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Abstract: Despite well-documented benefits of wearing a mask to reduce COVID-19 transmission, widespread opposition to mandating mask-wearing persists. Both our game-theoretic model and our unique survey dataset point to heterogeneity in the perceived benefits and perceived costs of mask-wearing. Young, healthy, Canadian-born adult males who are politically conservative or without a college education are all more likely to oppose mandatory mask laws, as are individuals who do not take climate change seriously and who express less trust in doctors and in elected officials. Political conservatives disproportionately cite not wanting to live in fear and infringements on personal freedoms as reasons for not wearing masks. Our findings cannot be explained by individuals who substitute physical distancing for mask-wearing. We show that these two precautionary measures are complements.

Keywords: COVID-19, mandatory protective masks, heterogeneity in beliefs, ideology, political partisanship.

JEL Codes: I12, I18, J38.

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1 Introduction

Wearing a mask has become routine around the world with the spread of COVID-19. At the same time, anti-mask demonstrations have received substantial media attention. Much of the public opposes laws that require and enforce the use of masks in public. The purpose of our study is to examine the factors that drive such differences in preferences for mask policies.

We develop a simple game-theoretic model to analyze individual choice around mask-wearing, and employ a unique dataset of Ontarians' survey responses at the onset of the COVID-19 pandemic in Canada to test the model's predictions. While the effectiveness of masks in controlling the pandemic has been well-documented for such coronaviruses, we find that support for mask laws varies substantially.

Our model suggests that differences in public support for mask laws are driven by heterogeneity in individual-level beliefs about the associated benefits and costs from mask usage. Such differences in beliefs can result from differences in objective factors associated with the risk of contracting the virus, such as differences in age, gender, and health status.

Our empirical analysis shows that, in addition to such objective measures affecting support for masks, "intrinsic" beliefs about factors not directly related to COVID-19, such as political partisanship, trust in doctors and beliefs about climate change are strongly associated with individual support for mandatory mask laws. We first present descriptive statistics from our survey demonstrating heterogeneity in mask support among liberals versus conservatives. For instance, conservatives are more likely to cite not wanting to have their freedom infringed upon or not wanting to live in fear as reasons not to wear a mask.

Next, we use an ordered logit model to quantify how different factors predict support for mandatory mask laws. Our baseline model encompasses demographics and health status variables such as age, the presence of chronic conditions, and gender. Individuals with chronic health conditions and those over the age of 65 are significantly more likely to support mandatory masks. We also find that women are more supportive of mask laws than men, even after controlling for risk and time preferences.

Our most striking results highlight the role of trust in institutions and political ideology in support for mask laws. For example, identifying as "very conservative" is associated with a

30-percentage-point reduction in the probability of fully supporting mandatory masks. When interacted with gender, we find that this result is restricted to males. Trust in doctors and in government are also strong predictors of mask support. These findings are robust to a generalized logit model that does not rely on the proportional-odds assumption and highlight the importance of improving trust in institutions and medical authorities in order to bolster support for mask laws and thereby mitigate the pandemic.

Our work is related to a growing literature on the COVID-19 pandemic and mask-wearing. Capraro and Barcelo (2020) study gender differences in mask wearing. Jehn and Zajavoca (2020) use Statistics Canada survey data to document differences in mask-wearing patterns by age and gender. Also using Canadian survey data, Brankston et al. (2020) find that those with university education or with high-risk health conditions are more likely to use masks. Survey evidence from van der Linden and Savoie (2020) shows that Canadians are more amenable to wearing masks when the messaging emphasizes protecting others from infection, rather than protecting oneself. We differ from these works in that we focus on support for mandatory mask laws. Using a unique dataset, we employ a discrete-choice model to quantify the role of health, cultural and ideological factors in explaining the variation in support for mask laws.

2 Model

2.1 Preliminaries

We introduce a two-person, game-theoretic model for mask-wearing with heterogeneous beliefs. Each individual i, $i = \{1, 2\}$, can choose between the set of two actions $a_i \in \{m, n\}$, where m is the choice to wear a mask in public and n is not to wear one. The payoffs for individual i, denoted $\pi_i(a_i, a_j)$, depend on their own action a_i and the other individual's action a_j.

The scientific evidence (Asadi et al., 2020) and public health messaging (Greenhalgh et al., 2020) states that wearing masks prevents transmitting the virus to others, and so an individual receives a benefit if those around them wear masks; however, wearing a mask comes with a personal cost.

It follows that:

$$\pi_i(n, m) \geq \pi_i(m, m) \tag{1}$$

$$\pi_i(n, n) \geq \pi_i(m, n) \tag{2}$$

Namely, both individuals weakly prefer to not wear a mask whether or not the other individual wears a mask.

From the payoffs, if at least one of (1) or (2) is strict, both individuals have a dominant strategy (n, n), that is, not to wear a mask.[1]

2.2 Heterogeneous beliefs

We now allow for heterogeneity in beliefs for the payoffs $\pi_i(m, m)$ and $\pi_i(n, n)$. First consider the homogeneous case where $\pi_i(m, m) > \pi_i(n, n)$ for both individuals: the equilibrium is inefficient and entails welfare losses. Both individuals would support a policy that makes mask-wearing mandatory, since it enables coordination on the preferred outcome. On the other hand, if $\pi_i(m, m) \leq \pi_i(n, n)$ for both individuals, then the non-cooperative outcome is efficient and both would oppose mandatory masks.

Next, suppose individuals' payoffs are heterogeneous, for example, $\pi_1(m, m) > \pi_1(n, n)$ and $\pi_2(m, m) \leq \pi_2(n, n)$. Now, individual 1 supports mandatory masks, while individual 2 opposes them. Our model therefore suggests that differences in support for mandatory masks result from individuals' opposite signs for the difference, $\pi_i(m, m) - \pi_i(n, n)$.

