice scenario			
Monthly cost	-0.01*** (0.0007)	-0.01*** (0.0009)	-0.015*** (0.004)

[11]This description of the basic model assumes pairwise choices between a single policy and the status quo. In the data, however, respondents are asked to choose between a pair of policies and the status quo alternative. The model in equation (3) can readily be generalized to accommodate three-way policy choices.

× Unemployment (v last month)			0.0069**
			(0.0025)
Policy duration	-0.02***	-0.013***	-0.013**
	(0.002)	(0.005)	(0.0048)
Log(base illnesses + 1)	-0.037·	0.32*	0.44**
	(0.02)	(0.13)	(0.15)
× County prop. Hispanic			-0.77***
			(0.14)
$\left[\text{Log(base illnesses + 1)}\right]^2$		-0.017*	-0.037**
		(0.0065)	(0.011)
× County log. median income			-0.082*
			(0.038)
× County poverty rate			-0.297**
			(0.113)
× County prop. obesity			-0.57*
			(0.238)
× County prop. excessive-drinking			-0.143*
			(0.065)
× Primary care physicians rate			-0.001***
			(0.0003)
Log(base illnesses + 1) × Log(duration)		-0.028	-0.061*
		(0.021)	(0.030)
× County log. median income			0.178***
			(0.043)
× County prop. obesity			-1.182**
			(0.328)
× PM2.5			0.008**
			(0.003)
× Primary care physicians rate			0.002**
			(0.0008)
Log(base illnesses + 1) × (Affected pop/1000)$^{-1}$		-2.43*	-3.67
		(1.33)	(7.15)
× County prop. Hispanic			69.49*
			(10.26)
× PM2.5			0.58*
			(0.295)

Log(base deaths + 1)	0.039 (0.031)	-0.4 (0.19)	-0.23 (0.31)
Log(base deaths + 1) $\times$ County prop. aged 65-84			12.96 6.235
Log(base deaths + 1) $\times$ County prop. excess.-drink.	0.039 (0.031)	-0.4 (0.19)	-6.234 (2.167)
$(\text{Log(base deaths} + 1))^2$		$0.011^{\cdot}$ (0.012)	-0.0016 (0.0056)
$\times$ County prop. Black			0.198^{*} (0.081)
Log(base deaths + 1) $\times$ Log(duration)		$0.06^{\cdot}$ (0.035)	0.063 (0.042)
$\times$ Primary care physicians rate			0.001^{**} (0.0004)
$\times$ Preventable hospitalization rate			0.003^{*} (0.001)
Log(base deaths + 1) $\times$ (Affected pop/1000)$^{-1}$		$3.65^{\cdot}$ (1.96)	14.82 * (9.47)
$\times$ County log. median income			-40.8^{*} (9.57)
$\times$ County prop. aged 65-84			-328.7^{*} (122)
Log(Δ illness + 1)	0.068^{***} (0.0097)	0.039 (0.052)	-0.26^{***} (0.035)
$\times$ Unemployment (v last month)			0.353^{*} (0.151)
$\times$ County prop. Asian			6.46^{***} (1.89)
$\times$ County poverty Rate			-4.05^{*} (1.85)
$\times$ County avg. physical unhealthy days			0.278^{**} (0.087)
$(\text{Log}(\Delta \text{ illness} + 1))^2$		0.0073 (0.0038)	$-0.016^{\cdot}$ (0.009)
$\times$ County prop. Republican			0.053^{***} (0.015)
$\times$ Unemployment (v last month)			0.029^{**}

			(0.011)
× County prop. aged 0-17			-0.534* (0.219)
× County prop. Black			0.097** (0.037)
× County prop. Asian			-0.304* (0.153)
× County log. median income			0.04* (0.018)
× County avg. physical unhealthy days			-0.031*** (0.007)
× County prop. obesity			-0.339* (0.171)
× Primary care physicians rate			-0.0004** (0.0001)
× Preventable hospitalization rate			0.0006* (0.0002)
Log(Δ illness + 1) × Log(duration)		-0.0061 (0.0088)	-0.111** (0.038)
× County log. median income			0.059* (0.029)
× preventable hospitalization rate			-0.013* (-0.0005)
Log(Δ illness + 1) × (Affected pop/1000)$^{-1}$		0.077 (0.052)	1.17* (0.50)
× Unemployment (v last month)			0.37* (0.17)
× County prop. Black			-3.48*** (0.84)
Log(Δ deaths + 1)	0.20*** (0.018)	0.45*** (0.091)	0.51*** (0.11)
(Log(Δ deaths + 1))^2		-0.0083 (0.007)	-0.14* (0.061)
× County prop. Black			0.198* (0.081)
× Primary care physicians rate			-0.0005*

			(0.0002)
Log(Δ deaths + 1) $\times$ Log(duration)		-0.034 (0.016)	0.23* (0.094)
$\times$ County poverty rate			-1.51** (0.51)
$\times$ County prop. excessive-drinking			-0.44* (0.23)
Log(Δ deaths + 1) $\times$ (Affected pop/1000)$^{-1}$		-0.21* (0.085)	1.01 (0.7)
$\times$ County prop. Asian			-8.97* (4.52)
$\times$ County prop. obesity			-14.8* (5.85)
$\times$ County excessive-drinking rate			-6.82* (3.17)
$\times$ Primary Care Physicians Rate			-0.008* (0.003)
1=Status quo	0.68*** (0.071)	1.13*** (0.13)	2.53* (1.11)
$\times$ Unemployment (v last month)			-0.88** (0.33)
$\times$ County prop. Black			5.62*** (1.67)
$\times$ County prop. Asian			8.78* (3.97)
$\times$ County prop. aged 65-84			-5.4* (2.2)
$\times$ Primary care physicians rate			-0.0051$^{\cdot}$ (0.0019)
1=Status quo $\times$ (Affected pop/1000)$^{-1}$		-2.75*** (0.62)	8.01$^{\cdot}$ (4.57)
$\times$ County prop. Republican			-10.77 ** (3.85)
$\times$ County prop. Black			36 *** (6.82)
$\times$ County log. median income			9.98 * (4.41)

× County prop. college			-39.35 ***
			(11.81)
× County prop. smoker			107.8***
			(23.51)
× County prop. excessive-drinking			39.6***
			(19.6)
(1=Status quo × (Affected pop/1000)$^{-1}$)^2		2.04***	-11.78*
		(0.60)	(5.12)
× Unemployment (v last month)			5.36**
			(1.96)
× County prop. Black			-30.91***
			(7.0)
× County prop. aged 65-84			-81.36*
			(39.52)
× County log. median income			-25.8**
			(7.24)
× County prop. Asian			75.1**
			(33.5)
× County prop. college			40.84**
			(14.03)
× County poverty rate			85.25***
			(25.72)
× County avg. physical unhealthy days			-7.08***
			(1.88)
× County prop. smoker			108.3**
			(24.82)
× County prop. excessive-drinking			-55.1**
			(19.65)
× Preventable hospitalization rate			0.11**
			(0.04)
Max. log-likelihood	-11674.45	-11627.78	-9935.82
No. respondents	1518	1518	1466
No. choices	7492	7492	7233
No. alternatives	22476	22476	21699

characteristics and select the most important interactions using LASSO model estimation.[12] We use a LASSO model with 10-fold cross-validation to yield the variables and interactions in the model specification in section 3. We then use the LASSO-selected variables in a conditional logit model with individual fixed effects to produce both the parameter means and their asymptotic variance-covariance matrix for use in deriving WTP estimates for our 2020 WTP simulation.[13] Table 2 provides the preliminary results based on LASSO-selected variables and binary choice model estimation.

