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# Advanced Econometrics Final Project

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# The COVID-19 Effects on U.S. Concerns About Climate Change

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**Abstract:**
This paper investigates the effect of the Covid-19 pandemic on people's beliefs about climate change. We use representative survey data on the U.S. population from waves in April 2019 and April 2020 to investigate the effect. By estimating binary choice models, we find that evidence of change in beliefs is limited. However, there is some evidence of a slight increase in the beliefs that climate change is happening and that it is anthropogenic. We also find that age, education, and political party affiliation appear to be significant determinants of these beliefs.
The R code for the project can be downloaded here, or sent by e-mail:
https://github.com/pajaKr/Advanced_Econometrics

# 1 Introduction

The public debate on climate change has become increasingly important in recent years as the consequences of global warming have become more apparent in many parts of the world. However, from 2020 to 2023, climate change received less public attention as many countries grappled with the COVID-19 pandemic and its economic consequences. This paper investigates the shift in public opinion toward climate change due to the COVID-19 pandemic, specifically examining changes in beliefs regarding the existence of global warming and its possible anthropogenic causes.

According to the finite-pool-of-worry hypothesis, one might expect decreased concerns about climate change as individuals experienced the COVID-19 pandemic, due to a limited capacity of concern that shifts their attention from one subject to another (Sisco *et al.*, 2023). This temporary shift in attention may lead individuals to focus less on relatively abstract issues, such as climate change, and more on immediate danger, such as the pandemic. Alternatively, one might argue that global crises, such as COVID-19, generally increase individuals' awareness of danger, making them more aware of potential threats. Therefore, concerns about climate change might increase due to experiencing the COVID-19 pandemic.

Understanding how public opinion on climate change develops is crucial for policymakers, as it may affect the receptiveness of policies directed toward reducing global warming and, therefore, affect the feasibility of such measures. Thus, identifying how crisis affects concerns is crucial when determining appropriate policy windows. Unfortunately, the literature on the effects of the COVID-19 pandemic on public concerns about climate change is inconclusive. Beiser-McGrath (2022) found that public concern about climate change decreased during the COVID-19 crisis in the United Kingdom. Contrary, Berazneva *et al.* (2023) found some evidence of increasing concerns in Germany. Our research contributes to the literature by analyzing the relationship between U.S. public opinion about climate change and the COVID-19 pandemic. We employ rich and representative U.S. national survey data and econometric modelling, including the probit and logit models, to uncover the effect of COVID-19 on U.S. concerns about climate change.

The rest of the paper is structured as follows: The next section will present relevant literature exploring the impact of economic uncertainty and COVID-19 on climate change concerns. Then, we present our data and methodology. Subsequently, we will elaborate on our empirical results and explore possible mechanisms behind the observed relationships. The last section concludes.

# 2 Literature Review

This paper builds on research conducted by Kahn & Kotchen (2011), who examine the relationship between business cycle fluctuations, proxied by unemployment rates, and public concern about climate change. In the first part of the analysis, the authors use Google keyword searches and answers to national surveys as outcome variables and find that changes in unemployment rates are associated with changes in searching behaviour and attitudes toward climate change. Specifically, they find that searching behavior on climate change decreases in favour of searches on unemployment and that residents are less likely to believe in global warming and support government action against climate change as unemployment rates rise. The authors argue that in economic crises, agents shift their attention away from long-term threats, such as global warming, to short-term threats, such as economic uncertainty. The shift in attention from long-term to short-term threats is reinforced by the national media's incentive to adapt their coverage accordingly. The authors support their argument by showing that the number of print media stories on climate change decreases as the number of stories about unemployment increases. They continue that social interactions may also explain the attention shift to short-term threats. The authors argue that changing individual interests in global warming may also affect one's peers' interests. Therefore, a recession may constitute an exogenous shock to concerns through individual and peer group effects, making the subject of climate change less important. In the second part, the authors estimate a linear probability model investigating the effect of the financial crisis on people's attitudes towards climate change. They find a negative and statistically significant effect of the recession, indicating that the climate concerns decrease during a crisis.

Another study investigating the relationship between one's perception of the economic state and views on climate change was conducted by Kenny (2018). The author uses an online question-order survey experiment and logistic regression with binarized outcome variables on a representative sample of 1,751 British adults and divides the sample into treatment and control groups. The author asked the treatment group two questions: First, how they perceive the state of the economy, and second, whether they believe in anthropogenic climate change and how urgent they think the issue is. The control group was asked the same questions in inverse order, without intending to be primed by the treatment group's first question. The author finds no relationship between one's perception of the economic state and belief in climate change. However, he notes that there is a statistically significant relationship between one's perception of the economic state and the support for urgent action on climate change. Specifically, the treatment group individuals who perceived the economy to be in a good state were more likely to support urgent action, with opposite results for those who perceived the economy as neither good nor bad or in a quite bad state. The author concludes that economic uncertainty significantly impacts one's endorsement of actions on climate change.

Drews *et al.* (2022) investigate the effect of the COVID-19 pandemic on public opinion about climate change in Spain using the ordered logistic regression. The authors use survey data from 1,172 Spanish participants collected before and after the first wave of COVID-19 and find that average concerns regarding climate change decreased and acceptance of policy actions against climate change increased. Furthermore, they find that at the individual level, adverse health outcomes and unfavorable economic experiences due to COVID-19 are generally unrelated to perceptual shifts toward climate change, except unemployment, which is associated with disapproval of some policies against climate change. Moreover, the authors find evidence of spillover effects that climate change concerns facilitate concerns about COVID-19. Likewise, they find that support for the government's COVID-19 measures positively relates to higher acceptance rates of some climate policies.