Proposition 1. *Individual i supports mandatory masks if and only if $\pi_i(m, m) - \pi_i(n, n) > 0$.*

Proof. If $\pi_i(m, m) - \pi_i(n, n) > 0$, then $\pi_i(m, m) > \pi_i(n, n)$. From our prior discussion, this individual supports a mandatory mask law to permit coordination on their preferred outcome. On the other hand, if $\pi_i(m, m) - \pi_i(n, n) \leq 0$, then $\pi_i(m, m) \leq \pi_i(n, n)$, this individual opposes mandatory masks, which establishes the contrapositive of the necessary condition. □

Therefore, we are interested in the payoff difference $\pi_i(m, m) - \pi_i(n, n)$. We can decompose

[1] An important caveat is that recent evidence demonstrates that masks also offer a protective benefit to the mask-wearer (see U.S. Centers for Disease Control and Prevention (2020)). Notwithstanding, the payoff structure described above accurately represents the evidence and public messaging at the time of our survey.

this difference into two parts: the benefit B_i received by i from the other individual j switching from $a_j = n$ to $a_j = m$, and the cost C_i that i incurs from switching from $a_i = n$ to $a_i = m$. We let $\pi_i(m, m) - \pi_i(n, n) = B_i - C_i$.

Corollary. *Individual i supports mandatory masks if and only if $B_i - C_i > 0$.*

Proof. Follows from Proposition. □

The benefit B_i is a function of objective factors like health status (e.g., less healthy and hence more susceptible people incur a greater protective benefit if others wear masks) and the prevalence of COVID-19 in one's community as well as subjective belief-shifting parameters like trust in doctors and in government.

The cost C_i is a function of objective factors like the monetary cost of wearing a mask, as well as subjective belief-shifting parameters like the belief that mask-wearing infringes on personal freedoms or creates a fear-based mindset or social stigma.

In our survey, we gather data on factors that influence both B_i and C_i, such as age, health status and the COVID-19 rate, the above belief-shifting parameters as well as reasons for not wearing a mask and whether these are associated with political affiliation.

3 Survey Design

To test the model's predictions and other variables that may explain the variation in support for mandatory masks, we designed an extensive online survey. We conducted the survey from June 29 to July 7, 2020. During this period, Ontario witnessed around 150 new cases per day, well past the worst days of the first wave of the epidemic (as of time of writing, Ontario is experiencing a resurgence in cases) (Public Health Ontario, 2020). At this time, few localities had mandatory mask rules, although some mandated them on transit or at specific establishments, or were otherwise considering it. The City of Toronto passed a sweeping bylaw that made masks mandatory in all public indoor spaces effective July 7. Other local governments followed suit – after our survey concluded. At the time of our survey, mask-wearing was a largely fragmented regulatory issue and more of a recommendation than a rule. The provincial government eventually made masks mandatory throughout Ontario in October.

Recall that the expected benefit from others wearing a mask is higher for those in poorer health and those who live in regions with high infection rates. Health measures that we collected include the respondent's age and whether they or someone they live with has a chronic health condition known to be a co-morbidity of COVID-19: hypertension, diabetes, cardiovascular disease and respiratory disease. We also gathered the cumulative number of reported COVID-19 cases per 100,000 population in the respondent's health district from Public Health Ontario's website at the launch of the survey.

The survey begins with a description of the Canadian government's social-distancing and self-isolation directives followed by two reading comprehension questions that test the respondent's understanding of these directives.[2] Anyone who answered incorrectly either question or a third attention-check question later in the survey that simply asks respondents to click 'Next' without choosing a multiple-choice answer was removed from our sample.

The survey proceeds to ask respondents how often they wear a mask or face covering when in public where the five response categories are "never (0% of the time)", "rarely (25% of the time)", "sometimes (50% of the time)", "usually (75% of the time)" and "almost always (near 100% of the time)". Those who choose "never" or "rarely" then indicate the relevance of each of a series of reasons for their choice not to wear a mask. Similarly, those who report wearing a mask "sometimes", "usually" or "almost always" select their reasons for doing so. In addition, all respondents indicate their degree of support or opposition "to a law whereby everyone is required to wear a mask, plastic face shield or other face covering outside the home with violators subject to a fine?"

When answering about one's mask-wearing behavior or support for proposed mask-wearing legislation, respondents may provide answers perceived to be socially accepted rather than accurate ones. We measure and control for this possible tendency to inflate one's reported mask-wearing behavior or support for masks using two social-desirability scales. Based on the original Crowne and Marlowe (1960) 33-question social-desirability scale, we implemented a shortened six-question scale from Fischer and Fick (1993). Each true-or-false question describes a behavior or attitude that almost all of us have displayed at some point (e.g., discourteous to someone, jealousy, felt irritated when asked a favor) that conflicts with the socially accepted response of not admitting to the behavior or attitude. We include the sum of the socially desirable responses

[2]These questions about social distancing serve as the basis for Papanastasiou, Ruffle, and Zheng (2020).

as a control in our regressions.

Finally, we collect a host of socio-demographic variables, the respondent's risk and time preferences, political beliefs and views on medical professionals and government.

We conducted our survey through Maru/BLUE, an international survey company. They sent survey invitations to a subset of their research participant pool that matches the distribution of Ontarians along the dimensions of age, gender, household income and region. From 3,079 completions, we excluded anyone who failed either reading-comprehension question or the attention-check question, resulting in a sample of 2,649 respondents. The average completion time was 25 minutes and 20 seconds.

4 Descriptive Statistics and Estimation Strategy

We begin with some descriptive statistics of our sample. Thirty-five percent of respondents strongly support mandatory mask laws while 11 percent strong oppose them. Respondents aged 22 and 76 are at the fifth and 95th percentiles, respectively, while the mean (modal) age is 47.5 (47). On a scale from "Poor" to "Excellent", almost half the respondents' self-reported health status is "Very Good", while 47% indicated having one or more chronic health conditions. We surveyed individuals across the political spectrum: 39% identify as Liberal or Very Liberal and 25% identify as Conservative or Very Conservative. Sixty-one percent of respondents have a Bachelor's degree or higher. Eighty-two percent or 2,148 respondents live with at least one other person. Among these, 1,018 or 47% report that at least one person living with them has one or more chronic health conditions.

Next, we show that support for mandatory mask laws varies substantially across Ontario. There are 34 public health units (PHUs) in the province, through which public health measures are administered. The government sometimes aggregates these into seven health regions (Government of Ontario, 2020). We collected the first three digits of respondents' postal code, and matched these to the corresponding PHU. We aggregated PHUs with fewer than 50 responses with neighboring PHUs. This essentially amounts to using the government's seven health regions, while keeping large cities and counties separate, yielding 14 health regions in total.[3]

[3]For example, the city of Hamilton was kept separate, while its surrounding areas were aggregated into the South West region.