5 Benefit transfer: 2020-21 WTP to avoid COVID-19 illnesses and deaths in each month

In contrast to the wide variety of choice scenarios presented to respondents in our 2003 study sample, we wish to use our estimated model to simulate WTP in 2020-21 by a representative individual in each U.S. county to prevent the numbers of COVID-19 cases and deaths recorded in each month for which data are available. We wish to simulate a measure of the household costs that people would have been willing bear, if a public health policy in 2020-21 could reduce new illnesses and baseline deaths to zero. COVID-19 is infectious, so until all of the cases are eliminated, people cannot return to a normal life. Table 3 shows the hundreds of new COVID cases each month across the entire U.S., along with the thousands of the reported deaths. The policy we wish to simulate for 2020-21 is the reduction of these baseline cases and deaths to zero.

[12]Package LASSO algorithms for logit models appear to be limited to binary choice specifications. We assume that the same set of preferences underlie our three-way choices as would drive the two pairwise choices that would be consistent with these three-way choice would remain the preferred alternatives if it was to be paired with either of the two non-chosen alternatives in pairwise choices.

[13]Double Lasso: Use machine learning Lasso algorithm to select the variables. Then take the selected variables back into the condition logit regression with individual fix effect, in this case.

Table 3: Descriptive statistics, 2020-21 COVID-19 new Cases and Deaths (in hundreds), county-level.

Month	03/2020 mean/sd	04/2020 mean/sd	05/2020 mean/sd	06/2020 mean/sd	07/2020 mean/sd
COVID-19 cases	0.58	2.74	2.24	2.62	5.97
	4.91	17.28	11.72	14.05	31.05
COVID-19 deaths	0.014	0.18	0.13	0.07	0.08
	0.16	1.61	0.79	0.39	0.44
Month	**08/2020** mean/sd	**9/2020** mean/sd	**10/2020** mean/sd	**11/2020** mean/sd	**12/2020** mean/sd
COVID-19 cases	4.54	3.74	5.84	13.50	19.77
	28.01	12.01	16.50	40.97	83.00
COVID-19 deaths	0.09	0.07	0.07	0.11	0.23
	0.46	0.29	0.19	0.30	0.71
Month	**1/2021** mean/sd	**2/2021** mean/sd	**3/2021** mean/sd	**4/2021** mean/sd	**5/2021** mean/sd
COVID-19 cases	19.11	7.33	5.51	6.05	2.82
	85.75	25.84	19.96	20.46	8.79
COVID-19 deaths	0.29	0.22	0.12	0.08	0.05
	1.42	1.06	0.57	0.36	0.21
Observations 3142	3142	3142	3142	3142	3142

5.1 Preferences for a representative individual in each county, for each county-month of the 2020-21 pandemic

In lieu of each individual respondent's characteristics, our estimating specification explains the choices of individuals using only the characteristics of the county in which the individual resides. The distribution of characteristics of the U.S. counties used in simulating our WTP amount for 2020 are shown in Table 4.

Table 4: Descriptive statistics, 2003 estimating sample vs 2020 simulation sample, county-level heterogeneity

	2003 Study Sample[a]		2020 Policy Sample[b]	
	mean	(sd)	mean	(sd)
County prop. aged 0-17	0.254	(0.0289)	0.22	(0.033)
County prop. aged 18-24	0.096	(0.029)	0.086	(0.033)
County prop. aged 65+	0.129	(0.038)	0.193	(0.046)
County prop. White	0.773	(0.168)	0.835	(0.161)
County prop. Black	0.114	(0.129)	0.091	(0.146)
County prop. Asian	0.029	(0.044)	0.013	(0.026)
County prop. Hispanic	0.105	(0.137)	0.093	(0.138)
County prop. Native American	0.008	(0.026)	0.015	(0.058)
County prop. uninsured	0.160	(0.057)	0.114	(0.050)
County fractionalization (0-1)	0.383	(0.219)	0.280	(0.196)
Rep/(Dem+Rep), Pres. Election	0.511	(0.121)	0.667	(0.161)
County Med. Income	34766.67	(9392.89)	37219	(10592.8)
Hospitals per 10000 population	0.221	(0.338)	0.56	(0.876)
County prop. college degree	0.509	(0.104)	0.524	(0.107)
County overall Poverty	0.124	(0.0433)	0.144	(5.65)
County pm25	11.066	(2.623)	6.59	(1.47)
County prop. Fair or Poor Health	0.158	(0.043)	0.179	(0.047)
Avg. Num. Physically Unhealthy Days	3.566	(0.72)	3.99	(0.6.95)
Avg. Num. Mentally Unhealthy Days	3.475	(0.682)	4.183	(0.594)

County prop. Smoker	0.203	(0.046)	0.175	(0.035)
County prop. Obesity	0.272	(0.0404)	0.33	(0.054)
County prop. Excessive Drink	0.165	(0.04)	0.175	(0.0317)
Primary Care Physicians Rate	0.906	(0.442)	0.543	(0.034)
Preventable Hospitalization Rate	70.7	(19.4)	48.67	(18.28)
Δ unempl (Jun. '03 vs previous month)	0.678	(0.408)		
Δ unempl (Mar. '20 vs previous month)			0.467	(0.934)
Δ unempl (Apr. '20 vs previous month)			7.663	(4.928)
Δ unempl (May '20 vs previous month)			-2.119	(2.451)
Δ unempl (Jun. '20 vs previous month)			-1.887	(2.227)
Δ unempl (Jul. '20 vs previous month)			-0.594	(1.523)
Δ unempl (Aug. '20 vs previous month)			-1.179	(1.354)
Δ unempl (Sep. '20 vs previous month)			-0.682	(1.258)
Δ unempl (Oct. '20 vs previous month)			-0.649	(1.092)
Δ unempl (Nov. '20 vs previous month)			0.0454	(1.052)
Δ unempl (Dec. '20 vs previous month)			0.2093	(1.024)
Δ unempl (Jan. '21 vs previous month)			0.4107	(1.058)
Δ unempl (Feb. '21 vs previous month)			-0.182	(0.593)
Δ unempl (Mar. '21 vs previous month)			-0.375	(0.570)
Δ unempl (Apr. '21 vs previous month)			-0.5905	(0.573)
Δ unempl (May. '21 vs previous month)				

Observations	1466 respondents	3142 counties

[a] Descriptive statistics, across respondents, for the counties in which they reside;
[b] Descriptive statistics across 3142 counties or other county FIPS geographic areas.

5.2 Parametric bootstrap estimates of predicted WTP in each county-month

We estimate our models in utility space, so the calculations of WTP involve dividing other coefficients by the estimated marginal utility of net income, where all the maximum likelihood parameters in the model are distributed asymptotically joint normal. We used a large number of draws from the joint distribution of the parameters to calculate the predicted distribution of WTP to reduce to zero all COVID cases and deaths in each county-month, with the distribution being determined by the noise in the parameters' estimates. Given that there were no opportunities for respondents to record a negative willingness to pay, we interpret negative calculated point values of WTP values as zero, using a Tobit-like interpretation. We calculate monthly average WTP to reduce to zero all cases and deaths from COVID-19 from March 2020 to February 2021 across all counties in the U.S.

