CCHE CCES
Canadian Centre for Health Economics
Centre canadien en économie de la santé

Working Paper Series
Document de travail de la série

COMPLIANCE WITH SOCIAL DISTANCING: THEORY AND EMPIRICAL EVIDENCE FROM ONTARIO DURING COVID-19

Anastasios Papanastasiou, Bradley J. Ruffle, Angela L. Zheng

Working Paper No: 200004

www.canadiancentreforhealtheconomics.ca

September, 2020

Canadian Centre for Health Economics
Centre canadien en économie de la santé
155 College Street
Toronto, Ontario

CCHE/CCES Working Paper No. 200004
September, 2020

Compliance with Social Distancing: Theory and Empirical Evidence from Ontario during COVID-19*

Anastasios Papanastasiou, Bradley J. Ruffle†, Angela L. Zheng

Department of Economics, McMaster University, Hamilton, ON, Canada

Abstract

We study the factors associated with compliance with social-distancing regulations using a unique dataset on the behaviour of Ontarians during the COVID-19 pandemic. To start, we build a simple theoretical model of social distancing in order to understand how some individual and community-level factors influence compliance. We test our model's predictions by designing and conducting a survey on Ontarians in which we elicit their degree of compliance with current distancing regulations as well as proposed regulations that impose different fine levels on violators or grant wage subsidies to encourage staying at home. In line with the model's predictions, we show that variables related to one's risk of infection (e.g., health status, age, necessity of working outside the home, regional COVID-19 cases) are significant predictors of compliance as are gender, political beliefs, risk and time preferences. Furthermore, we demonstrate that fines and wage subsidies can be powerful policy tools for promoting full compliance with regulations.

JEL Classification: I12; I18; J38

Keywords: COVID-19; physical distancing; non-compliance fines; wage subsidies; risk of infection

*Acknowledgments: This paper has benefited from helpful exchanges with Bram Cadsby, Brian Ferguson, Andrew Leal, Fei Song, Thanasis Stengos, Arthur Sweetman and Michael Veall. Zachary Holdworth, Abigail Hudecki, Muhammad Maaz and Jenny Yu all provided outstanding research assistance. Papanastasiou and Ruffle thank the McMaster COVID-19 Research Fund for funding this research. This research received ethics clearance from McMaster University's Research Ethics Board, MREB #4882.

†Corresponding Author: Bradley Ruffle, ruffleb@mcmaster.ca

1 Introduction

The outbreak of COVID-19 has led to the introduction of an unprecedented degree of government intervention in the markets for labour and leisure throughout the globe. Days after the World Health Organization declared the virus a global pandemic on March 11, 2020, the Ontario provincial government announced a state of emergency and mandated the closure of non-essential businesses, all indoor recreational programs, schools, public libraries, theatres and, some days later, all outdoor recreational spaces including parks and walking trails. Public gatherings of more than 50 people were prohibited, further reduced to five people on March 28, 2020.[1] The main message to Ontarians from public health officials was to "stay at home" so that they do not contract or spread the virus. We study the compliance behaviour with these measures in Ontario, and how it is affected by the introduction of non-compliance fines and wage subsidies for not working.

In practice, there are costs and benefits for individuals who are called upon to remain at home, and the success of these policies on "flattening the curve" depends on the extent in which individuals are willing to comply with the directives. However, little is known about individuals' willingness to stay at home and comply with these regulations during the pandemic. Our paper provides a basic framework for understanding the factors that drive risky behavior and self-compliance with stay-at-home directives. Moreover, we build a unique dataset by collecting responses on individual behaviour during the COVID-19 pandemic.

The aim of our paper is three-fold: 1) to provide a basic model of individual choice to understand the factors that influence compliance with stay-at-home directives during a pandemic; 2) to design a survey that allows us to assess the magnitude of each factor's influence on Ontarians' compliance with social-distancing directives; 3) to use our survey responses to identify additional factors associated with compliance that are not predicted by our theoretical framework.

[1]See the Wikipedia entry on "COVID-19 pandemic in Ontario" for further details and other precautions taken.

We use our survey data in combination with the theoretical predictions of the model to quantify the different factors associated with compliance with social distancing. More precisely, we estimate the likelihood of compliance using an ordinal logit model. In our main specification, individual characteristics such as age, health, gender, and ability to work from home are significant predictors for compliance behaviour. For instance, the odds of complying for individuals with a chronic health condition associated with higher risk of complications from COVID-19 is 1.2 times higher. We also find that compliance increases with the number of cumulative COVID-19 cases per capita in an individual's health district. Strikingly, the odds of compliance for women are 1.5 times higher than they are for men, even after controlling for elicited risk and time preferences.

When there is no fine for not complying, the predicted probability of full compliance increases steeply with age. With the threat of a fine, however, this relationship flattens as age is no longer a significant predictor. Most individuals now choose to fully comply. Similarly, an income subsidy induces substantially higher rates of compliance.

Because self-reported compliance behaviour may be subject to social desirability bias (Crowne and Marlowe, 1960), namely, a tendency to overstate a willingness to follow rules in order to conform with perceived societal norms, we measure and control for this bias in all of our analyses. In a robustness check, we show that if, instead of asking about one's own compliance, we ask about the compliance of a typical person in one's neighbourhood, we obtain similar results.

Our findings are also robust to the inclusion of other significant predictors of compliance behaviour such as political beliefs, confidence in various public institutions and professionals, views on the enforceability of the regulations and time and risk preferences. In addition, we obtain similar results when using a generalized ordered logit.

In the next section, we provide some background on the situation with COVID-19 in Ontario and the provincial and federal governments' responses to it leading up to our survey period. In section 3, we present the theoretical model and its predictions. Section 4 outlines the survey we constructed to test the model and other possible predictors of compliance with social distancing and self-isolation. In section 5, we present some descriptive statistics along with our estimation strategy. The empirical results appear in section 6 followed by robustness checks in section 7. Section 8 offers some concluding remarks.

2 Background on COVID-19 in Ontario

The province of Ontario, Canada's most populous province with about 14.6 million residents and its economic centre, has borne a large share of the country's COVID-19 burden. Indeed, the first case of COVID-19 in Canada was identified in Toronto, Ontario on January 25, 2020 (Marchand-Senécal et al., 2020). In the following weeks, public health officials maintained that the risk to the public remained low but continued to monitor the situation. Following a sharp rise in the number of cases in early March, Ontario's provincial government declared a state of emergency on March 17 (Rodrigues, 2020). At the time, new daily cases numbered approximately 270 (Public Health Ontario, 2020). The declaration of a state of emergency mandated the closure of schools, indoor recreation spaces, public libraries, bars, restaurants and theatres. As the case count continued to trend upwards, the provincial government expanded these closures a week later to include all non-essential businesses and outdoor recreation spaces (Dawson, 2020). Officials also announced that Ontarians must practice physical distancing with anyone not in their household and that they should stay home except for essential trips (Office of the Premier, 2020).

As the economic fallout from closures in Ontario and around the country was beginning to crystallize, the Canadian government announced a massive spending program at the end of March to keep the economy afloat. Central to the so-called COVID-19 Economic Response Plan was the Canadian Emergency Response Benefit (CERB) that paid out \$2000 CAD per month for up to four months to workers who suffered a loss of income or employment due to COVID-19 (Department of Finance Canada, 2020).

In the weeks after the state of emergency declaration, COVID-19 continued to spread at an increasing rate, at last peaking mid-April, about a month after the closures began, at around 600 new cases per day, and slowly declining in the weeks afterwards (Public Health Ontario, 2020). The province began slowly reversing lockdown restrictions in May, using a three-stage framework applied on a regional basis, with epidemiological milestones dictating when a health district of Ontario could progress to the next phase. Phase 1 of reopening allowed non-essential businesses to re-open for the first time in nearly two months, with caveats like allowing only stores with street-facing (i.e., outdoor) entrances. Phase 2 entailed re-opening some workplaces, additional malls and shopping centres, and allowing small public gatherings, including with people outside your household. Phase 3 consisted of opening all workplaces, with certain precautions, and further relaxing restrictions on public spaces, with concerts and sporting events continuing to be restricted (Government of Ontario, 2020).

We designed a survey in order to understand how Ontarians responded to the regulations (more on the survey design in Section 4). The survey was conducted from June 29 to July 7, 2020 during which Ontario recorded around 150 new cases per day, well past the worst days of the epidemic (Public Health Ontario, 2020). It is worth noting that there were no exceptional COVID-19 related events or announcements in Ontario or Canada during this survey period (see http://news.ontario.ca/) that could have swayed or unduly influenced public opinion. During this period, 29 of Ontario's 30 health districts, including Toronto, its largest city, had entered Phase 2 of reopening. Only the municipality of Leamington and the town Kingsville, both part of the district of Windsor-Essex remained in Phase 1 due to an earlier COVID-19 outbreak among agricultural workers (Government of Ontario, 2020). South of the border, new daily cases were setting all-time highs in many southern states, California and the U.S. as a whole with over 50,000 new diagnoses per day.