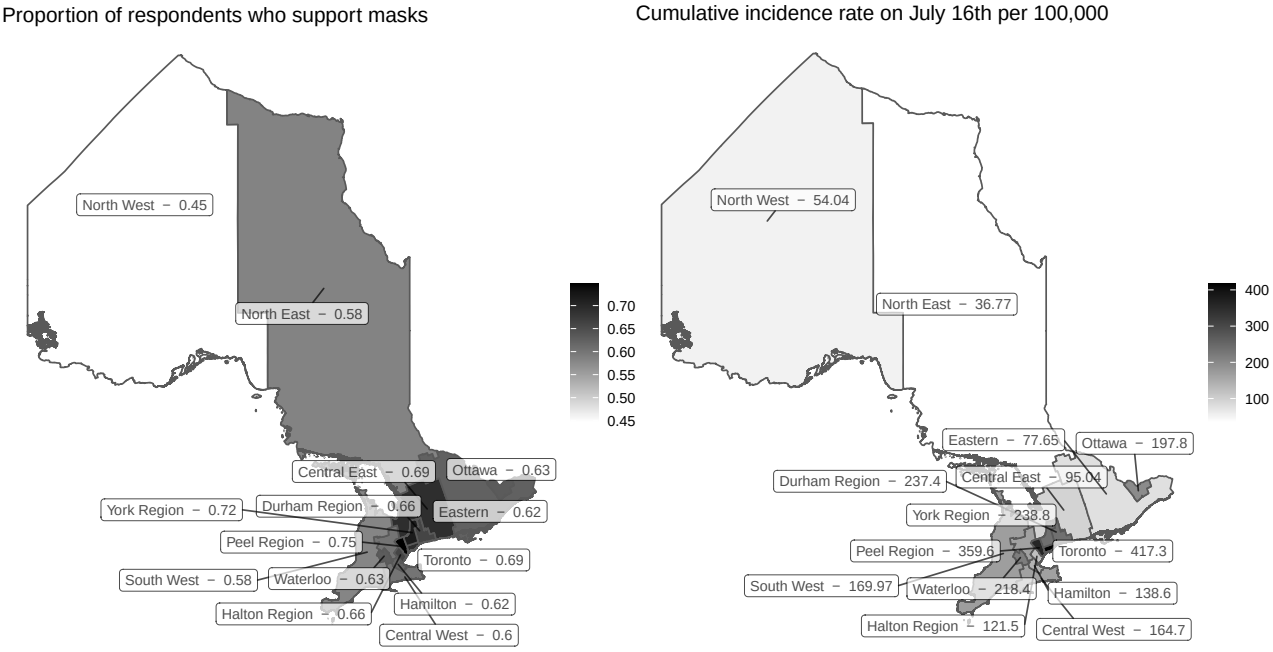

Figure 1: Support for mandatory mask laws (left panel) and cumulative COVID-19 cases per 100,000 population on June 27, 2020 (right panel) by Ontario health region.

The left panel of Figure 1 shows the proportion of respondents by health region who fully support mandatory masks. The right panel displays the cumulative incidence of COVID-19 per 100,000 individuals on June 27th, 2020. The two panels reveal a link between the cumulative COVID-19 rate and support for mandatory masks. Urban areas, which experienced the highest case rates, tend to display higher support for mask laws. For example, Toronto had a case rate of 417.3 and 69% of respondents who fully supported a mask law compared to the North West region with a case rate of only 54.04 and only 45% of respondents who fully support mask laws. Spearman's rank-correlation coefficient between the COVID-19 rate and percentage who fully support mask-wearing is 0.69 ($p < .01$).

Next, we examine the reasons that individuals choose to wear or not wear masks, before mask-wearing was mandatory in Ontario. To begin, we ask respondents how often they wear masks with the options: "Never", "Rarely", "Sometimes", "Usually" or "Always". Among those who answered "Never" or "Rarely", we then inquired about the degree of relevance for different reasons for not wearing a mask.

Figure 2 highlights stark differences in the reasons for not wearing a mask among Liberals, Moderates and Conservatives. Conservatives cited three reasons as "very relevant" to their choice not to wear a mask in substantially higher proportions than did Liberals: "Don't want to live in fear", "I'm not infected and not a risk to others" and "Infringes on personal freedom" were cited by 28%, 26% and 17%, respectively, of the 218 Conservatives who never or rarely wear a mask compared to just 10%, 10% and 4% of the 143 Liberals. At the same time, 45% of Liberals indicated that they are in public only for activities for which they can physically distance as a very relevant reason for not wearing a mask compared to 25% of Conservatives. A chi-squared test shows that the difference in distributions of Liberal vs Conservative for all three of these plots is statistically significant. On the other hand, reasons such as "Masks are too expensive" or "Masks are not readily available" were neither highly cited nor associated with differences in views across the political spectrum.

These initial findings suggest possible differences in the support for mask laws by political views. We next build a logit model in order to quantify more precisely how political views, other expressions of ideology, and factors such as demographics predict support for mask laws.

The main variable of interest, support for masks, follows an ordered response scale with five