Table 5 shows for a representative county resident across all U.S. counties' average WTP to reduce the risk of COVID-19 from March 2020 to February 2021. These monthly estimates vary by the changes of monthly new cases, deaths, and unemployment rate at the county level. May, July, August, September, and October 2020 had relatively high WTP to reduce new COVID cases and deaths compared to other months. These monthly WTP amounts were larger during the first wave of the pandemic spring and summer. The average monthly WTP decreased from November 2020 to Feb 2021. Figure 3 shows the progression in the distribution of U.S. counties' WTP to reduce the risk of COVID-19 from March 2020 to February 2021. These distributions (each month from Mar 2020 to Feb 2021) are all rightskewed.[14] The dashed vertical lines are the average WTP to reduce the risk of COVID-19 each month across representative residents of all counties. August 2020 had the highest average WTP of all counties (90 percentile).

Table 5: County Representative Individual's
(monthly) WTP to Reduce COVID-19 cases and death through 2020-21

Month	**03/2020** mean/sd	**04/2020** mean/sd	**05/2020** mean/sd	**06/2020** mean/sd	**07/2020** mean/sd
WTP(dollars)	111.19	954.69	230.93	255.78	1084.63
	(483.69)	(5902.04)	(989.29)	(1014.05)	(8863.67)
Month	**08/2020** mean/sd	**09/2020** mean/sd	**10/2020** mean/sd	**11/2020** mean/sd	**12/2020** mean/sd
WTP(dollars)	377.38	453.63	532.97	636.93	693.35
	(1228.37)	(2068.25)	(1834.24)	(2278.77)	(2445.96)
Month	**01/2021** mean/sd	**02/2021** mean/sd	**03/2021** mean/sd	**04/2021** mean/sd	**05/2021** mean/sd
WTP(dollars)	679.62	500.20	432.96	433.46	366.32
	(2830.37)	(2038.80)	(1676.48)	(1691.01)	(1202.98)
Observations	3142	3142	3142	3142	3142

[c] The monthly median WTP to reduce COVID-19 cases and deaths are: Mar20 (0), Apr20 (321.12), May20 (0), Jun20 (6.82), Jul20 (384.86), Aug20 (113.33), Sep20 (164.62), Oct20 (204.56), Nov20 (309.94), Dec20 (342.14), Jan21 (327.46), Feb21 (232.55), Mar21(189.10), Apr21 (180.07), May21(163.82);

[14] Plots include only the lowest 90 percent of cases, to prevent the distributions from being bunched near zero.

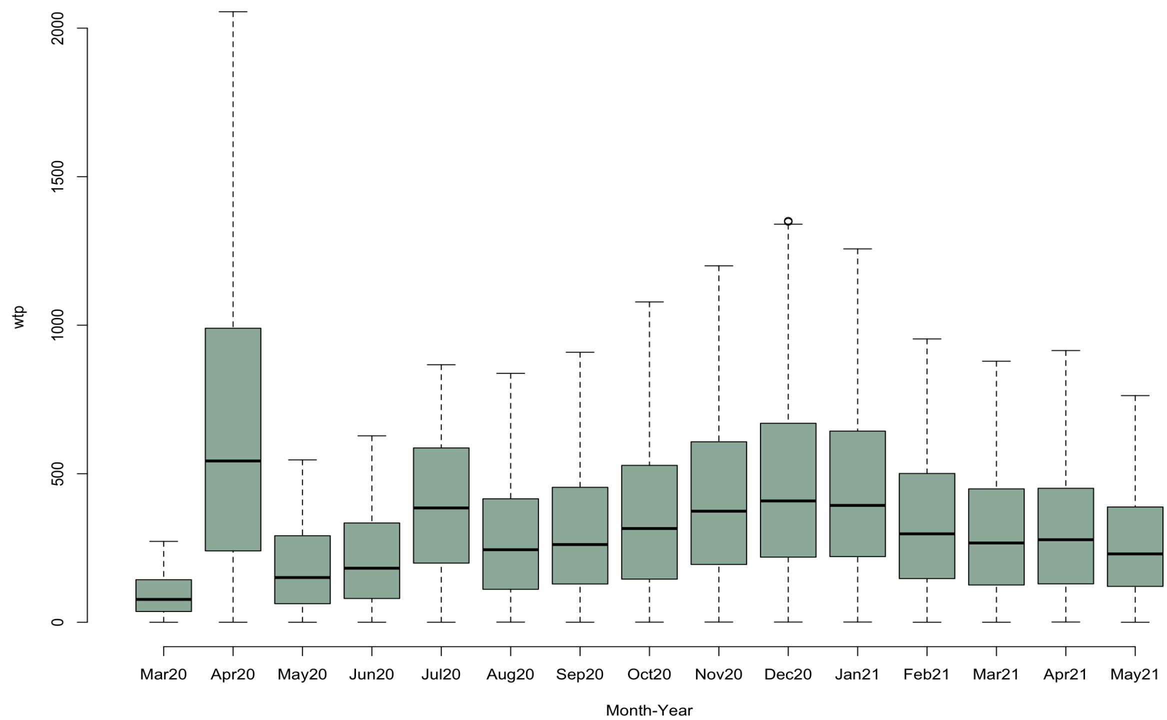

Figure 3. WTP to reduce the risk of COVID-19 among all U.S. counties in 2020-21.

5.3 Scaling to monthly total WTP amounts to avoid COVID-19 cases and deaths

Our benefits transfer exercise predicts monthly WTP amounts for a representative adult in each U.S. county over the course of the pandemic from March 2020 through February 2021. It is possible to scale these WTP amounts to a national average for all U.S. adults by weighting these county averages by the population of adults aged 18 and over in each county. We use county populations aged 18 and over, according to the 2019 5-year ACS estimates, to build a set of weights that sum to the overall number of counties. To get a rough estimate of the national average WTP in each month, we multiply the WTP point estimate for each county in that month by the corresponding weight, sum, and divide by the number of counties to yield average WTP that can be applied for all 251 million adults in the U.S.

Then the aggregate WTP across the whole population of U.S. adults is just this national average times 251 million. These totals, by month, are, for 2020: March (123 billion), April (606 billion), May (118 billion), June (125 billion), July (402 billion), August (104 billion), September (130 billion), October (160 billion), November (221 billion), December (253 billion); and for 2021: January (262 billion), February (192 billion), March (174 billion), Apr (179 billion), and May (154 billion). The cumulative U.S. national WTP of all adults over 18 through March 2020 to May 2021 is about 3 trillion dollars.

It may be tempting to compare this aggregate WTP amount to the sizes of the various "stimulus packages" provided during the pandemic. However, the context for the trade-offs between policy cost and reductions in cases and deaths, in our study sample, did not include an economic shutdown or excessive job losses or business failures. The various stimulus packages during the pandemic were intended to compensate for the collateral economic damages caused by the pandemic, rather than simply to reduce cases and deaths. Our 3 trillion dollar estimate of WTP for March 2020 through Apr 2021 should probably be interpreted as people's *net* WTP to reduce cases and deaths, after the compensation for other pandemic costs represented by the various stimulus programs.