3 Model

We develop a model to investigate the labour and leisure choices of a representative individual before and during the pandemic. In each period, the individual allocates a unit of time across labour L and two types of leisure activities, ℓ and r, to maximize their utility function,

$$u_t(C_t, r_t, \ell_t, H_t)$$

where H is the stock of health capital and C denotes current consumption which is a strictly increasing function of earned wages $w(L)$ with $w'(L) > 0$. Hence, the supply of labour derives from the demand for consumption. The two types of leisure are mutually exclusive and the time constraint is $L_t + \ell_t + r_t = 1$ for period $t = \{1, 2\}$.

Before the pandemic ($t = 1$), H_1 is assumed exogenous. After the outbreak ($t = 2$), the stock of health is negatively affected by the amount of time spent on r and L: there is a risk of contracting the virus at work and during "risky" leisure r (e.g., parties and large social gatherings), while ℓ is risk-free leisure (e.g., watching TV at home). That is, $H_t(p(L_t, r_t), z)$ where p is the probability of infection with $p_{L_t} > 0$, $p_{r_t} > 0$ for $t = 2$ whereas $p_{L_t} = 0$, $p_{r_t} = 0$ for $t = 1$. Lastly, $H_p < 0$, which captures the health effect from a small increase in the probability of infection, and z denotes exogenous factors affecting H in both periods.

The outbreak of the virus is unforeseen by the individual who solves

$$\max_{\{L,r\}} u(C(w(L)), r, \ell, H(p(r, L), y))$$

in each period, where $\ell_t = 1 - r_t - L_t$. The first-order conditions for an interior solution are

$$u_C C_w w_L - u_\ell + u_H H_p p_L = 0 \tag{1}$$

and

$$u_r - u_\ell + u_H H_p p_r = 0 \tag{2}$$

which, together with $\ell_t = 1 - r_t - L_t$, must hold for $t = \{1, 2\}$.

Let (L_t, r_t, ℓ_t) denote the solution for period t. The optimality conditions then imply $\ell_2 > \ell_1$, that is, a shift to more risk-free leisure in period two.[2] Intuitively, there is an additional marginal cost component associated with the choice of L_2 and r_2 as a result of the negative impact of an increase in p on health status.

Combining (1) and (2) yields

$$u_C C_w w_L - u_r + u_H H_p[(p_L) - (p_r)] = 0 \tag{3}$$

which determines the optimal allocation of r relative to L. If p_r is greater than (less than) p_L for all L and r, the individual allocates a larger (smaller) proportion of $(1 - \ell)$ to L in period 2 relative to period 1. On the other hand, if L and r entail approximately the same risk of infection ($p_r - p_L \approx 0$) for all (L, r) in period 2, then $r_1/L_1 \approx r_2/L_2$. We adopt this last assumption, which also guarantees that $r_2 < r_1$ and $L_2 < L_1$.

Our model predicts an increase in time allocated to risk-free activities ℓ whenever:

1) the probability of infection per time spent in risky activities is high;

2) the health impact for any given increase in the probability of infection is severe.

Consider a stay-at-home policy where the individual is asked to *voluntarily* increase ℓ in period two. Because $\ell_2 > \ell_1$, the policy directives align with the individual's private benefits and costs of labour and leisure in period two. Our model predicts that our representative individual would generally comply with such a recommendation.

A direct measure of the individual's level of voluntary compliance with stay-at-home directives is the difference $d = (\ell_2 - \ell_1)$ in our model, which depends on the two factors discussed above.

In the context of the policy in Ontario for non-essential businesses and outdoor recre-

[2] Evidence of this comes from large surges in sales of home-renovation products, home fitness equipment, in-ground, above-ground and inflatable pools and streaming services like Netflix and Disney+. See Healing (2020); Foran (2020); MacDonald and Azpiri (2020); Elber (2020), respectively.

ational spaces during the early stages of the pandemic, consider the recommendation $d^* = 1 - \ell_1$: the individual is asked to not work or participate in risky leisure activities at all. Then, there is no guarantee that the individual will fully comply with such a recommendation. A solution involving $L_2 = r_2 = 0$ arises only if the expressions in (1) and (2) are negative for all admissible (r, L). But if the individual is willing to accept at least some small amount of risk of infection at work and at leisure so that conditions (1) and (2) are indeed satisfied with equality in period 2, the individual must be provided with additional incentives to voluntarily comply with $d = d^*$ and $\ell_2 = 1$.

Condition (1) suggests one reason why the individual may choose low values of compliance (i.e., $d < d^*$) is to avoid large utility losses from consumption shocks associated with lost wages when $L_2 = 0$. At an interior solution, the consumer accepts some positive level of infection risk at work to prevent wages and hence consumption in period 2 from falling precipitously. Insofar as voluntary compliance rates are driven down by lost wages from staying at home, our policy recommendation for increasing compliance is a wage subsidy.

For example, the policy can offer a subsidy $s = w(L_1)$ conditional on the individual choosing $L_2 = 0$, and $s = 0$ otherwise. Then $L_2 = 0$ is optimal. In fact, the individual would accept $s < w(L_1)$ to provide $L_2 = 0$ even in the absence of infection risk at work. The intuition is that consumption and leisure are substitutes at (L_1, r_1) and so the individual is willing to accept a small reduction in wages to enjoy an increase in leisure.

The larger the health risks from working in period two, the larger the wage and consumption sacrifices the consumer is willing to incur to avoid them – a dismal prediction. For example, COVID-19 mortality rates seem to be significantly higher for the elderly as well as for individuals with a history of cardiovascular and respiratory illness or diabetes. As the personal health costs of spending time at work increase for such individuals, private choices become better aligned with the policy goal d^*.

Condition (2) identifies utility losses from $r_2 = 0$ as another possible source of noncompliance with d^*. Intuitively, the individual may accept some risk of infection from leisure activities when the utility loss associated from foregoing them is large relative to the health cost of infection. In such cases, the *lowest* subsidy s that guarantees $L_2 = 0$ may not induce full compliance in the sense of $d = d^*$.

In such circumstances, our model suggests that, to ensure full compliance, monetary incentives need be conditioned on the choices of *both* L_2 and r_2. For example, the policy can reward $r_2 = 0$ through a subsidy s as long as *both* $L_2 = 0$ and $r_2 = 0$ – a pure subsidy scenario. For individuals with relatively low health risks, $s > w(L_1)$ may be required. If private consumption benefits from s outweigh the losses from reducing r_2 to zero, such a pure subsidy policy can increase compliance d. Alternatively, the policy can keep the wage subsidy unchanged, and instead impose monetary fines for non-compliance with $r_2 = 0$. If the utility losses from the effect of the fine on consumption outweighs the utility gains associated with $r_2 > 0$, a mixture of wage subsidies and fines can lead to full individual compliance.

Finally, we consider a special case in which $p_L = 0$ and $p_r > 0$ after the outbreak. Our justification is that individuals working from home do not face any risk of infection. The negative health effect from $L_2 > 0$ in condition (1) then vanishes and the condition is the same for both periods. As a result, the individual will *choose* switching to working from home when presented with that option, and so working-from-home directives are consistent with stay-at-home directives more generally.

To summarize, our model suggests that wage subsidies and fines are effective policy tools for increasing the individual's willingness to stay at home during the pandemic. In Ontario, a mixture of wage subsidies and fines are used conditional on L_2, while pure fines are the tool for keeping r_2 low. In retrospect, while $L_2 = 0$ was the policy recommendation for non-essential businesses at the onset of the pandemic, the focus has since shifted from encouraging $\ell_2 = 1$ to maintaining $r_2 = 0$, partly because of the productivity losses associated with $L_2 = 0$, partly because of the fiscal costs of large-scale wage subsidies, and partly because of the success of early-stage policies in containing the virus.