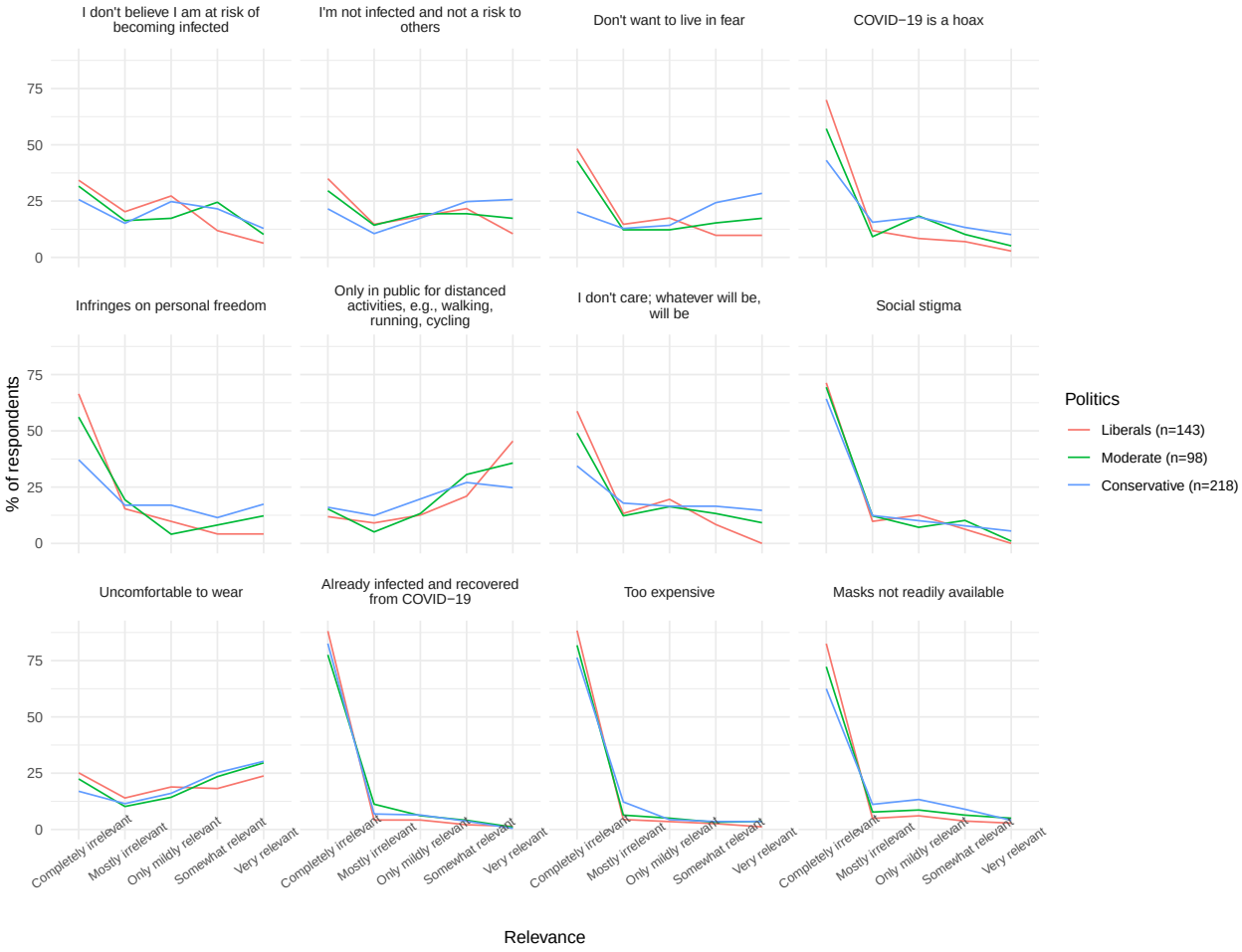

Figure 2: Reasons for not wearing a mask by political affiliation.

categories.[4] Accordingly, we use an ordered logit model to estimate how different individual characteristics are associated with the likelihood of supporting mandatory mask laws.[5] To this end, we assume that the observed support value reported, y, is a function of y^*, a latent continuous variable measuring the likelihood of support. Furthermore, we assume that there exist specific cut-off points ζ_1, ζ_2, ζ_3, and ζ_4, where we observe y such that:

$$y_i = 1 \text{ if } y_i^* \leq \zeta_1$$

$$y_i = 2 \text{ if } \zeta_1 \leq y_i^* \leq \zeta_2$$

$$y_i = 3 \text{ if } \zeta_2 \leq y_i^* \leq \zeta_3$$

$$y_i = 4 \text{ if } \zeta_3 \leq y_i^* \leq \zeta_4$$

$$y_i = 5 \text{ if } \zeta_4 \leq y_i^*$$

where $y_i = 5$ is Strongly Support a mandatory mask law, $y_i = 1$ is Strongly Oppose, and $y_i = 3$ is Neutral.

We run the following ordinal logit model:

$$\mathbb{E}(y_i^*) = \alpha_1 \text{chronic}_i + \alpha_2 \text{chronicfam}_i + \beta \text{age}_i + \xi \text{female}_i + \delta \text{COVID-19 rate}_i + \phi \text{sds}_i + \varepsilon_i \quad (3)$$

where chronic_i (chronicfam_i) is an indicator for whether (someone living with) the respondent has a chronic health condition, age_i is the respondent's age, female_i is an indicator for being female, COVID-19 rate_i is the cumulative number of COVID-19 cases per 100,000 residents in a respondent's health district, and sds_i is respondent i's score on the social-desirability scale.

5 Results

Table 1 presents the results from the ordered logit specified in Equation (1). The coefficients are presented as odds ratios, with 95% confidence intervals. An odds ratio of γ means that the odds of being in a response group greater than k versus being in the response groups less than or equal to k is γ times larger, where $k \in \{1, 2, 3, 4, 5\}$ and the levels of support for masks are y_k. Recall that we measured support for mask laws as a discrete variable on a five-point scale

[4] The seven response categories in the survey were collapsed to five to simplify the analysis.

[5] This model makes the assumption of proportional odds. In a robustness check, we use a generalized ordered logit and show that our findings are similar.

where y_1 means "Strongly Opposed" to mask laws and y_5 means "Strongly Support".

Table 1

	support				
	(1)	(2)	(3)	(4)	(5)
Age65	1.371***	1.278**	1.300***	1.311***	1.333***
	(1.132, 1.662)	(1.052, 1.554)	(1.069, 1.581)	(1.078, 1.595)	(1.096, 1.623)
chronicind	1.229**	1.219**	1.227**	1.250**	1.246**
	(1.028, 1.470)	(1.016, 1.462)	(1.023, 1.472)	(1.042, 1.501)	(1.039, 1.495)
chronicfam	0.941	0.946	0.945	0.938	0.951
	(0.811, 1.093)	(0.812, 1.101)	(0.811, 1.100)	(0.806, 1.092)	(0.817, 1.108)
COVID-19 rate	1.002***	1.002***	1.002***	1.002***	1.002***
	(1.001, 1.002)	(1.001, 1.002)	(1.001, 1.002)	(1.001, 1.002)	(1.001, 1.002)
female	1.472***	1.374***	1.378***	1.332***	1.384***
	(1.271, 1.704)	(1.182, 1.598)	(1.185, 1.602)	(1.145, 1.550)	(1.190, 1.610)
risk		0.900***	0.900***	0.899***	0.900***
		(0.871, 0.930)	(0.871, 0.930)	(0.870, 0.929)	(0.871, 0.930)
switch		0.976	0.981	0.982	0.979
		(0.938, 1.015)	(0.943, 1.020)	(0.944,1.021)	(0.941,1.019)
university			1.201**	1.167**	1.176**
			(1.032, 1.398)	(1.002, 1.359)	(1.010, 1.370)
knowcovid				1.698***	
				(1.423,2.029)	
East Asian					2.007 ***
					(1.389,2.927)
sds	1.019	1.005	1.006	1.009	1.005
	(0.973, 1.067)	(0.959, 1.054)	(0.960, 1.055)	(0.963,1.058)	(0.958, 1.053)
Observations	2,483	2,415	2,415	2,415	2,415
Brant test	0.43	0.41	0.22	0.10	0.20

Note: *p<0.1; **p<0.05; ***p<0.01

Entries are exponentiated odds ratios (95% confidence intervals).