5.4 Systematic heterogeneity in predicted WTP to Reduce COVID-19 cases and deaths

We first employ the latent class model uses policy attributes in the utility-difference function, but introduce county-level covariates for each respondent to explain each person's probability of preference-class membership in 2003. In our latent class model, we find three distinct classes of people driven by different features of the preventative public health policies. We label these three preference classes as "cost-conscious," "comprehensive," and "indifferent-or-altruistic."[15] Then, we explore the systematic heterogeneity in predicted WTP to Reduce COVID-19 cases and deaths in our 2020-21 simulation. We find that the counties with a population where the proportion of people aged below 45 is lower than the national median have a higher WTP to reduce the risk of COVID-19, especially when entering the winter season (Nov 2020 to Feb 2021). For different ethnic and political groups, we find that for our policy sample in2020-21, counties with a higher proportion of Black residents greater than the median have a higher WTP to reduce the risk of COVID-19 than White counties. For political affiliation, we find that Democrat-dominated counties have a higher WTP through March 2020 to April 2021. For the health access level, the higher health-access counties with the primary care physicians rates and preventable hospitalization rates above the median rates among all counties have a higher WTP to reduce the risk of COVID-19 through public health policies and interventions. And lastly, for income level, the WTP of higher-income counties is higher than the lower-income counties.[16]

6 Conclusions

This paper models people's willingness to bear the costs of public health policies to reduce health risks to their communities. We re-purpose an existing 2003 survey of public health policy preferences, omitting the available individual-level characteristics for the 2003 sample, and expanding the variety of county-level characteristics employed. Almost 18 years have passed since the original nationwide survey. However, the U.S. EPA is still making use of a suite of empirical estimates of people's willingness to trade off money for mortality risk reductions—the so-called "value of a statistical life"—from the 1970s, 1980s, and 1990s, after scaling these numbers up to current dollars. This suggests an implicit assumption that

[15] See Latent class analysis detail in Appendix C2.
[16] See heterogeneity analysis details in Appendix C3.

people's preferences with respect to mortality risks are highly stable over time.

We have noted several examples of stated-preference choice experiments concerning COVID-19, conducted very early during the current pandemic. However, none of these contemporaneous studies has elicited such detailed data from its survey respondents.

In our re-analysis of the 2003 survey data, we use both a latent class model and a conditional logit model with heterogeneous preferences (where variable selection is based on double LASSO estimation). In our latent class model, we identify three distinct preference classes in our sample: "cost-conscious," "comprehensive," and "indifferent-or-altruistic." In our conditional logit model with heterogeneity in preferences, we allow for heterogeneity only with county-level demographic characteristics and other contextual variables, rather than any individual-specific characteristics. We first use a machine learning algorithm—double LASSO—to winnow down all of the possible interaction terms between the policy attributes and the county-level characteristics that are available for both the 2003 context and the 2020 context.

Finally, we simulate WTP amounts during the COVID-19 pandemic by transferring our fitted model from our "study" sample in 2003 to our "policy" sample consisting of all U.S. counties in 2020. We replace the "cases prevented" and "premature deaths prevented" attributes for the randomized public health policies described in the original stated-preference choice experiments with the actual county-level monthly COVID-19 cases and deaths during March 2020 through February 2021. We also update all the county-level characteristics from the 2003 era to the 2020 era. We interpret predicted WTP amounts in 2020-21 as WTP for a representative adult in every U.S. county. To illustrate the heterogeneity implied by our model, we split the set of all U.S. counties into different subgroups to explore how their predicted WTP to have avoided COVID-19 cases and deaths has varied differently across the months of the pandemic. The heterogeneity in WTP amounts within a given month stems from all the different county characteristics that interact with the policy attributes. The main drivers of the month-to-month variation are the actual cases and deaths in each county and the change in unemployment in that county since the previous period, since these are the only county characteristics for which the values change over time.

We find that people in counties with younger populations have higher WTP to reduce the risk of COVID-19 than people in counties with older populations. There are also differences across different ethnic mixes across U.S. counties, driven partly by different preferences across these groups, but also by different case and death rates, and the different patterns of unemployment across thes counties over time. Republican-dominated counties have lower WTP than Democratic counties. Counties with higher levels of health-access have higher WTP to reduce the risk of COVID-19 compared to counties with lower levels of health-access. The counties that have lower income (or suffer a higher poverty rate) are less willing to pay the cost to reduce the risk of COVID-19 compared to the counties with a higher income (lower poverty rate).

Our estimated aggregate WTP across the U.S. population from March 2020 to April 2021 is about 3 trillion dollars. In April 2020, the U.S. had the highest total WTP to reduce cases and deaths of COVID-19 because of the drastic increase in new COVID-19 cases, deaths, and unemployment during the month. The large aggregate WTP persisted for the rest of 2020 and started decreasing in February 2021 as the pandemic is more under control because of the vaccination and the stabilized unemployment numbers.

Information about the public's willingness to bear the costs of pandemic control will be important in the event of future pandemics, or even in the event that the current pandemic continues longer than expected. An understanding of systematic differences in this willingness to pay across counties with different sociodemographics can potentially help county-level governments decide upon locally appropriate and acceptable public health interventions.

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7 Appendixes

A Figures and Tables

Recall that these two policies will be implemented for the 50,000 people living around you.

Would you be most willing to pay for policy A, policy B, or neither of them?

		Policy A	Policy B
(1)		reduces air pollutants that cause heart disease	reduces pesticides in foods that cause adult leukemia
(2)	Policy in effect	over 20 years	over 25 years
(3)	Without policy With policy	1,100 get sick only 100 get sick	30 get sick only 5 get sick
(4)	**Cases Prevented**	**1,000 fewer cases**	**25 fewer cases**
(5)	Without policy With policy	220 will die only 20 will die	6 will die only 1 will die
(6)	**Deaths Prevented**	**200 fewer deaths over 20 years**	**5 fewer deaths over 25 years**
(7)	**Cost to you**	$90 per month (= $1,080 per year for 20 years)	$25 per month (= $300 per year for 25 years)
(8)	**Your choice**	○ Policy A reduces air pollutants that cause heart disease	○ Policy B reduces pesticides in foods that cause adult leukemia
		○ Neither Policy	

Figure A1. One example of a choice set in the original 2003 survey

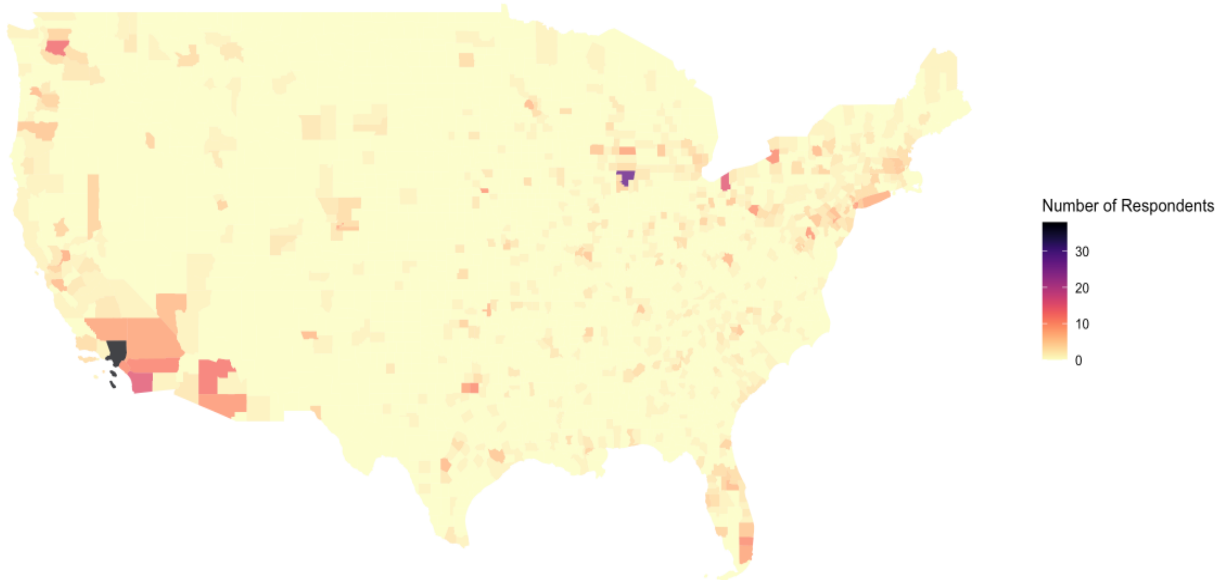

Figure A2. Geographic Coverage Map for the original 2003 survey

B County-level Data

Table B6: Sources of county-level data for estimation and simulation

Variable	Sources for ca. 2003 data (estimation)	Sources for ca. 2020 data (simulation)
County population	2000 Census	2018 5-yr ACS
Population affected	"People living around you" in choice scenario, as a proportion of the population in the respondent's county	1.0 (i.e. county population as a proportion of county population)
Median household income	2000 Census STF3 Table P53, P053001	2018 5-yr ACS
Unemployment rate, county-level, current month	BLS monthly for May, June 2003	for Feb-May for 2020