4 Survey Design

To test the theoretical model's predictions and other variables that may explain the variation in the extent of compliance with social distancing, we designed an extensive online survey. We included several questions to measure the health impact from contracting COVID-19 (H_1) such as age, a chronic health condition and a household member with a chronic health condition. Questions that gauge the risk of infection, ($p(r, L)$), include whether their job is classified by the government as essential and whether the respondent's job obliges them to work outside the home. An additional measure of risk of infection is the cumulative number of reported COVID-19 cases per capita in the respondent's health district, which we collected from Public Health Ontario's website at the dawn of the survey. In addition, lack of compliance with social distancing is not always a choice, but sometimes a constraint imposed on an individual due to the circumstances they face at home or at work. Just as essential workers are at higher risk at work (L_2), apartment dwellers may be more limited in their pursuit of risk-free leisure (ℓ_2) than owners of larger living spaces and thus may necessarily consume more risky leisure (r_2). With this distinction in mind, we ask respondents about the type of dwelling in which they live.[3]

The survey begins with a description of the current physical distancing and self-isolation directives taken from the Canadian government's website. Two reading comprehension questions test that respondents read and understood these directives. Specifically, they needed to know that the recommended distance individuals are expected to maintain from others is at least 2 metres and that individuals returning from travel abroad are required to self-isolate at home for 14 days. Anyone who answered incorrectly either one of these or a third attention-check question toward the end of the survey that simply asks respondents to click 'Next' without choosing one of the multiple-choice answers was removed from our sample.

The survey then asks respondents to what extent they have been obeying the cur-

[3] The entire survey is available in the Online Appendix. It includes numerous questions about protective masks for an unwritten paper on Ontarians' attitudes toward mask-wearing.

rent social-distancing and self-isolation directives and to what extent they would obey these directives if there were no fine, a $250 fine or a $1000 fine plus possible jail time for first-time violators. Whether respondents saw the three fine amounts in ascending or descending order was randomized to counter-balance any possible anchoring effects (Tversky and Kahneman, 1974). Identical compliance measures were also collected in response to proposed government wage-subsidy policies. Participants were asked to what extent they would obey a government request "to stay at home without pay and leave only for essential trips (e.g., grocery store, emergency medical attention)" as well as the same request except now "the government offered you your entire income in exchange for staying at home and leaving only for essential trips (e.g., grocery store, emergency medical attention)."

When answering about one's own compliance with social-distancing laws, respondents may provide answers perceived to be socially accepted rather than accurate ones (Edwards, 1953). We measure and control for this possible tendency to inflate one's reported degree of compliance using two social desirability scales. Based on the original 33-question social desirability scale in Crowne and Marlowe (1960), we adopted two shortened scales that consist of 10 (Form X1 from Strahan and Gerbasi (1972)) and six (Form X2 from Fischer and Fick (1993)) true-or-false questions. Each question describes a behaviour or attitude that almost all of us have displayed at some point (e.g., disliked someone intensely, jealousy, not admitting to making a mistake) that conflicts with the socially desirable or accepted response (i.e., not admitting to ever have behaved or felt in the socially undesirable way described). For each scale, we sum the number of socially desirable responses and include this count as a control variable in our regression analyses.

Each respondent also answered the question, "How likely do you think the typical person in your neighbourhood is to obey the above rules for self-isolation and social distancing" for each of the three fine levels. Asking about a "typical person" serves as a robustness check that circumvents the social desirability concerns associated with asking about own compliance behaviour.

Finally, we also collected a host of socio-demographic variables, questions about one's own health and the health of family members living with the respondent, and their employment and housing situation.

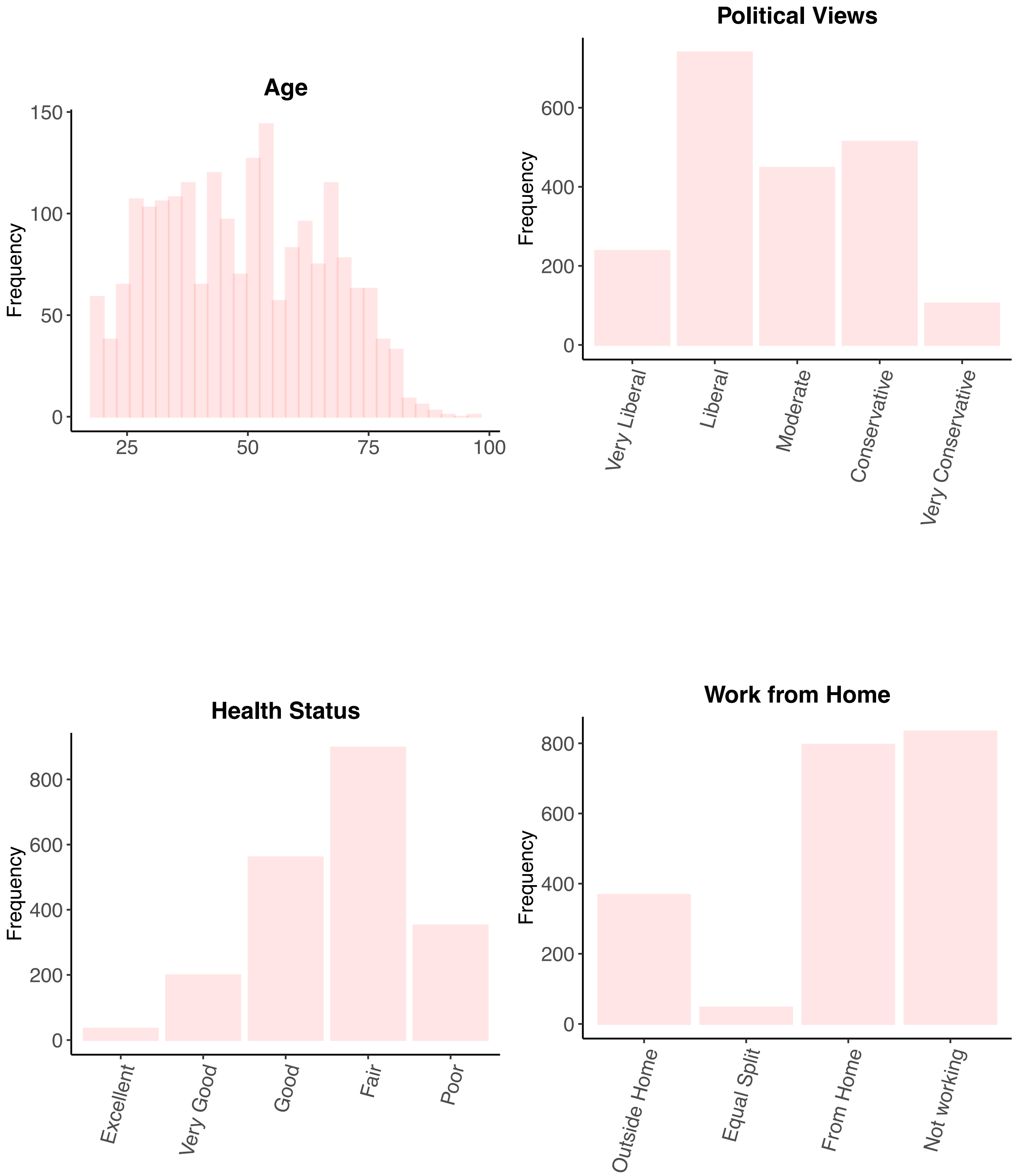
We conducted our survey through Maru/BLUE, an international data solutions company. They sent invitations for our survey to a subset of their research participant pool that matches the distribution of Ontarians along the dimensions of age, gender, household income and region. Our survey was piloted on June 29, 2020, launched fully on July 2, 2020 and finished on July 7, 2020. Three thousand and seventy-nine Ontarians completed the survey. After excluding those who failed to correctly answer either of the two test questions about the social-distancing and self-isolation rules or those who did not leave blank the attention-check question, our sample consists of 2,649 respondents who completed our survey in an average time of 25 minutes and 20 seconds.

5 Descriptive Statistics and Estimation Strategy

We begin with some descriptive statistics of our respondents. The graphs in Figure 1 are frequency plots for age, health status, political views and educational attainment. In terms of the age distribution, respondents who are 22 and 76 years old are at the fifth and 95 percentiles, respectively, while the mean (modal) age is 47.5 (47). On a scale from "Poor" to "Excellent", almost half of the respondents self-reported their health status as "Fair", with 47% indicating that they have one or more chronic health conditions. We surveyed individuals across the political spectrum: 39% identified as Liberal or Very Liberal and 25% identified as Conservative or Very Conservative. In terms of educational achievement, 61% of respondents have a Bachelor's degree or higher. We also found that 82%, 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. Consistent with our model, among the employed, the percentage of those working "always or mostly outside the home" in our sample plunges from 86% before the onset of the pandemic to 33% during our sample period, whereas those who report working "always or mostly from home" soars from a mere 10% before the pandemic to 64%. Essential workers make up 46% of our sample. They constitute 47% of the respondents who worked always or mostly outside the home before the pandemic and thus are proportionately represented. However, their representation among this group becomes disproportionate during the pandemic, accounting for 77% of those working always or mostly outside the home.