Column (1) reports estimates for the health and gender predictor variables. *Age*65 is an indicator for 65 years of age or more. The proportional odds ratio (henceforth *OR*) on *Age*65 is 1.37 and significant, meaning that older respondents are more likely to support mask-wearing. Calculations of the marginal effect indicate that being over 65 increases the probability of being in group y_5 by 0.074. This is significant at the five-percent level.[6] This finding supports our intuition: since older adults are more likely to be adversely affected by COVID-19, they are stronger proponents of laws to limit its spread. We also find that an individual's health status predicts support for mask laws. Having a chronic condition, *chronicind*, has an OR of 1.23 and is statistically significant. On the other hand, an indicator for a member of the respondent's

[6]Marginal effects are calculated holding independent variables at their mean level. If the independent variable is categorical, it is held at the reference category.

household having a chronic condition is not a significant predictor of support for mask laws.

Next we show that individuals in regions with more COVID-19 cases support stricter preventative measures. A one-unit increase in $COVID-19\ rate$ (the total reported COVID-19 cases in a health district per 100,000 population two days before our survey launched) has an OR of 1.002 ($p < .01$).

In addition, we find that females are significantly more supportive of mask laws than males with an OR of 1.47. The computed marginal effect shows that being female increases the probability of "strongly supporting" a mandatory mask law by 0.087. The finding that women tend to favor stronger restrictions is consistent throughout several different specifications, and in line with other works studying gender and views on COVID-19, such as Galasso et al. (2020). Capraro and Barcelo (2020) finds that possible explanations for the gender difference in mask-wearing include that men attribute more of a stigma to mask-wearing.

Lastly, *sds* measures the respondent's tendency to give socially desirable answers. We actually do not find this to be a significant predictor of support for mask laws, contrary to its significance in predicting reported compliance with social distancing in Papanastasiou, Ruffle, and Zheng (2020). We suspect that one reason for this is that at the time of our survey masks were not yet compulsory or even the social norm, thereby allowing respondents who oppose mandatory masks to freely express their opinion without fear of negative judgment.

As mentioned previously, our ordered logit estimates rely on the assumption of proportional odds, that is, the OR is constant at each point in the scale of mask support. We use the Brant test to assess the validity of this assumption. In the last row of Table 1, Brant Test reports the p-value for the null hypothesis that the proportional odds assumption is satisfied. We cannot reject the null of proportional odds in column (1).

In column (2) of Table 1 we add controls for time (*switch*) and risk preferences. We borrow our risk-preferences question from Dohmen et al. (2011). On a 0 ("not at all willing") to 10 ("very willing") scale, respondents answer, "How willing are you to take risks, in general?" The OR for *risk* of 0.90 implies, quite intuitively, that individuals more willing to take risks are less likely to support mask laws. An adaptation of Coller and Williams (1999), our time-preferences measure is not a significant predictor of support for masks.

Next, column (3) assesses the link between education and support for mask laws. The indica-

tor, *university*, for whether a respondent possesses a bachelor's degree or higher has an OR of 1.21. Even with these additional controls, our key demographics such as age and female remain significant predictors of support for mandatory masks.

In addition, we investigate social and cultural factors that may predict support for mandatory masks. The variables from the previous specifications are kept as controls. Column (4) includes an indicator *knowcovid* for whether the respondent knows someone who contracted COVID-19. The highly significant OR on this variable is 1.70 and the marginal effect for "strongly supporting" mandatory masks is 0.127 ($p < .05$). This finding suggests that individuals' views about the pandemic are influenced by the experiences of their family and friends.

Column (5) explores whether individuals from East Asian countries are more likely to support mask laws. China, Japan, and South Korea are countries where mask-wearing has been a norm during public-health crises for decades (Friedman, 2020). The indicator *eastasian* equals one for respondents born outside of Canada and an ethnicity from one of the above countries, and zero otherwise. Individuals from these cultures have a significantly higher probability of supporting mask laws: OR equals 2.01.

Now we turn to the link between political views/ideology and views on mask laws. Our findings reveal stark differences in mask support along political views and ideology such as confidence in doctors and in government to act in the public's best interest.[7] Column (6) in Table 2 begins by looking at how support varies with political views. "Very Liberal" is the reference category. The results are striking. The OR for supporting masks for someone who is politically "Moderate" is 0.64, whereas for someone who is "Very Conservative" it falls to 0.13. The marginal effects also suggest significant polarization. For instance, being "Very Conservative" reduces the probability of "strongly supporting" mandatory masks laws by 30 percentage points. Column (7) shows that political partisanship is a robust predictor of support for mandatory masks for males only: both male moderates and male conservatives are significantly less supportive than male liberals.[8] No such robust relationship between partisanship and support for masks exists among females. To the best of our knowledge, we are the first to demonstrate the dependence of this political partisanship finding on gender. This finding is robust when running a generalized

[7] Allcott et al. (2020) demonstrate political partisanship in Americans' attitudes toward the pandemic. Pennycook et al. (2020) compare attitudes toward COVID-19 in the U.S., Canada and the U.K. as a function of political views and cognitive sophistication.

[8] Here, the categories for liberal and very liberal are collapsed into one, and conservative and very conservative are collapsed into one.

logit specification.

Column (8) of Table 2 investigates how trust in certain institutions corresponds with support for mask laws (Pew Research Center, 2020). We ask individuals how confident they are that doctors and medical scientists act in the best interests of the public. The reference category is "not confident"; $doctors : neutral$ ($doctors : confident$) is individuals who feel neutral (confident) about doctors. Confidence in doctors has an OR of 3.82. In terms of marginal effects, moving from "not confident" to "confident" in doctors increases the probability of fully supporting mandatory mask laws by 0.27.