Continued on next page

Table B6 – continued from previous page

Change in unemployment rate since last month, county level	BLS May-June 2003	Feb-Mar, Mar-Apr, Apr-May, May-June for 2020
Ethnic mix. Proportion of county population: pblack, pasian, phispanic, pother	2000 Census	2018 5-yr ACS
Ethnic fractionalization. For 7 racial groups: white, black, asian, amerind, hawaii-pacisl, other, multi-race	calculated from 2000 Census	calculated from 2018 5-yr ACS
Age distribution. Proportions of population in each age group: 0-17, 18-24, 65 plus	2000 Census	2018 5-yr ACS
Last Presidential election vote shares: Democratic, Republican, Green, Libertarian, Other	David Leip's US Election atlas for 2000	David Leip's US Election atlas for 2016
Hospitals per 100,000 population.	https://opendata.dc.gov/	https://opendata.dc.gov/
Health insurance coverage, county level	(US Census Bureau, 2008 - 2018 Small Area Health Insurance Estimates (SAHIE) using the American Community Survey (ACS)[a])	same
Air quality[17]	Van Donkelaaret al.	same

Continued on next page

[17]Given that COVID-19 is primarily a respiratory disease, baseline airquality may be important. We have only one environmental variable in this research– particular matter (PM2.5). PM2.5 pollution consist of tiny particles in the air ofdiameter less than 2.5 micrometres. These particles of dust or soot can be inhaled andhave the potential to cause long-term health problems.

Table B6 – continued from previous page

Health indicators[18]	Robert Wood Johnson Foundation Program County Health Rankings and Roadmaps	same

[a]https://www.census.gov/data/datasets/time-series/demo/sahie/estimates-acs.html

C Heterogeneity as a finite mixture: the Latent Class Model

Our baseline utility-difference model that assumes homogeneous preferences is a conditional logit model using only the main attributes of each policy without any covariates that shift the estimated preference parameters. A latent class (LC) model is one way to allow for heterogeneous preferences. The LC model uses policy attributes in the utility-difference function, but introduce county-level covariates for each respondent to explain each person's probability of preference-class membership.
To decide upon the appropriate number of classes for the model, we compare the AIC and BIC for different models and selected the number of classes based on which model has the lowest AIC and highest log-likelihood.

C.1 Appropriate number of latent classes

See Table 2. The respondents are more likely to choose a policy when it has a lower monthly cost, a shorter time period, a greater reduction in cases of illness and deaths, and has a higher level of potential private benefits. Based on the AIC and BIC model selection, we decided on a three-class LC model.

Table C7: LCM class selection

	2-class	3-class
AIC	11829.21	11785.76
BIC	12135.58	12344.04
Log Likelihood	-5869.6	-5810.9

[18]The variableswe employ in our re-estimation and simulation models include the percentage of adultswho report smoking, obesity, and excessive drinking. For seniors in each county, we alsouse clinical care data for "access to care", and "quality of care" from Medicare claims

C.2 A Three-classes LC model

Table 4 provides some estimates. There appear to be three main classes of respondent: "cost-conscious" (class 1), "comprehensive" (class 2), and "indifferent-or-altruistic" (class 3). We divide all the policy attributes into three genres: cost-related attributes, including monetary cost and time cost; case-and-death related attributes, which include baseline and prevented cases and deaths; the self-interest variable, which is the level of private benefits of the policy. We employ our available county-level socioeconomic and demographic covariates to explain respondents' propensities to be in each latent preference class. In the portion of the model that separates classes, the cost-conscious class is assumed to be the numeraire class, with its coefficients to zero. Recall that all of the covariates in the class-membership portion of the latent class model are county-level characteristics instead of individual characteristics, so that these county-level characteristics around 2003 sample period can be substituted by their values in the 2020 "policy" period in our simulation of preferences. Also recall that our main research question concerns how community-level circumstances affect people's attitudes toward community-based public health policies. The cross-sectional variation in county-level characteristics between the 2003 study period and the 2020 pandemic era is sufficient to answer the main research question posed in this paper.

C.2.1 The Cost-conscious Class

The "cost-conscious" preference class derives negative marginal utility from both the cost and the duration of the policy. This class of preference associates no significant marginal utility with cases reduced or premature deaths avoided. This class is the "numeraire" class.

Table C8: Homogeneous preferences versus model with three latent classes

Description		Three Latent Classes of Preferences		
	Homog. Pref.	Class 1 Cost-Consc.	Class 2 Compre-hensive	Class 3 Indiff./ Altruist.
Latent classes of preferences (marginal utilities of policy attributes)				
Monthly cost of policy	-0.004***	-0.01***	-0.003*	0.1
Policy duration	-0.01***	-0.02**	-0.01***	-0.5
Base. cases of illness	-	-	-	0.028
Reduction in cases	0.00008***	-	0.0001**	0.06
Base. prem. deaths	-	-	0.0003*	0.022
Reduction in deaths	0.000098.	-	0.0004	0.33
Private benefit	0.6***	-0.53***	2.1***	0.74
Status quo alternative	1.54***	-0.77**	3.9***	13.53
Class membership propensities (relative to Class 1)				
log(County population)	n/a	0		1.91***
Cnty pr. Repub. vote	n/a	0	1.18*	3.49*
Proportions of county population in different age brackets				
% pop. age 0-17	n/a	0		
% pop. age 25-44	n/a	0	-8.31*	-22.52*
% pop. age 45-64	n/a	0	9.36*	20.39*
% pop. age 65-84	n/a	0	-8.15*	
Proportions of county population in different racial/ethnic groups				
% pop. White	n/a	0	-5.86*	

% pop. Black	n/a	0		
% pop. Native Amer.	n/a	0	-27.57***	
% pop. Asian	n/a	0	-10.89**	-37.32*
% pop. multi-race	n/a	0		
% pop. Hispanic	n/a	0		
log(Med. income/100K)	n/a	0	-1.69***	
Hospitals per 10K pop.	n/a	0		
County unempl (current)	n/a	0		
Δ unempl (v last month)	n/a	0		
Health insurance coverage	n/a	0	0.13.	
% adults completing college or bachelor degree	n/a	0		8.05*
Poverty percent, all ages	n/a	0	-0.089**	
Average PM2.5	n/a	0		
% Fair or Poor Health	n/a	0		
Average Number of Physically Unhealthy Days	n/a	0		
Average Number of Mentally Unhealthy Days	n/a	0		
% Smokers	n/a	0		
% Adults with Obesity	n/a	0		
% Excessive Drinking	n/a	0	-0.032	0.23***
Prim. Care Physic. Rate	n/a	0	-0.003	

Preventable Hosp. Rate	n/a	0
Observ.	1466	1466

Relative to this class, the coefficients for the "Comprehensive" and "Indifferent-or-Altruistic" classes tell whether the probability of being in, say, "Comprehensive" class, is greater or less than probability of being in the left-out numeraire class, "Cost-conscious" class.