Next, we present the raw distribution of the compliance variables in Figure 2. We are interested in how individuals respond to the following four questions about compliance with social distancing. The plot "Compliance" shows how respondents answer the question: "To what extent have you been obeying the above [current] rules for self-isolation and social distancing?" In "Compliance: No Fine" we ask how they would comply if there were no fine. "Compliance: $250 fine" shows the distribution of compliance under the scenario of a $250 fine, while "Compliance: $1000 fine" shows the compliance variable with a $1000 fine and possible jail time for a first offence. Category 7 (Fully Obey) is the highest level of compliance. Due to very few responses in Categories 1-4, we collapse these into a single category for our analysis.

Figure 1: Descriptive Statistics



Notes: This figure presents descriptive statistics for our sample of respondents. Top left is the distribution of age; top right is the distribution of political views; bottom left is the distribution of self-reported health status; bottom right is the distribution of working from home. "Outside Home" refers to always or mostly working outside the home. "Equal split" refers to an equal split between working from home and outside the home. "From Home" refers to always or mostly working from home.

The raw compliance data shows that most individuals fully obey the social-distancing rules or at least almost always, and that compliance levels rise as the threat of a fine increases. For instance, under the scenario of no fine, 53% of respondents stated that they would fully comply. This percent increases to 63% under a $250 fine, and 77% under a $1000 fine plus possible jail time. In our estimation, we study which individual factors predict compliance.

We empirically test the predictions of the model using our unique survey dataset. The main variable of interest, compliance with social distancing, follows an ordered response scale with four categories. Accordingly, we use an ordered logit model to estimate how different individual characteristics are associated with the likelihood of following social distancing rules.[4] To this end, we assume that the observed compliance value reported, y, is a function of y^*, a latent continuous variable measuring the likelihood of compliance. Furthermore, we assume that there exists specific cut-off points ζ_1, ζ_2 and ζ_3 where we observe y such that:

$$
\begin{aligned}
&y_i = 1 \text{ if } y_i^* \leq \zeta_1\\
&y_i = 2 \text{ if } \zeta_1 \leq y_i^* \leq \zeta_2\\
&y_i = 3 \text{ if } \zeta_2 \leq y_i^* \leq \zeta_3\\
&y_i = 4 \text{ if } \zeta_3 \leq y_i^*
\end{aligned}
$$

where $y_i = 4$ is Fully Obey, $y_i = 3$ is Almost Always Obey, $y_i = 2$ is Mostly Obey, Occasionally Disobey and $y_i = 1$ encompasses the remaining options from Sometimes Obey, Sometimes Disobey to Ignore Altogether.

We run the following ordinal logit model:

$$\mathbb{E}(y_i^*) = \alpha \text{health}_i + \beta \text{age}_i + \xi \text{gender}_i + \kappa \text{ work from home}_i + \delta \text{COVID-19 rate}_i + \phi \text{sds}_i + \varepsilon_i \tag{4}$$

[4]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.

Figure 2: Distribution of Compliance with Social Distancing

Notes: This figure shows how our respondents comply with social distance regulations. The plot "Compliance" shows how respondents answer the question: "To what extent have you been obeying the above rules for self-isolation and social distancing? ". In "Compliance: No Fine" we ask how they would comply if there were no fine. "Compliance: $250 fine" shows the compliance under the scenario of a $250 fine, while "Compliance: $1000 fine" shows the compliance with a $1000 fine and possible jail time for a first offense. Category 7 is the highest level of compliance: Fully Obey.

where health_i is a vector of health status dummies for an individual and for family members residing in the same household, age_i is the respondent's age, gender_i is the gender, work from home_i denotes whether the respondent is able to work from home, COVID-19 rate_i is the cumulative number of reported COVID-19 cases per 100,000 residents in an individual's health district, and sds_i is respondent i's score on the social desirability scale. Using this specification, we aim to quantify how these different predictor variables affect the likelihood of compliance.

6 Results

Table 1 presents the results from the ordered logit outlined in Equation (1). The coefficients are presented as odds ratios, with 95% confidence intervals. An odds ratio greater than one means that the individual is more likely to comply. More precisely, the interpretation of the coefficients is the odds of being in compliance group greater than k versus the odds of being in the compliance groups less than or equal to k, where $k \in \{1, 2, 3, 4\}$ and the levels of compliance are y_k.[5] The proportional odds assumption states that the odds ratio is independent of the compliance group k (we relax this assumption later in a robustness check). The main takeaway from this table is the importance of age, gender, health, and the regional rate of COVID-19 for reported compliance with social distancing.

Column (1) presents the findings from our main specification. A number of individual characteristics are significant predictors of the extent to which the individual has been complying with the current social-distancing rules. For instance, the odds ratio for compliance increases by 1.01 times for an individual who is one year older. Women are significantly more likely to obey social-distancing rules – being female increases the odds of complying by 1.54 times. The variable "chronic" is an indicator for having one of the four chronic health conditions that are associated with a higher chance of complications from COVID-19.[6] For individuals with one of these conditions, their odds of compliance increases 1.2 times. On the other hand, having a family member with a chronic condition does not seem to be a significant predictor. In addition, someone who is able to work from home is 1.6 times more likely to comply.[7] This finding is quite intuitive as it may be hard to maintain social distance at a workplace.

Those living in smaller living spaces, an apartment for example, may find it more challenging to stay at home (consume ℓ in the language of our model) and may thus be more likely to violate social distancing. Chan (2020) uses Facebook mobility data to show that census divisions with larger shares of apartments exhibit smaller reductions in mobility from February to April 2020, suggesting less adherence to social distancing. Consistent with Chan (2020), we find direct evidence that those living in an apartment

[5]For ease of exposition, when we discuss odds ratios we will use the terminology "more likely" or "less likely" to comply.

[6]These four chronic conditions are hypertension, diabetes, cardiovascular disease and respiratory disease (e.g., COPD). See Yang et al. (2020).

[7]Also included in the ordinal logit are indicators "not working at all" and "working equally from home and outside the home". For simplicity we report only the coefficient on "working from home". A coarser measure of the extent to which the respondent works from home is whether they are an essential or non-essential worker. If we replace the work-from-home indicator with an indicator for essential worker, we find that the odds for complying for a non-essential worker is 1.434 and significant. The coefficients on all other variables are similar to our baseline estimates. Our findings suggest that the effects on compliance for essential worker status versus ability to stay at home are similar.

are 0.81 times as likely to comply with social distancing. One might think that living in an apartment is simply correlated with being in a more populous city which in turn predicts less compliance with social distancing. Nevertheless, we find that living in an apartment is still a significant predictor of compliance and that the estimate is very similar, even after controlling for health district fixed effects.

Next we study the link between the rate of COVID-19 and compliance. Our measure is the total number of reported COVID-19 cases in a health district per 100,000 population as of June 27th, two days before our survey launched. This is also a significant predictor: a one-unit increase in the infection rate is associated with a 1.001 increase in the odds of complying. Finally, our social desirability measure is a significant predictor of compliance: the greater the number of socially acceptable responses given in the six-question scale, the greater the level of the respondent's reported compliance with social-distancing regulations.[8]

Now we discuss how imposing fines affects compliance behaviour. In column (2) we ask how much individuals would comply if there were no fine, in column (3) if there were a $250 fine and in column (4) if there were a $1000 fine and possible jail time. As expected, the threat of a fine reduces the importance of several predictor variables. From "No Fine" to "$250 Fine" to "$1000 Fine", the odds ratio on age decreases and is no longer significant for a $1000 fine. Similarly, a chronic health condition and type of housing are no longer important predictor variables. We can make this point visually by plotting the predicted probabilities of compliance, and how they change with the fine.

Figure 3 shows the predicted probabilities of fully complying with social distancing as age increases. Each panel in the figure corresponds to a different fine level: no fine, $250 fine, and $1000 fine. In comparing the three panels, two points stand out. First, as expected, increasing the fine amount shifts the predicted probability of full compliance

[8]In this and every subsequent regression, the number of socially desirable responses is a positive and highly significant predictor of reported compliance. The odds ratios for the X1 and X2 scales (discussed in section 4) and their levels of significance are identical in each and every regression and which one is included does not change the estimates or the significance of any of the many regressors. Thus, we opt to report the X2 scale since, with fewer questions than X1, it offers more bang for the buck.

upwards. Second, as the magnitude of the fine increases, the relationship between age and the probability of compliance flattens: age loses its predictive power as more individuals choose full compliance.

Table 1 showed that an increase in social desirability increases the odds of complying. Figure 4 now plots how the predicted probabilities of full compliance increase with the social desirability score. As expected, there is a sharp increase in the likelihood of full compliance the more individuals wish to be seen as conforming to social norms. Again, the probabilities for full compliance rise as the monetary amount of the fine increases. In addition, we saw in Table 1 that the odds ratio on the social desirability score (SDS) falls closer to one as the fine increases. This is seen graphically in Figure 4 as a decrease in the slope of the curve between SDS and full compliance as the fine rises.