Column (9) performs a similar exercise but instead looks at confidence in government and elected officials; $government : neutral$ ($government : confident$) is an indicator for individuals who feel neutral (confident) toward government. The reference category and definitions of other categories are identical. Similar to confidence in doctors, confidence in the government is also associated with increased support for mandatory mask laws.

Finally, column (10) measures ideology by asking individuals whether they agree with the statement, "I believe climate change is an imminent threat to humanity." With "Disagree" as the reference category, $climate : neutral$ is "Neutral" while $climate : agree$ is "Agree". We show that those who take climate change seriously are more likely to support mask laws.

Brant tests for all specifications appear in Table 2. For all of them we reject the null of proportional odds. The Appendix establishes the robustness of all our findings in these specifications to generalized logits.

At this point, the reader may wonder whether mandatory masks are a desirable policy. Other precautionary behaviors exist to reduce the risk of COVID-19. For example, maintaining a distance of two meters (six feet) or more (i.e., social distancing) can be viewed as an alternative to masks. Vulnerable populations (e.g., the elderly or chronically ill) and the risk averse may willingly adopt both social distancing and mask-wearing. On the other hand, those in less densely populated regions may practice social distancing and regard mandatory masks as unnecessary. These examples illustrate that masks and physical distancing may act as substitute or complementary protective measures. We evaluate which of these pertains to our sample. Figure 3 plots the conditional distribution for support for mandatory mask laws at different levels of compliance with social distancing. The leftmost (rightmost) panel is the lowest (highest) level

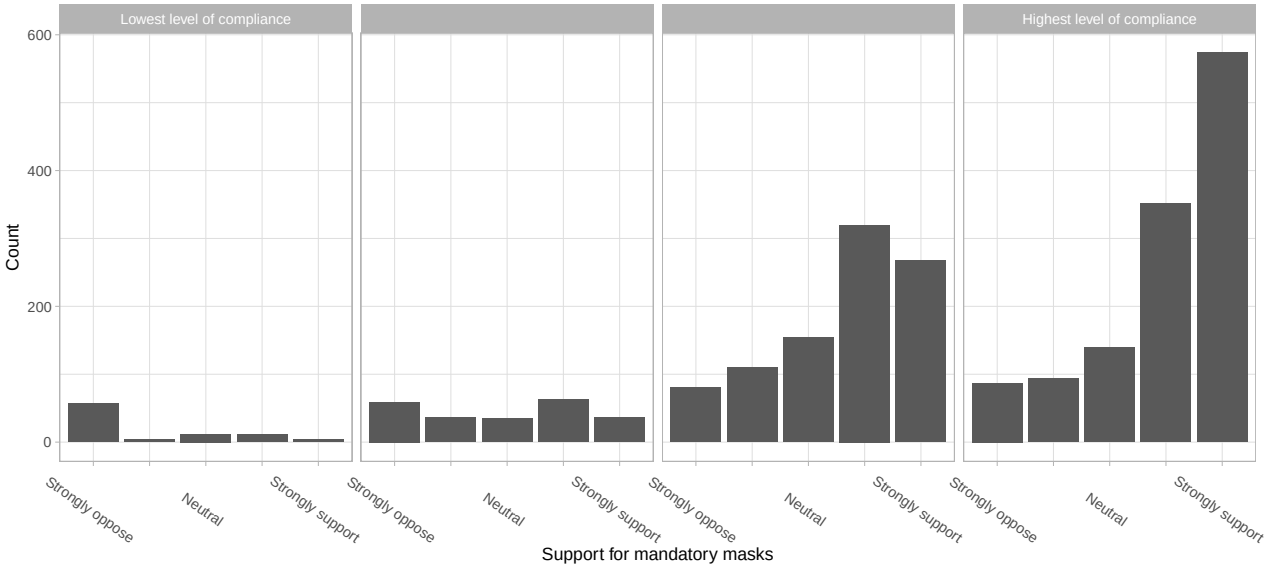

Figure 3: Relationship between support for mandatory masks and compliance with social distancing regulations.

of social-distancing compliance. We see that at the lowest level of social-distancing compliance, the overwhelming majority of respondents strongly opposes mandatory masks. However, as social-distancing compliance increases so does support for mask laws, to the point that the majority strongly supports mandatory masks at the highest level of compliance. The positive ($\rho = 0.29$) and highly significant ($p < .01$) Spearman's rank-correlation coefficient confirms the complementarity of mask support and social distancing.

Table 2

	support				
	(6)	(7)	(8)	(9)	(10)
Age65	1.332***	1.354***	1.220**	1.345***	1.370***
	(1.076, 1.652)	(1.094, 1.678)	(1.003, 1.486)	(1.105, 1.639)	(1.124, 1.670)
chronicind	1.202*	1.172	1.242**	1.217**	1.265**
	(0.985, 1.467)	(0.962, 1.430)	(1.034, 1.492)	(1.014, 1.460)	(1.053, 1.520)
chronicfam	0.943	0.933	0.926	0.948	0.944
	(0.796, 1.117)	(0.787, 1.105)	(0.795, 1.079)	(0.814, 1.104)	(0.810, 1.100)
COVID-19 rate	1.001***	1.001***	1.002***	1.002***	1.002***
	(1.001, 1.002)	(1.001, 1.002)	(1.001, 1.002)	(1.001, 1.002)	(1.001, 1.002)
female	1.369***	1.113	1.429***	1.353***	1.252***
	(1.157, 1.621)	(0.872, 1.420)	(1.228, 1.663)	(1.164, 1.574)	(1.075, 1.459)
liberal	0.967				
	(0.733, 1.272)				
moderate	0.640***				
	(0.475, 0.861)				
conservative	0.448***				
	(0.333, 0.601)				
very conservative	0.127***				
	(0.080, 0.200)				
male:moderates		0.533***			
		(0.386, 0.735)			
male:conservatives		0.304***			
		(0.229, 0.403)			
female:moderates		1.425			
		(0.934, 2.176)			
female:conservatives		1.525**			
		(1.039, 2.240)			
doctors:neutral			2.045***		
			(1.240, 3.388)		
doctors:confident			4.952***		
			(3.250, 7.591)		
government:neutral				1.451***	
				(1.206, 1.745)	
government:confident				1.622***	
				(1.361, 1.934)	
university	1.060	1.075	1.162*	1.168**	1.116
	(0.889, 1.262)	(0.902, 1.280)	(0.997, 1.354)	(1.003, 1.360)	(0.957, 1.301)
risk	0.907***	0.907***	0.907***	0.902***	0.909***
	(0.875, 0.941)	(0.874, 0.940)	(0.877, 0.937)	(0.873, 0.932)	(0.879, 0.939)
switch	0.964	0.967	0.984	0.981	0.985
	(0.921, 1.008)	(0.924, 1.012)	(0.946, 1.024)	(0.943, 1.020)	(0.947, 1.025)
sds	1.019	1.017	1.010	0.991	1.016
	(0.966, 1.074)	(0.965, 1.072)	(0.963, 1.059)	(0.945, 1.040)	(0.969, 1.066)
climate:neutral					3.646***
					(2.820, 4.722)
climate:agree					5.753***
					(4.452, 7.449)
Observations	1,982	1,982	2,415	2,415	2,415
Brant test	< .001	< .001	< .001	< .001	< .001