C.2.2 Comprehensive Class

People in the "comprehensive class" pay attention to both cost-related attributes and case-and-death-related variables. They prefer less-expensive public health policies of shorter duration that saves more people's lives, and which are likely to benefit themselves or their families more. Individuals from communities with a higher percentage of population aged 45-64 are more likely to be in the "comprehensive class." People in this age group are mostly retired adults with relatively good health conditions. They tend to have less financial stress compared to people from other age groups. Counties with a higher share of Republican votes, a greater percentage of middle or lower class, and lower primary care physicians rate are more like to have members of comprehensive class. People from counties with higher poverty rates are less likely to be in this class. However, lower-income people with limited health resources and access are more likely to support public health policies. For these groups, public health policies may be cheaper than the cost of private insurance, and overall community health can be improved when such public policies are available.

C.2.3 Indifferent-or-Altruistic Class

The "indifferent-or-altruistic class" cares neither for cost-related attributes nor about the case-and-death-related attributes. They might choose a policy to improve public health in their community altruistically, without considering any of the private costs and benefits of the policy. Or they might not choose any policy indifferently no matter what the attributes of the policy were. Individuals from the "indifferent-or-altruistic" group care neither for the cost-related attributes nor the case-and-death related attributes of when they choose or do not choose a policy. These people might gain the emotional reward of choosing a health policy altruistically that benefits others without considering any attributes of the policy. People from counties with more hospitals are more likely to choose a policy altruistically or indifferently. This shows that those with more accessibility to health are more secured to invest in a public health policy. People from counties with a higher share of Republican votes, a higher population of ages between 45 and 64, and higher proportion of college degrees are more likely to be in the indifferent-or-altruistic class compared to the cost-conscious class. People from counties with higher rates of excessive drinking are also more likely to be in this preference class compared to the cost-conscious class.

C.3 Systematic heterogeneity in predicted WTP to Reduce COVID-19 cases and deaths

Age. Akbarpour et al. (2020) study how outcomes of various public health (social distancing) policies vary across areas in relation to the underlying heterogeneity in population density, social network structures, population health, and employment characteristics. They find that policies by which individuals who can work from home continue to do so, or in which schools and firms alternate schedules across different groups of students and employees, can be effective in limiting the health and healthcare costs of the pandemic outbreak while also reducing employment losses.

We can explain how the distribution of simulated WTP amounts differs across groups of counties with different characteristics by splitting the 3141 counties into sub-samples according to specific characteristic. Figure 4 shows the difference in the predicted WTP distribution to reduce the risk of COVID-19 between counties with older versus younger populations. We define older counties as counties with a proportion of people aged over 45 is higher than the national median. The younger age group includes the counties with a population where the proportion of people aged below 45 is lower than the national median. The Figure 4 reveals that the younger counties have a higher WTP to reduce the risk of COVID-19, especially when entering the winter (Nov 2020 to Feb 2021). According to CDC, people in their 50s are at higher risk for severe illness than younger people in their 40s. People in their 60s or 70s are, in general, at higher risk for severe illness than people in their 50s. The greatest risk for severe illness from COVID-19 is among those aged 85 or older.[19]

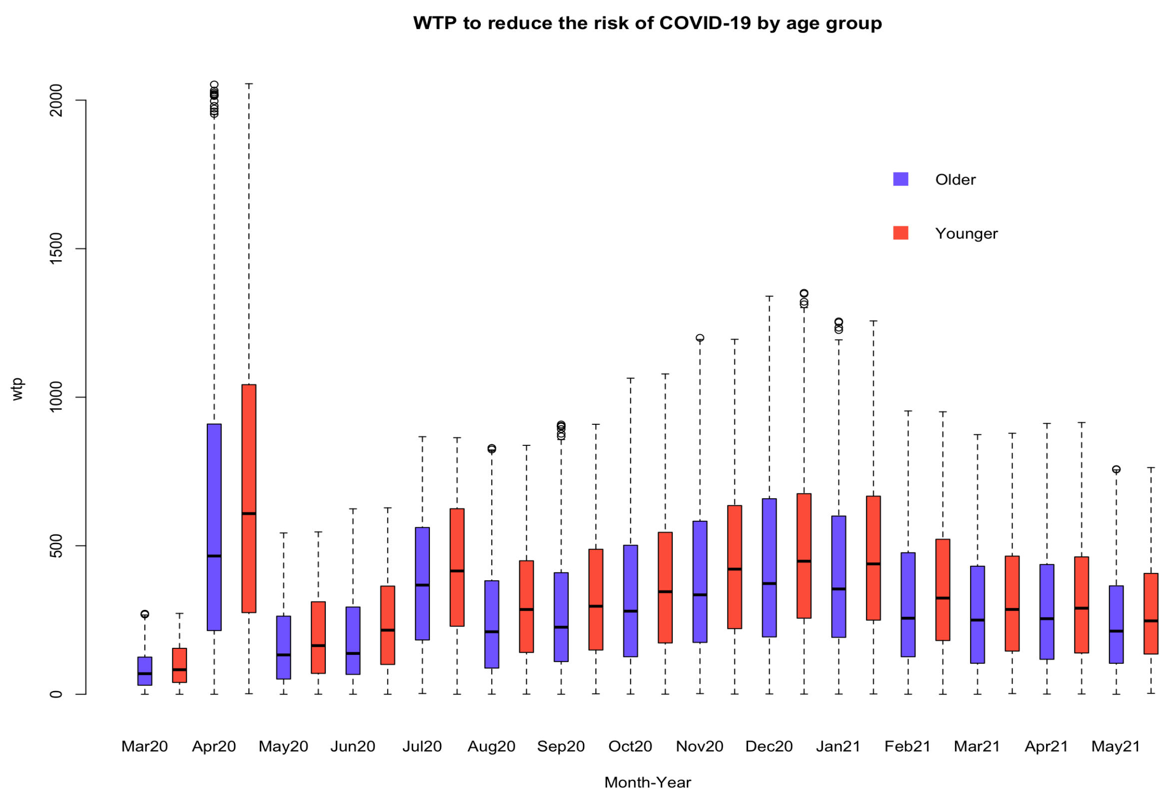

Figure C1. WTP to reduce the risk of COVID-19 in older versus younger counties

The case fatality rate of COVID-19 is higher among older adults than younger adults

[19]https://www.cdc.gov/nchs/nvss/vsrr/covid_weekly/index.htmRace_Hispanic

(Barber and Kim, 2021). Older people were more likely to comply with suggested behaviors and regulations to prevent COVID-19 and less likely than young people to engage in risky behaviors (Kim and Crimmins, 2020). Seniors are at greater risk of requiring hospitalization or dying if they are diagnosed with COVID-19.[20] Although older counties have a higher death risk of COVID-19, younger communities could suffer more from high COVID-19 cases and unemployment rates. The increased COVID-19 cases and unemployment rates in younger counties may offset the low death rate and drive slightly higher WTPs to reduce the risk of COVID-19 compared to older counties.