On the other hand, the predictive power of the rate of COVID-19 in a respondent's health district is mostly unchanged as the fine rises. The fine shifts up the likelihood of full compliance for a given COVID-19 rate, but there is not a noticeable change in the slope of the curve.

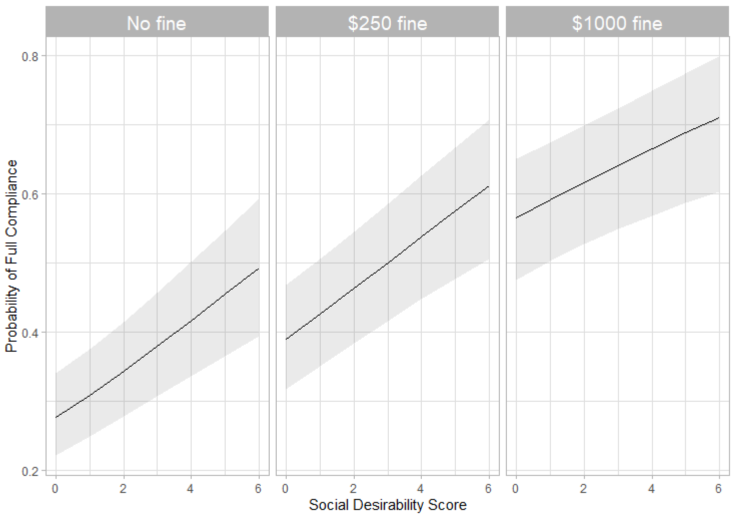
These empirical findings line up well with the predictions of our theoretical model. Namely, factors affecting health (age, chronic conditions), the chance of contracting COVID-19 as measured by the total number of cases in one's region and the ability to work from home are all important predictors in how likely individuals are to comply with social distancing.

Thus far, we studied how compliance varies across several predictor variables and fine levels. Now we study an alternative policy to induce full compliance. Instead of fines, we look at how individuals change their compliance behaviour in the presence of a wage subsidy. We asked respondents the following question: "If, in accordance with the best advice of the medical community, the government asked you to stay at home <u>w</u>ithout pay and leave only for essential trips (e.g., grocery store, emergency medical attention), to what extent would you obey?" Then, we consider a scenario in which the government can completely subsidize their income. We ask, "If, in accordance with the best advice

Figure 3: Predicted Probability of Full Compliance: Age

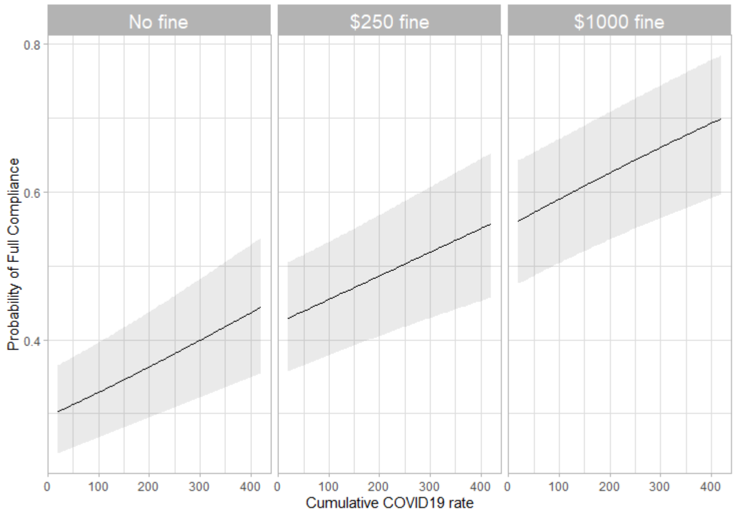
Notes: This figure shows the probability of full compliance with social distancing as a function of the age when there is no fine (left panel), a $250 fine (middle panel), and a $1000 fine (right panel). Predicted probabilities for age are calculated with other continuous variables held constant at their average, and discrete variables are held constant at their reference category.

Figure 4: Predicted Probability of Full Compliance: Social Desirability



Notes: This figure shows the probability of full compliance with social distancing as a function of the social desirability score when there is no fine (left panel), a $250 fine (middle panel), and a $1000 fine (right panel). Predicted probabilities for the social desirability score are calculated with other continuous variables held constant at their average, and discrete variables are held constant at their reference category.

Figure 5: Predicted Probability of Full Compliance: COVID-19 Rate



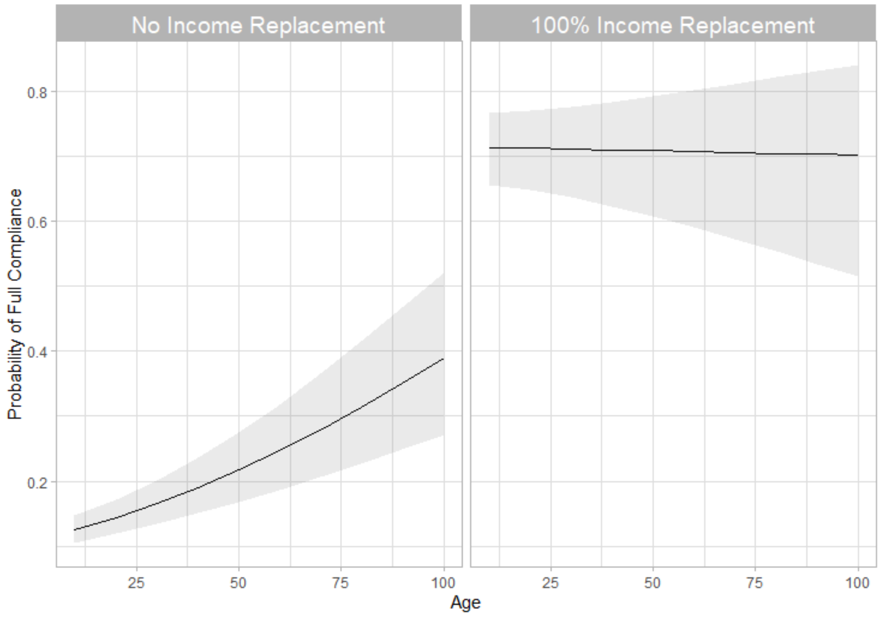
Notes: This figure shows the probability of full compliance with social distancing as a function of the COVID-19 rate when there is no fine (left panel), a $250 fine (middle panel), and a $1000 fine (right panel). Predicted probabilities for the rate of COVID-19 (the total number of reported COVID-19 cases in a health district per 100,000 population as June 27th) are calculated with other continuous variables held constant at their average, and discrete variables are held constant at their reference category.

of the medical community, the government offered you your entire income in exchange for staying at home and leaving only for essential trips (e.g., grocery store, emergency medical attention), to what extent would you obey?" Table 2 presents our findings from estimating the likelihood of compliance under these two scenarios.

In the raw data, just 38% of respondents say that they will fully comply without pay compared to 78% with a full wage subsidy. Column (1) contains the odds ratios when there is no subsidy. These findings are similar to our previous results in that age, gender, ability to work from home, and the rate of COVID-19 are all significant predictors of compliance. In column (2), we show the odds ratio for compliance under a full subsidy. The 40 percentage-point surge in full compliance results in most predictors losing their significance.[9] The exceptions are working from home and being female, which remain significant predictors. The gender result is consistent with work by Capraro and Barcelo (2020) and Jordan et al. (2020) who show that women are more likely to comply with

[9]Bodas and Peleg (2020) report an increase in reported compliance of a similar magnitude for individuals suspected of having been exposed to the virus: in the absence of compensation for lost wages, 57% of a sample of Israelis would agree to comply with a self-quarantine request by a medical officer compared to 94% when lost wages are fully compensated.

Figure 6



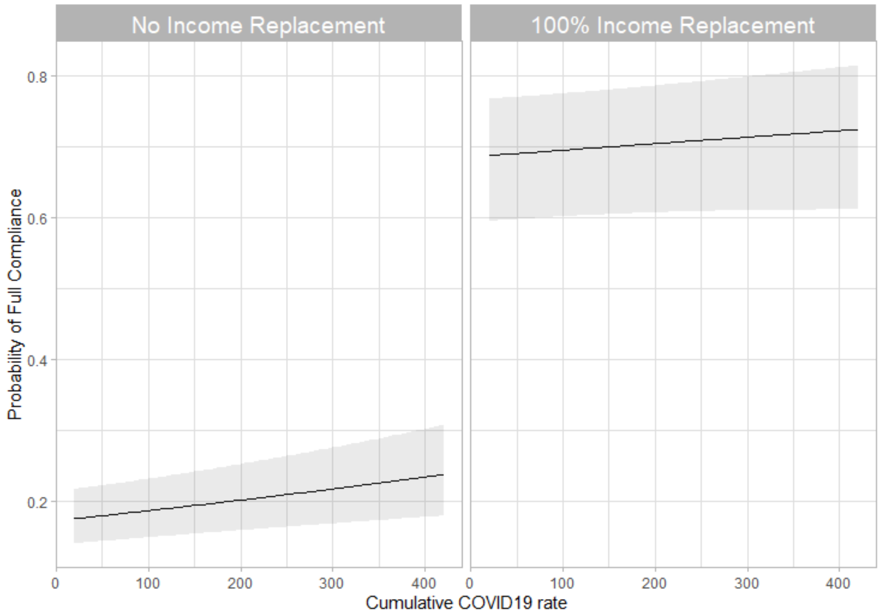
Notes: The left panel is the probability of full compliance when there is no income replacement, and the right panel is the probability of full compliance when there is a 100% wage subsidy. Predicted probabilities age are calculated with other continuous variables held constant at their average, and discrete variables held constant at their reference category.