*p<0.1; **p<0.05; ***p<0.01. Entries are exponentiated odds ratios (95% confidence intervals).

6 Conclusion

Our paper presents a number of highly significant and robust predictors of support for mandatory mask laws. Many of these findings readily prescribe an appropriate policy response. Ninety percent of respondents express confidence in doctors to act in the public's best interests compared to just 36% who indicate the same for government. When combined with the strength of the result that the more confidence respondents have in doctors the more likely they are to support mask laws, the implication is that elected officials ought to leave the messaging about medical advice and best health practices to medical professionals. Knowing someone who has contracted COVID-19 and the cumulative caseload in one's health region are both associated with higher support for mandatory masks. These two findings testify to the importance of the salience of the virus for generating mask support. The virus can be made more salient to everyone through more education, outreach and public appeals from COVID-19 victims. The observation that individuals from mask-wearing cultures are more strongly supportive of mask laws suggests the need to shift cultural norms toward broader acceptance of mask-wearing. Again, education, outreach and the media can all contribute to this goal. In light of Abaluck et al. (2020)'s estimate that "the benefits of each additional cloth mask worn by the public are conservatively in the $3,000-$6,000 range due to their impact in slowing the spread of the virus", these efforts are all imperative and highly cost-effective.

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7 Appendix

We drop the assumption of proportional odds and run generalized logit models for the specifications in Table 2. The generalized logits allow for the variables of interest to have separate effects at different points on the scale for mandatory mask support.

Table 3 presents the specifications when considering the effects of confidence in doctors (column (1)), confidence in government (column (2)), and belief in climate change (column (3)). Column (1) shows that across the different levels of support for mask laws, trust in doctors remains a significant predictor. However, the effect is not equal across the different response categories. For instance, look at the coefficient $doctors : confident$. The OR is highest for having a support for the masks law that is above "strongly oppose": it takes a value of 8.17. On the other hand, for someone confident in doctors, the OR for response group y_4 is 2.296. This variation in the odds ratios reveals why the proportional odds assumption was violated here. Notwithstanding, we see that confidence in doctors is an important predictor for mask support.

Column (2) presents the results for the generalized logit when studying the effect of confidence in government. The variables $government : neutral$ and $government : confident$ are significant across the first three levels of support, y_1, y_2, and y_3, but not at the fourth one. In other words, trust in government is not a significant predictor of being in group y_4 of mask support or higher. These findings demonstrate the importance of improving public confidence at the lowest levels to bolster support for mandatory masks. Column (3) of Table 3 presents the results for the relationship between belief in climate changes as a serious threat and support for mask laws. Similarly to the variables "trust in doctors" and "trust in government", the OR on the climate variable is larger at the lower end of the support for masks scale.

Next, Table 4 presents the generalized logit model for the relationship between political views and support for mask laws. The results further emphasize that support for mandatory mask laws is very polarized and that the divisiveness is most pronounced at the bottom of the scale ("Strongly opposed") for mark support. For instance, the OR for being in a response group greater than y_1 versus being in y_1 for "Very Conservative" (reference group: "Very Liberal") is 0.064. In comparison, the OR for being in the response group greater than y_4 versus being in y_4 or lower for "Very Conservative" is 0.275. A similar pattern holds when looking at the estimates of being "Conservative".

The generalized logit models highlight that our findings concerning the importance of trust in doctors and in government for mask support are robust to relaxing the proportional-odds assumption.