Ethnicity. For different ethnic groups, Figure 5 shows that for our policy sample in 2020-21, counties with a higher proportion of Black residents greater than the median have a higher WTP to reduce the risk of COVID-19 than White counties. This higher WTP from Black counties may be because Black communities suffer more of COVID-19 cases and deaths. It may also because of the high unemployment rates among Black workers.[21] Benitez et al. (2020) examine racial and ethnic disparities in confirmed COVID-19 cases and find that differences in confirmed COVID-19 cases explain the majority of the observed racial disparities in COVID-19 fatalities. The hospitalization rate of Black or African American is three times higher than that of White persons. The death rate of Black or African Americans is two times higher than that of White persons.[22] According to the American Community Survey, Blacks have lower insurance coverage under ACA.[23] The higher WTP for public health policies to reduce COVID-19 risk may also reflect this lower insurance coverage and access to medical care (which may be attributed to systemic racism.) It may also reflect a

[20]https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/older-adults.html

[21]https://www.rand.org/blog/2020/09/laid-off-more-hired-less-black-workers-in-the-covid.html

[22]https://www.cdc.gov/coronavirus/2019-ncov/covid-data/investigations-discovery/hospitalization-death-by-race-ethnicity.html

[23]https://www.kff.org/racial-equity-and-health-policy/issue-brief/changes-in-health-coverage-by-race-and-ethnicity-since-the-aca-2010-2018/

stronger sense of community among residents of counties with larger Black populations.

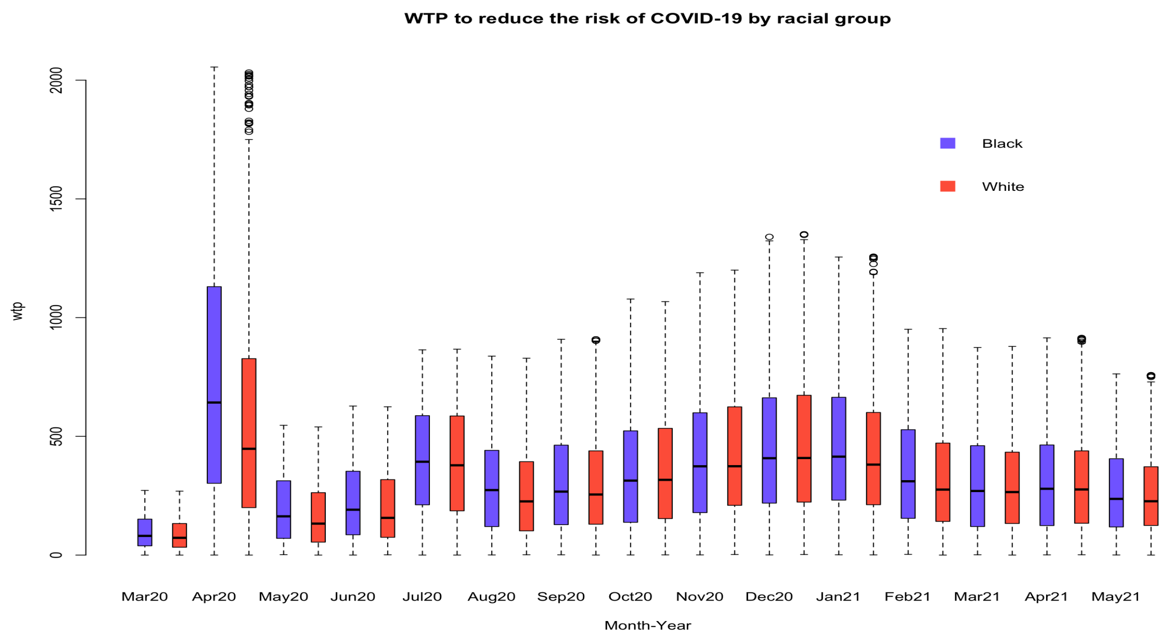

Figure C2. WTP to reduce the risk of COVID-19 by racial groups

Political Affiliation. Figure 6 shows the WTP to reduce COVID risk by population of each county voting for the Democrat/Republican candidate in the most recent presidential election 2000 for 2003 study sample and 2016 for our 2020 policy sample. Democrat-dominated counties have a higher WTP through March 2020 to February 2021. However, the monthly WTP gaps between the Democrat-dominated counties and the Republican-dominated counties decreased during summer 2020 (Jun to Sep). The Democratic counties had higher cases and deaths during the pandemic since most of the democratic counties are in urban or metropolitan areas. Allcott et al. (2020) study partisan differences in Americans's responses to COVID-19 and find that areas with more Republicans engage in less social distancing, as the political

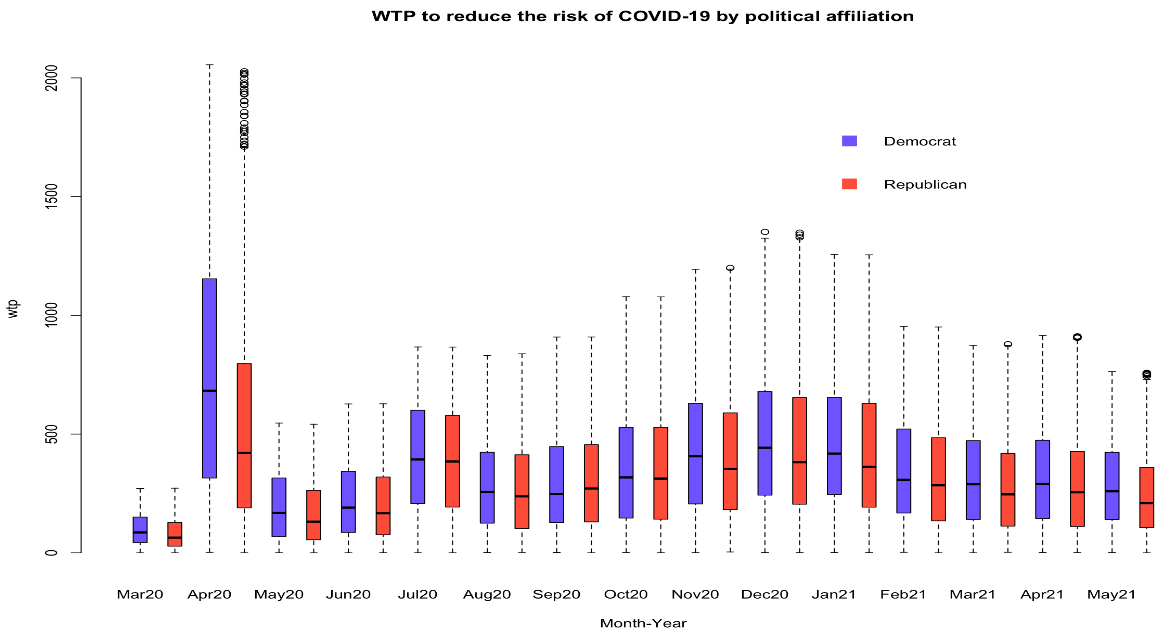

Figure C3. WTP to reduce the risk of COVID-19 by political affiliation

leaders and media outlets sending divergent messages about the severity of the crisis. As the cases and deaths of Republican counties increased more from June to September, the WTP of those counties to reduce the COVID-19 risk approached the WTP of the Democratic counties, even though most of the Republican counties have smaller populations.

Health-Access. As for health-access, the higher health-access counties have the primary care physicians rates and preventable hospitalization rates above the median rates among all counties. And vice versa for the lower health-access counties. Figure 7 shows that the lower health-access counties have a slightly lower WTP to reduce the risk of COVID-19 through public health policies and interventions. People from these counties are more limited by private health care and tend to suffer from higher death rates because of the lack of medical access.