COVID-19 related regulations.

Figure 6 shows how the predicted probabilities for full compliance change with age. The first panel reveals that full compliance rises sharply with age in the absence of income replacement. In the second panel, similar to when the threat of fines was present, a 100% income replacement flattens the relationship between age and full compliance. Figure 7 displays how the predicted probabilities of full compliance change as a function of changes in the regional COVID-19 rate with no subsidy (left panel) and a full income subsidy (right panel). Again, we see that the slope of the compliance curve falls when an income subsidy is offered. These results highlight that fines and income subsidies achieve similar results in terms of promoting full compliance with social-distancing regulations and can thus be seen as substitute policies.

In the next section we include additional controls to the empirical model that may be related to social distancing but were not explicitly modeled in our theoretical framework.

Figure 7



Notes: The left panel is the probability of full compliance when there is no income replacement, and the right panel is the probability of full compliance when there is a 100 percent wage subsidy. Predicted probabilities for the rate of COVID-19 (the total number of reported COVID-19 cases in a health district per 100,000 population as June 27th) are calculated with other continuous variables held constant at their average, and discrete variables are held constant at their reference category.

7 Robustness

7.1 Additional Factors involved in Compliance

To start, we ran a specification that included categorical variables for income and education, but these were not significant, and did not significantly change the odds ratios on the other variables. This specification is presented in Column (1) of Table 3.

Next, we add measures of self-reported risk preferences and elicited time preferences to our baseline model. Compliance with social distancing should depend on an individual's willingness to take risks and how an individual trades off the current cost of compliance with social distancing with the future benefits gained through the reduced probability of contracting COVID-19. 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?" Originally developed by Coller and Williams (1999), our time-preferences task involves choosing between Option A and Option B in each of seven pairs of monetary amounts. Option A always pays \$10 today. Option B pays an ever-increasing amount in one month, starting at \$10 in Pair 1, \$12.50 in Pair 2 and rising to \$50 in Pair 7. Our variable "switch" is the pair (1-7) at which the respondent switches from the lower, immediate payment (Option A) to the larger, more temporally distant one (Option B). The later the switching pair, the more impatient or present-oriented the respondent is.[10]

Results from this model are presented in column (2) of Table 3. In line with our predictions, the odds ratios on risk and time preferences are both less than one: individuals who are more willing to take risks or more impatient are less likely to comply with social distancing. At the same time, our main variables of interest (health factors, COVID-19 risk factors, apartment-dwelling and female) all remain significant predictors.

Another factor likely to play a role in compliance is an individual's self-perception of how likely they would be reported if they flouted social-distancing rules. With this in mind, we asked individuals how likely they feel that they would be reported to authorities by a neighbour if they hosted a large party at their home. Column (3) of Table 3 shows that this whistleblow variable is a significant predictor of compliance. If individuals feel that they are less likely to be reported, then they are also less likely to comply with social distancing. The odds ratios on this variable imply that someone who thinks they are very likely to be reported is 2.78 times more likely to comply than someone who thinks it is very unlikely they will be reported.

Finally, we consider how political views and confidence in doctors are related to compliance. For political beliefs the reference category is "Very Liberal". Column (4) of Table 3 demonstrates a clear link between compliance with social distancing and political views. Someone who identifies as "Conservative" is 0.47 times less likely to comply, and someone who identifies as "Very Conservative" is 0.23 times less likely to.[11] This result on polit-

[10]Respondents who never switch to Option B are coded as 8, whereas anyone who switches more than once violates monotonicity and is dropped from the analysis.

[11]This finding is replicated in Table 6 of the Appendix as a generalized logit. In a similar vein, Merkley et al. (2020) poll a sample of Canadian citizens on their attitudes toward COVID-19. They find that those with left-wing views regard COVID-19 as a more serious threat and report working from home more than those with more right-wing views, whereas no difference is observed in reported tendencies to

ical views is quite stark and highlights the partisan nature of regulations around social distancing.

Similar conclusions emerge when considering respondents' confidence in doctors and medical scientists as seen in column (5) of Table 3. A respondent who expresses a great deal of confidence in doctors is 2.2 times more likely to comply than someone who is neutral or lacks confidence in doctors. We also find (not reported in the table) that confidence in government and in the news media predict significantly increased compliance (and do not alter the significance of the other regressors). On the other hand, neither confidence in business leaders nor in religious leaders is significantly associated with compliance.

Our main variables of interest all remain significant with the inclusion of these additional controls. The presence of chronic illnesses is also significant except when political beliefs are included.

7.2 Minimizing Social Desirability Concerns

In asking individuals to report the extent to which they are complying or would comply with social-distancing regulations, we have until now attempted to measure and control for individual social desirability bias. In this subsection, we report the findings from a different approach. We ask respondents, "How likely do you think the typical person in your neighbourhood is to obey the above rules for self-isolation and social distancing if there was no fine for violators?" Since this question asks an individual about not their own behaviour, but about someone in their neighbourhood, the answers here should be unaffected by social desirability concerns. We estimate the compliance answers for a typical person in the neighbourhood on the ordinary logit model in Equation (1) without the social desirability score. The results are presented in Table 4. For ease of comparison, we also make available the results from the self-reported compliance model from Table 1.

avoid crowds. For evidence of the role of political ideology in social distancing in the U.S. context, see Allcott et al. (2020) and the references therein.

Apart from the indicator for gender, the estimates from self-reported compliance controlling for social desirability and from the compliance for a typical person without social desirability are qualitatively similar. In particular, the odds ratios for age and the regional COVID-19 rate are quantitatively similar under the self-reported and typical person compliance measures. This similarity attests to the effectiveness of the social desirability score in controlling for the tendency to inflate one's own likelihood of complying with social-distancing regulations.

7.3 Generalized Ordered Logits

The ordinal logit model makes use of the assumption of proportional odds; namely, the odds of being in compliance group greater than k versus the odds of being in the compliance groups less than or equal to k is independent of k.

Here we check whether our coefficients change when we run a generalized ordered logit model. A likelihood ratio test of the generalized ordered logit and the ordered logit with proportional odds on the "Compliance" variable returns a p-value of 0.26 suggesting that the two models are not significantly different. Similar likelihood tests for the compliance variables under the scenarios of "No Fine", "$250 Fine" and "$1000 Fine" yield p-values less than 0.05. So, for comparison with our ordered logits with proportional odds, we present the coefficients from these generalized ordered logits in Table 5.

The first panel shows the estimated coefficients for the odds of being in category $y = 1$ or $y = 2$,[12] the category of least compliance. The second panel shows the odds of being in compliance category $y = 3$ or higher.

Some of the estimates are very similar in terms of quantitative predictions such as age, and the effect of the COVID-19 rate on compliance. Being a female increases the odds of being in a compliance category above $y = 1$ or $y = 2$ by two times in the different fine scenarios whereas in the proportional odds assumption model this value was around

[12]These two categories were collapsed into one for this estimation due to the small number of observations.

1.7. Overall though, the predictions from our standard ordinal logit model versus the more generalized version are quite similar leading us to confirm the validity of our main results.

8 Conclusion

The Canadian federal government with the support of the provincial governments adopted social-distancing measures early on in the pandemic as the main tool to control the spread of COVID-19. We develop a theoretical model that highlights the roles of health factors and the perceived risk of contracting the virus in compliance behaviour and the potential usefulness of monetary fines and wage subsidies to promote staying at home. We design a survey to test the predictions of the model and to collect other behavioural measures hypothesized to predict compliance not part of standard economic models.

Our empirical strategy estimates a model of compliance using an ordinal logit model. We find that the probability of compliance is strictly increasing with an individual's age and the rate of COVID-19 in their health district (perceived risk factors). For instance, someone who is one year older is 1.01 times more likely to comply. Other factors such as having a chronic health condition, being female and working from home are also associated with increased compliance. We also show that the link between these factors and compliance significantly weakens when either a non-compliance fine or a wage subsidy is introduced. Both of these policy tools substantially boost full compliance with social distancing. Our findings can help guide policymakers in forming effective regulations to combat future waves of the pandemic.