Table 3

	(1) support		(2) support		(3) support	
1						
Age65	1.336	[0.922,1.935]	1.753**	[1.215,2.530]	1.803**	[1.239,2.625]
chronicind	1.147	[0.832,1.582]	1.154	[0.835,1.596]	1.117	[0.798,1.565]
chronicfam	0.879	[0.674,1.148]	0.912	[0.701,1.187]	0.882	[0.674,1.155]
COVID-19 rate	1.002***	[1.001,1.003]	1.002***	[1.001,1.003]	1.002***	[1.001,1.003]
female	1.678***	[1.282,2.196]	1.428**	[1.100,1.852]	1.213	[0.920,1.601]
university	1.353*	[1.039,1.762]	1.250	[0.966,1.617]	1.270	[0.967,1.667]
risk	0.894***	[0.840,0.951]	0.869***	[0.820,0.922]	0.889***	[0.836,0.946]
switch	0.941	[0.882,1.005]	0.953	[0.891,1.020]	0.959	[0.895,1.027]
doctors:neutral	2.831***	[1.563,5.127]				
doctors:confident	8.168***	[5.113,13.05]				
sds2	1.014	[0.933,1.101]	0.959	[0.885,1.039]	0.995	[0.914,1.084]
government:neutral			3.417***	[2.431,4.804]		
government:confident			3.823***	[2.742,5.331]		
climate:neutral					6.833***	[4.857,9.612]
climate:agree					8.430***	[6.006,11.83]
2						
Age65	1.137	[0.863,1.498]	1.308	[0.991,1.725]	1.340*	[1.013,1.772]
chronicind	1.177	[0.913,1.517]	1.172	[0.910,1.509]	1.195	[0.924,1.546]
chronicfam	0.860	[0.699,1.059]	0.893	[0.725,1.099]	0.878	[0.711,1.085]
COVID-19 rate	1.002***	[1.001,1.003]	1.002***	[1.001,1.003]	1.002***	[1.001,1.003]
female	1.441***	[1.171,1.773]	1.313**	[1.069,1.612]	1.195	[0.968,1.475]
university	1.130	[0.918,1.392]	1.097	[0.892,1.349]	1.068	[0.864,1.321]
risk	0.910***	[0.868,0.953]	0.904***	[0.863,0.947]	0.917***	[0.875,0.962]
switch	0.978	[0.927,1.031]	0.977	[0.928,1.030]	0.982	[0.931,1.037]
doctors:neutral	2.367**	[1.349,4.156]				
doctors:confident	4.330***	[2.761,6.793]				
sds2	1.033	[0.968,1.103]	1.003	[0.940,1.071]	1.036	[0.969,1.108]
government:neutral			1.991***	[1.551,2.555]		
government:confident			2.197***	[1.726,2.796]		
climate:neutral					4.231***	[3.160,5.664]
climate:agree					5.784***	[4.322,7.741]
3						
Age65	1.353*	[1.066,1.719]	1.531***	[1.205,1.945]	1.543***	[1.210,1.967]
chronicind	1.280*	[1.028,1.593]	1.254*	[1.008,1.560]	1.333*	[1.068,1.665]
chronicfam	0.920	[0.768,1.102]	0.955	[0.797,1.143]	0.937	[0.780,1.125]
COVID-19 rate	1.001***	[1.001,1.002]	1.001***	[1.001,1.002]	1.001***	[1.001,1.002]
female	1.441***	[1.206,1.722]	1.343**	[1.126,1.602]	1.234*	[1.031,1.478]
university	1.244*	[1.039,1.490]	1.248*	[1.044,1.492]	1.220*	[1.017,1.464]
risk	0.918***	[0.882,0.955]	0.914***	[0.879,0.950]	0.922***	[0.886,0.960]
switch	0.977	[0.933,1.023]	0.971	[0.927,1.016]	0.974	[0.930,1.021]
doctors:neutral	1.561	[0.885,2.753]				
doctors:confident	4.294***	[2.685,6.867]				
sds2	1.012	[0.956,1.071]	0.993	[0.938,1.051]	1.016	[0.959,1.077]
government:neutral			1.594***	[1.288,1.974]		
government:confident			1.844***	[1.502,2.263]		
climate:neutral					2.928***	[2.203,3.892]
climate:agree					4.735***	[3.568,6.285]
4						
Age65	1.152	[0.919,1.445]	1.198	[0.956,1.502]	1.224	[0.974,1.539]
chronicind	1.243*	[1.007,1.534]	1.243*	[1.008,1.533]	1.265*	[1.023,1.563]
chronicfam	0.965	[0.807,1.153]	0.981	[0.821,1.171]	0.983	[0.821,1.176]
COVID-19 rate	1.002***	[1.001,1.002]	1.002***	[1.001,1.002]	1.002***	[1.001,1.002]
female	1.370***	[1.145,1.638]	1.336**	[1.118,1.596]	1.260*	[1.052,1.509]
university	1.104	[0.922,1.322]	1.113	[0.931,1.331]	1.058	[0.883,1.269]
risk	0.903***	[0.870,0.938]	0.902***	[0.869,0.936]	0.907***	[0.873,0.942]
switch	1.002	[0.956,1.050]	1.000	[0.954,1.047]	1.005	[0.959,1.054]
doctors:neutral	1.013	[0.517,1.985]				
doctors:confident	2.296**	[1.332,3.958]				
sds2	1.003	[0.949,1.060]	0.993	[0.940,1.050]	1.015	[0.960,1.074]
government:neutral			0.987	[0.794,1.226]		
government:confident			1.129	[0.923,1.381]		
climate:neutral					1.866***	[1.327,2.624]
climate:agree					3.161***	[2.269,4.403]
Observations	2415		2415		2415	

Exponentiated coefficients [95% confidence intervals in brackets].
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4

		(4) support
1		
Age65	1.649*	[1.103,2.463]
chronicind	1.300	[0.912,1.854]
chronicfam	0.777	[0.577,1.047]
COVID-19 rate	1.002**	[1.000,1.003]
female	1.609**	[1.183,2.189]
university	1.110	[0.820,1.503]
liberal	2.164*	[1.022,4.581]
moderate	0.580	[0.297,1.135]
conservative	0.290***	[0.153,0.549]
very conservative	0.0637***	[0.0314,0.129]
sds2	1.045	[0.949,1.151]
2		
Age65	1.328	[0.984,1.793]
chronicind	1.171	[0.890,1.541]
chronicfam	0.881	[0.698,1.111]
COVID-19 rate	1.002***	[1.001,1.002]
female	1.369**	[1.087,1.725]
university	1.082	[0.851,1.375]
liberal	1.328	[0.859,2.055]
moderate	0.659	[0.425,1.021]
conservative	0.429***	[0.280,0.656]
very conservative	0.149***	[0.0859,0.257]
sds2	1.080*	[1.003,1.162]
3		
Age65	1.592***	[1.228,2.064]
chronicind	1.267	[0.999,1.607]
female	1.420***	[1.167,1.727]
university	1.203	[0.981,1.475]
chronicfam	0.937	[0.767,1.145]
COVID-19 rate	1.001*	[1.000,1.002]
liberal	0.875	[0.610,1.255]
moderate	0.522***	[0.359,0.760]
conservative	0.363***	[0.252,0.525]
very conservative	0.151***	[0.0898,0.255]
sds2	1.049	[0.984,1.118]
4		
Age65	1.286*	[1.011,1.637]
chronicind	1.185	[0.947,1.484]
chronicfam	0.985	[0.812,1.195]
COVID-19 rate	1.001***	[1.001,1.002]
female	1.449***	[1.197,1.754]
university	0.977	[0.802,1.190]
liberal	0.956	[0.710,1.289]
moderate	0.702*	[0.506,0.973]
conservative	0.551***	[0.397,0.764]
very conservative	0.276***	[0.153,0.498]
sds2	1.003	[0.944,1.065]
Observations	2034	

Exponentiated coefficients [95% confidence intervals in brackets]
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$