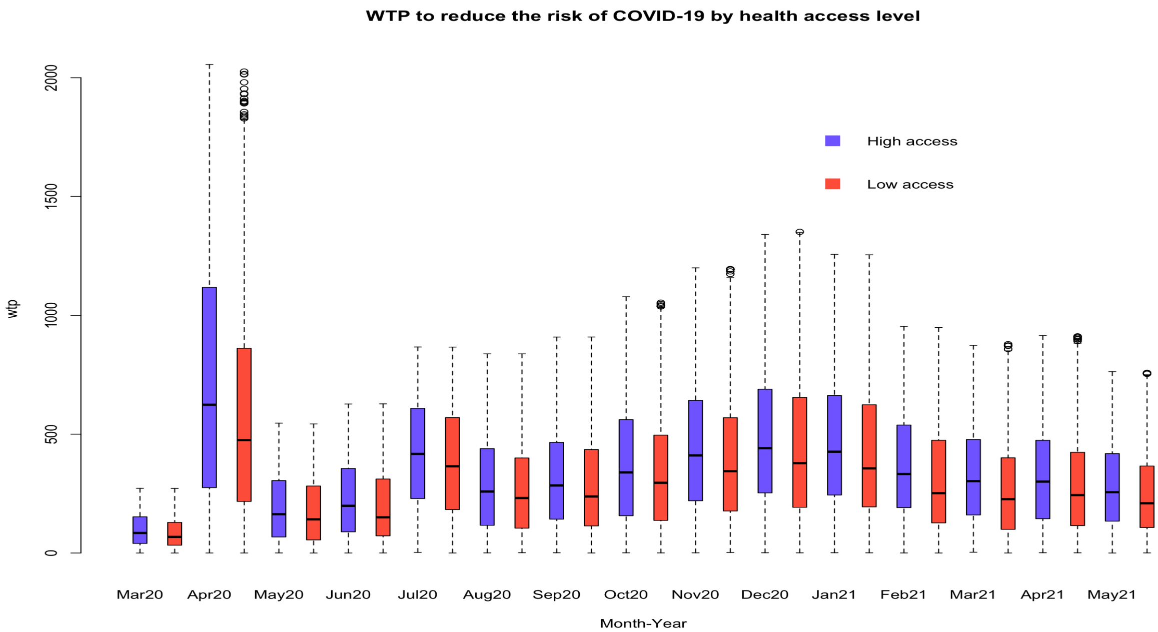

Figure C4. WTP to reduce the risk of COVID-19 by health-access levels

Income. As for the counties with different poverty levels, we divide all counties into higher-income counties whose income medians exceeds the national median. The lower-income counties are those whose income medians are below the national median. Figure 8 shows that the WTP of higher-income counties is higher than the lower-income counties. It shows that the higher-income counties have a higher need for public health intervention to reduce the risk of a pandemic like COVID-19.

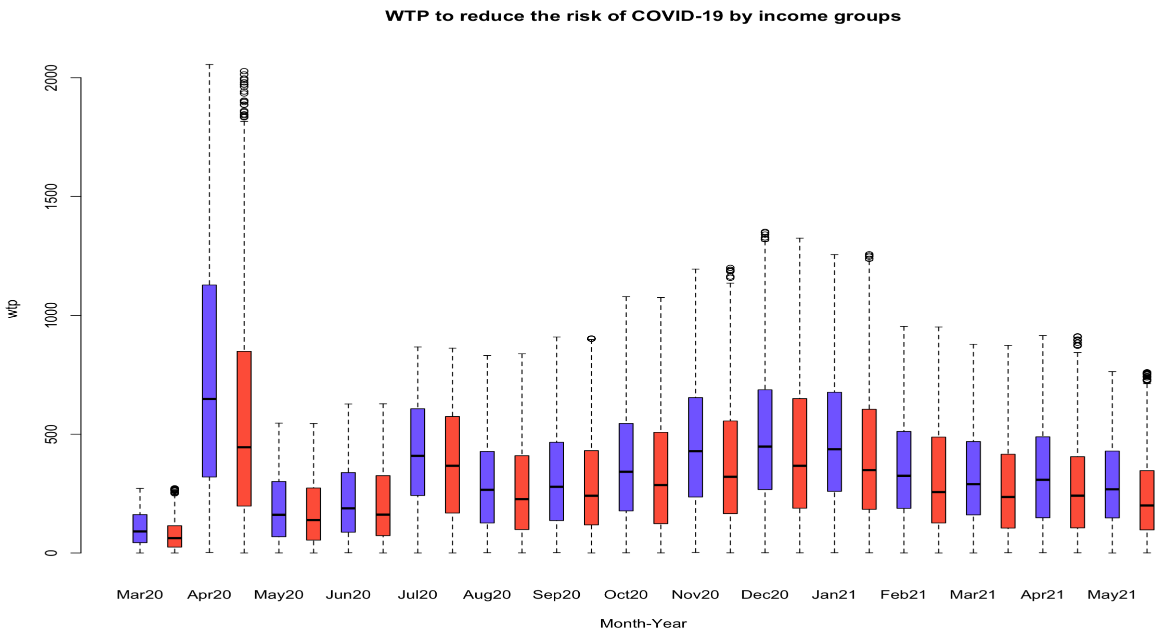

Figure C5. WTP to reduce the risk of COVID-19 by County Median Income

This result matches the studies which find that quarantine policies were effective in higher-income communities and had smaller effect in lower-income or higher-poverty communities both in the U.S. and Chile (Bennett, 2021; Lou et al., 2020; Jung et al., 2021). Papageorge et al. (2020) examine factors associated with the adoption of self-protective health behaviors. They find that higher income is associated with larger changes in self-protective behaviors.

Table C9: Descriptive statistics, 2003 estimating sample vs 2020 simulation sample, county-level heterogeneity

	2003 Study Sample[a]		2020 Policy Sample[b]	
	mean	(sd)	mean	(sd)
County prop. aged 18-24	0.096	(0.029)	0.086	(0.033)
County prop. aged 65+	0.129	(0.038)	0.193	(0.046)
County prop. White	0.773	(0.168)	0.835	(0.161)
County prop. Black	0.114	(0.129)	0.091	(0.146)
County prop. uninsured	0.160	(0.057)	0.114	(0.050)
County fractionalization (0-1)	0.383	(0.219)	0.280	(0.196)
Rep/(Dem+Rep), Pres. Election	0.511	(0.121)	0.667	(0.161)
County Med. Income	34766.67	(9392.89)	37219	(10592.8)
Hospitals per 10000 population	0.221	(0.338)	0.56	(0.876)
County prop. college degree	0.509	(0.104)	0.524	(0.107)
County overall Poverty	0.124	(0.0433)	0.144	(5.65)
County pm25	11.066	(2.623)	6.59	(1.47)
County prop. Fair or Poor Health	0.158	(0.043)	0.179	(0.047)
Primary Care Physicians Rate	0.906	(0.442)	0.543	(0.034)
Preventable Hospitalization Rate	70.7	(19.4)	48.67	(18.28)
Δ unempl (Jun. '03 vs previous month)	0.678	(0.408)		
Δ unempl (Mar. '20 vs previous month)			0.467	(0.934)
Δ unempl (May. '21 vs previous month)				
Observations	1466 respondents			3142 counties

[a] Descriptive statistics, across respondents, for the counties in which they reside;
[b] Descriptive statistics across 3142 counties or other county FIPS geographic areas.