Finally, our robustness checks highlight several other factors associated with compliance, one of them being political beliefs. Those who view themselves as Conservatives are much less likely to comply. This ideological component to compliance may surprise many Canadians. Indeed, Ontario's Conservative Premier, Doug Ford, is widely regarded as having taken serious measures in sync with those of the federal Liberal government from the outset of the pandemic (Globe and Mail, 2020; Taylor-Vaisey, 2020). Many Canadians likely believe political ideology to colour only their American counterparts' views of the pandemic, whereas our results attest to similar ideological bias among us, perhaps in part due to Canadians' exposure to the American media.

References

ALLCOTT, H., L. BOXELL, J. CONWAY, M. GENTZKOW, M. THALER, AND D. Y. YANG (2020): "Polarization and public health: Partisan differences in social distancing during the Coronavirus pandemic," *Journal of Public Economics*.

BODAS, M. AND K. PELEG (2020): "Self-Isolation Compliance In The COVID-19 Era Influenced By Compensation: Findings From A Recent Survey In Israel: Public attitudes toward the COVID-19 outbreak and self-isolation: a cross sectional study of the adult population of Israel," *Health Affairs*, 39, 936–941.

CAPRARO, V. AND H. BARCELO (2020): "The effect of messaging and gender on intentions to wear a face covering to slow down COVID-19 transmission," *arXiv preprint arXiv:2005.05467*.

CHAN, J. (2020): "The Geography of Social Distancing in Canada: Evidence from Facebook," *Canadian Public Policy*, 46, S19–S28.

COLLER, M. AND M. B. WILLIAMS (1999): "Eliciting individual discount rates," *Experimental Economics*, 2, 107–127.

CROWNE, D. P. AND D. MARLOWE (1960): "A new scale of social desirability independent of psychopathology." *Journal of Consulting Psychology*, 24, 349.

DAWSON, T. (2020): "COVID-19: Ontario and Quebec order non-essential businesses closed after spike in coronavirus totals," *National Post*.

DEPARTMENT OF FINANCE CANADA (2020): "Government introduces Canada Emergency Response Benefit to help workers and businesses," *Government of Canada*.

DOHMEN, T., A. FALK, D. HUFFMAN, U. SUNDE, J. SCHUPP, AND G. G. WAGNER (2011): "Individual risk attitudes: Measurement, determinants, and behavioral consequences," *Journal of the European Economic Association*, 9, 522–550.

EDWARDS, A. L. (1953): "The relationship between the judged desirability of a trait and the probability that the trait will be endorsed." *Journal of Applied Psychology*, 37, 90.

Elber, L. (2020): "Viewers turn to streaming services as they self-isolate amid coronavirus pandemic," *Global News.*

Fischer, D. G. and C. Fick (1993): "Measuring social desirability: Short forms of the Marlowe-Crowne social desirability scale," *Educational and Psychological Measurement*, 53, 417–424.

Foran, P. (2020): "Backyard pool sales surge during the COVID-19 pandemic," *CTV News.*

Globe and Mail (2020): "American conservatives ramped up COVID-19. Canadian conservatives helped flatten it," *The Globe and Mail.*

Government of Ontario (2020): "A framework for reopening our province. Government of Ontario," *Government of Ontario.*

Healing, D. (2020): "Do-it-yourselfers keep renovation sector hopping during COVID-19 pandemic," *CTV News.*

Jordan, J., E. Yoeli, and D. Rand (2020): "Don't get it or don't spread it? Comparing self-interested versus prosocially framed COVID-19 prevention messaging," .

MacDonald, S. and J. Azpiri (2020): "'Dumbbells are now the new toilet paper': COVID-19 leads to demand for fitness equipment," *Global News.*

Marchand-Senécal, X., R. Kozak, S. Mubareka, N. Salt, J. B. Gubbay, A. Eshaghi, V. Allen, Y. Li, N. Bastien, M. Gilmour, et al. (2020): "Diagnosis and Management of First Case of COVID-19 in Canada: Lessons applied from SARS," *Clinical Infectious Diseases.*

Merkley, E., A. Bridgman, P. J. Loewen, T. Owen, D. Ruths, and O. Zhilin (2020): "A Rare Moment of Cross-Partisan Consensus: Elite and Public Response to the COVID-19 Pandemic in Canada," *Canadian Journal of Political Science/Revue canadienne de science politique*, 1–8.

Office of the Premier (2020): "Ontario Extends Emergency Declaration to Stop the Spread of COVID-19," *Government of Ontario.*

Public Health Ontario (2020): "COVID-19 Data Tool," *Government of Ontario.*

Rodrigues, G. (2020): "Ontario Government Declares State Of Emergency Amid Coronavirus Pandemic," *Global News.*

Strahan, R. and K. C. Gerbasi (1972): "Short, homogeneous versions of the Marlowe-Crowne social desirability scale." *Journal of Clinical Psychology.*

Taylor-Vaisey, N. (2020): "What happened to the old Doug Ford?" *Maclean's.*

Tversky, A. and D. Kahneman (1974): "Judgment under uncertainty: Heuristics and biases," *Science*, 185, 1124–1131.

Yang, J., Y. Zheng, X. Gou, K. Pu, Z. Chen, Q. Guo, R. Ji, H. Wang, Y. Wang, and Y. Zhou (2020): "Prevalence of comorbidities and its effects in patients infected with SARS-CoV-2: a systematic review and meta-analysis," *International Journal of Infectious Diseases*, 94, 91–95.

Tables

Table 1

	Dependent variable:			
	Compliance	No Fine	$250 Fine	$1000 Fine
	(1)	(2)	(3)	(4)
Age	1.008***	1.016***	1.005*	1.003
	(1.002, 1.013)	(1.011, 1.022)	(0.999, 1.011)	(0.996, 1.010)
Female	1.544***	1.679***	1.683***	1.787***
	(1.316, 1.812)	(1.429, 1.975)	(1.416, 2.001)	(1.472, 2.170)
Chronic	1.229**	1.248**	1.149	0.962
	(1.011, 1.496)	(1.024, 1.523)	(0.929, 1.426)	(0.760, 1.222)
Chronic family	0.958	0.906	0.989	1.064
	(0.816, 1.126)	(0.771, 1.065)	(0.830, 1.179)	(0.873, 1.298)
Work from home	1.565***	1.399***	1.528***	1.406***
	(1.265, 1.936)	(1.130, 1.732)	(1.217, 1.918)	(1.091, 1.810)
COVID-19 Rate	1.001***	1.002***	1.001***	1.001***
	(1.001, 1.002)	(1.001, 1.002)	(1.001, 1.002)	(1.001, 1.002)
Apartment	0.814**	0.862	0.931	0.944
	(0.676, 0.982)	(0.714, 1.040)	(0.760, 1.144)	(0.749, 1.194)
Social Desirability Score	1.167***	1.168***	1.162***	1.111***
	(1.111, 1.227)	(1.111, 1.228)	(1.101, 1.226)	(1.046, 1.181)
Observations	2,493	2,493	2,493	2,493
Note:			*p<0.1; **p<0.05; ***p<0.01	

This table presents the odds ratios from our baseline ordinal logit model. The variable "Compliance" is an ordered response to the question "To what extent have you been obeying the above [current] rules for self-isolation and social distancing?" The variables "No Fine", "$250 Fine", and "$1000 Fine" then ask about compliance when there is no fine, a $250 fine, and a $1000 fine, respectively. 95% Confidence intervals are presented with the odds ratios estimation.

Table 2

	Dependent variable:	
	No Income Replacement	Full Income Replacement
	(1)	(2)
Age	1.017***	0.999
	(1.012, 1.022)	(0.992, 1.007)
Female	1.262***	1.373***
	(1.083, 1.471)	(1.113, 1.694)
Chronic	1.077	0.920
	(0.893, 1.300)	(0.713, 1.193)
Chronic family	0.924	0.932
	(0.792, 1.078)	(0.752, 1.158)
Work from home	1.483***	1.361**
	(1.206, 1.824)	(1.045, 1.769)
COVID-19 Rate	1.001***	1.000
	(1.000, 1.002)	(1.000, 1.001)
Apartment	0.839*	0.813
	(0.704, 1.001)	(0.634, 1.047)
Social Desirability Score	1.134***	1.153***
	(1.082, 1.189)	(1.080, 1.233)
Observations	2,493	2,110

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

This table presents the odds ratios from estimating an ordinal logit on compliance under different wage subsidy scenarios. The variable "No Income Replacement" is an ordered response to the question "If, in accordance with the best advice of the medical community, the government asked you to stay at home without pay and leave only for essential trips (e.g., grocery store, emergency medical attention), to what extent would you obey?" The variable "Full Income Replacement" is the same question except with a 100% wage subsidy. 95% Confidence intervals are presented with the odds ratios estimation.

Table 3: Additional Factors involved in Compliance

	Dependent variable:				
	Compliance				
	Education, Income	Risk, Time	Whistleblow	Political Beliefs	Confidence in Doctors
	(1)	(2)	(3)	(4)	(5)
Age	1.011***	1.005*	1.007***	1.010***	1.007**
	(1.005, 1.017)	(0.999, 1.010)	(1.002, 1.013)	(1.004, 1.016)	(1.001, 1.012)
Female	1.518***	1.363***	1.524***	1.468***	1.557***
	(1.291, 1.786)	(1.155, 1.610)	(1.297, 1.790)	(1.228, 1.755)	(1.326, 1.828)
Chronic	1.241**	1.227**	1.198*	1.195	1.214*
	(1.020, 1.512)	(1.004, 1.500)	(0.984, 1.461)	(0.966, 1.478)	(0.997, 1.479)
Chronic family	0.963	0.925	0.944	0.915	0.956
	(0.819, 1.131)	(0.784, 1.091)	(0.803, 1.111)	(0.765, 1.094)	(0.814, 1.124)
Working from home	1.526***	1.531***	1.652***	1.600***	1.543***
	(1.225, 1.901)	(1.231, 1.905)	(1.333, 2.048)	(1.257, 2.035)	(1.247, 1.910)
COVID-19 Rate	1.001***	1.001***	1.001***	1.001***	
	(1.001, 1.002)	(1.001, 1.002)	(1.001, 1.002)	(1.001, 1.002)	
Apartment	0.792**	0.819**	0.771***	0.766**	0.811**
	(0.656, 0.957)	(0.677, 0.992)	(0.638, 0.931)	(0.622, 0.944)	(0.673, 0.978)
Risk		0.857***			
		(0.827, 0.888)			
Switch		0.939***			
		(0.900, 0.979)			
Social Desirability Score	1.170***	1.159***	1.162***	1.185***	1.165***
	(1.113, 1.230)	(1.101, 1.219)	(1.106, 1.222)	(1.121, 1.253)	(1.109, 1.225)
Whistleblow			2.78***		
			(2.135, 3.611)		
Liberal				0.715**	
				(0.531, 0.958)	
Moderate				0.555***	
				(0.403, 0.760)	
Conservative				0.471***	
				(0.342, 0.645)	
Very Conservative				0.235***	
				(0.145, 0.379)	
Confidence in Doctors					2.201***
					(1.677, 2.887)
Observations	2,493	2,425	2,493	2,039	2,493
Note:					*p<0.1; **p<0.05; ***p<0.01

This table presents the odds ratios from different robustness checks for our estimation. The variable "Compliance" is an ordered response to the question "To what extent have you been obeying the above [current] rules for self-isolation and social distancing?" Column (1) includes controls for income and education attainment (those coefficients are not shown). Column (2) includes controls for time and risk preferences. Column (3) includes controls for perceptions about the likelihood of being reported for hosting a party (whistleblow). Column (4) controls for Political beliefs and Column (5) for confidence in doctors. 95% Confidence intervals are presented with the odds ratios estimation.

Table 4: Self-Reported Compliance vs. Compliance of a Typical Person in Neighbourhood

	Dependent variable:					
	Self: No Fine	Self:$250 Fine	Self: $1000 Fine	Typical: No Fine	Typical: $250 Fine	Typical: $1000 Fine
	(1)	(2)	(3)	(4)	(5)	(6)
Age	1.016***	1.005*	1.003	1.020***	1.011***	1.008***
	(1.011, 1.022)	(0.999, 1.011)	(0.996, 1.010)	(1.015, 1.025)	(1.006, 1.016)	(1.003, 1.013)
Female	1.679***	1.683***	1.787***	0.984	0.947	1.068
	(1.429, 1.975)	(1.416, 2.001)	(1.472, 2.170)	(0.847, 1.143)	(0.816, 1.100)	(0.919, 1.243)
Chronic	1.248**	1.149	0.962	1.031	1.044	0.887
	(1.024, 1.523)	(0.929, 1.426)	(0.760, 1.222)	(0.861, 1.235)	(0.872, 1.250)	(0.739, 1.064)
Chronic family	0.906	0.989	1.064	0.840**	0.944	0.979
	(0.771, 1.065)	(0.830, 1.179)	(0.873, 1.298)	(0.722, 0.978)	(0.813, 1.097)	(0.841, 1.140)
Work from home	1.399***	1.528***	1.406***	1.079	1.147	1.281**
	(1.130, 1.732)	(1.217, 1.918)	(1.091, 1.810)	(0.878, 1.326)	(0.935, 1.407)	(1.044, 1.571)
COVID-19 rate	1.002***	1.001***	1.001***	1.000	1.001**	1.001***
	(1.001, 1.002)	(1.001, 1.002)	(1.001, 1.002)	(1.000, 1.001)	(1.000, 1.001)	(1.000, 1.001)
Apartment	0.862	0.931	0.944	0.792***	0.836**	0.825**
	(0.714, 1.040)	(0.760, 1.144)	(0.749, 1.194)	(0.663, 0.945)	(0.701, 0.997)	(0.690, 0.985)
Social Desirability Score	1.168***	1.162***	1.111***			
	(1.111, 1.228)	(1.101, 1.226)	(1.046, 1.181)			
Observations	2,493	2,493	2,493	2,493	2,493	2,493
Note:						*p<0.1; **p<0.05; ***p<0.01

This table compares the estimates from the baseline ordinal logit "Self" to one where individuals are asked about compliance behaviour for a typical person in their neighbourhood "Typical". Columns (1) to (3) are for compliance under different fine scenarios for their own behaviour. Columns (4) to (6) are for compliance under different fine scenarios for a person in their neighbourhood. In the estimation for a typical person, there are no social desirability controls included.

Table 5: Generalized Ordered Logits

	(1) No Fine	(2) \$250 Fine	(3) \$1000 Fine
$y = 1$ *or* 2			
Age	1.027***	1.013*	1.006
Female	2.091***	2.301***	2.617***
Chronic	1.307	1.214	1.188
Chronic Family	1.014	0.935	1.031
Work from home	1.658**	2.058***	1.588*
COVID-19 rate	1.001*	1.002**	1.002**
Apartment	0.903	0.802	0.786
Social Desirability Score	1.124*	1.140**	1.011
$y = 3$			
Age	1.014***	1.004	1.003
Female	1.57***	1.607***	1.737***
Chronic	1.244	1.140	0.946
Chronic family	0.883	0.998	1.070
Work from home	1.301*	1.429**	1.382*
COVID-19 rate	1.002**	1.001***	1.001***
Apartment	0.849	0.951	0.956
Soical Desirability Score	1.183**	1.167***	1.121***
N	2493	2493	2493

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents the odds ratios from the generalized ordinal logit model. The variables "No Fine", "\$250 Fine", and "\$1000 Fine" ask about compliance when there is no fine, a \$250 fine, and a \$1000 fine, respectively. 95% Confidence intervals are presented with the odds ratios estimation. The first panel shows the estimated coefficients for the odds of being in category $y = 1$ or $y = 2$. These two categories were collapsed into one for this estimation due to the small number of observations. The second panel shows the odds of being in compliance category $y = 3$ or higher.

Table 6: Generalized Ordered Logits: Political Beliefs

	(1) Compliance
$y = 1$ *or* 2	
Age	1.034***
Female	1.760***
Chronic	1.272
Chronic family	0.930
Liberal	0.679
Moderate	0.361***
Conservative	0.294***
Very Conservative	0.0871***
Work from Home	1.721**
COVID-19 Rate	1.001
Apartment	0.848
Social Desirability Score	1.127**
$y = 3$	
Age	1.017***
Female	1.496***
Chronic	1.154
Chronic family	0.843
Liberal	0.711*
Moderate	0.599**
Conservative	0.518***
Very Conservative	0.385***
Work from home	1.341*
COVID-19 Rate	1.001***
Apartment	0.828
Social Desirability Score	1.207***
N	2039

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table presents the odds ratios from the generalized ordinal logit model with political views as an additional control. The variables "No Fine", "$250 Fine", and "$1000 Fine" ask about compliance when there is no fine, a $250 fine, and a $1000 fine, respectively. 95% Confidence intervals are presented with the odds ratios estimation. The first panel shows the estimated coefficients for the odds of being in category $y = 1$ or $y = 2$. These two categories were collapsed into one for this estimation due to the small number of observations. The second panel shows the odds of being in compliance category $y = 3$ or higher.