Beiser-McGrath (2022) uses survey data for the UK, and estimates fixed effects regressions with several dependent variables measuring how important or how big of a priority should climate change be. The author finds that the COVID-19 crisis caused a decline in environmental concern and lower prioritization of climate change.

## 3 Data

Survey data was downloaded from the Yale Program on Climate Change Communication (Ballew *et al.*, 2020). The data contains 26 rounds of nationally representative surveys involving U.S. adults, conducted between 2008 and 2022. Each observation represents an individual participating in the survey for the given year. Since we focus on the effects of the COVID-19 crisis, we limit our analysis to the waves of interest: April 2019, and April 2020, totalling 2,320 observations, 1,291 belonging to April 2019 and 1,029 to April 2020. Data from April 2022, containing 1,017 observations, further serves for subsequent robustness checks. The survey was conducted several times during the pandemic. We choose April 2020, because several economic indicators point to it as the zenith of the crisis in the U.S., with unemployment peaking at 14.8 percent, and GDP falling to just below $20,000 billion (FRED, 2024a,b). The pre-pandemic April 2019 wave serves for comparative purposes, and the post-pandemic April 2022 wave as a robustness check.

We choose several variables for modeling. Summary statistics for each are available in Table 7.1. We use the following survey questions for our analysis:

1. Variable ***Happening***: Do you think that global warming is happening? (a) No, (b) Don't know, (c) Yes.
2. Variable ***Human_Cause***: Assuming global warming is happening, do you think it is... (a) Don't know, (b) Neither because global warming isn't happening, (c) Caused mostly by natural changes in the environment, (d) Caused by human activities and natural changes, (e) Caused mostly by human activities.

Following Kahn & Kotchen (2011), we converted all outcome variables to binary to simplify the analysis. We denote the variable *Happening* as 1 if the answer to question (1) was (c), and 0 otherwise. Furthermore, we denote the variable *Human_Cause* as 1 if the answer to question (2) was (d) or (e), and 0 otherwise, to indicate whether the respondent thinks that global warming is at least partially anthropogenic. This is a common approach shared with other survey data papers (Barroso *et al.*, 2016; Zavras *et al.*, 2013, for example). We realize that this is a strong assumption. Therefore, we tried to run the analysis on a restricted sample, where we dropped all observations with answer (b) to question (1), leaving just a binary Yes or No answer. We also tried an analysis where we dropped all answers except (c) and (e) for question (2), leaving in the dataset just those who believe that global warming is caused either mainly by natural changes or mainly by human activity. In both cases, the results remain robust.

As independent variables, we have the respondent's age, gender, income, years of obtained education, an unemployment dummy variable, their race, marital status, household size, whether they own a home, and political party affiliation. We also include a dummy to indicate whether the observation comes from the wave of April 2020 or not. Definitions and summary statistics of both the dependent and independent variables are available in Table 7.1.

Over the whole sample, 70% of people believe that global warming is happening, a 3.2 percentage points increase when compared to the sample by Kahn & Kotchen (2011), which contains data for 2008 and 2009. 61% think that it is at least partially caused by humans.

The choice of the independent variables is largely determined by the original paper by Kahn & Kotchen (2011) and the available variables in the survey. We went through all the variables the survey collects, and looked for additional variables that might help explain the relationship. While the original paper already uses most of them, we decided to add variables indicating whether the respondent considers themselves a Democrat, Republican, Independent, or other. To some extent, climate change and its regulation can be considered a political issue, and so we want to test whether the respondent's political affiliation significantly determines their beliefs about climate change.

The correlation matrix of the independent variables is available in Figure 7.1. Since there are no high correlations, we conclude that multicollinearity is unlikely an issue with our data. The numerical independent variables were inspected for outliers. Since there are no extreme values, we leave our sample without any further modifications. The sample does not contain any missing observations.

# 4 Methodology

We estimate three binary choice models, a linear probability, probit, and logit model, on two outcome variables to test how public opinion toward climate change shifted due to the COVID-19 pandemic. The dependent and independent variables are described in chapter 3. As a baseline model, we use the linear probability model in the following form

$$Y_i = \alpha + \beta \mathbb{X} + \gamma \text{Wave\_2020}_i + \epsilon_i \tag{4.1}$$

Where $Y_i$ is either the variable *Happening* or *Human_Cause*, $\mathbb{X}$ denotes the independent variables from the survey as described in the previous chapter. Finally, we include a dummy *Wave_2020* to indicate whether the observation comes from the survey conducted in April 2020. $\alpha, \beta, \gamma$ denote the parameters to be estimated, $\epsilon_i$ is the error term.

We use the linear probability model above as a baseline model; however, we cannot ensure that the model represents valid probabilities. Therefore, we extend the linear probability model by a probit and logit model, transforming the regression equation into nonlinear models with a standard normal and logistic cumulative distribution function, respectively. This will ensure that we estimate probabilities in the interval (0,1).

Following the literature (Kahn & Kotchen, 2011; Beiser-McGrath, 2022; Zavras *et al.*, 2013) we use so-called before-after analysis, using data from two surveys and studying the effect of some event (crisis in case of all of these papers) by including a dummy for the survey conducted during that event. This approach assumes that no other factors influenced the relationship during that time.

# 5 Results

We estimate the relationship specified in Equation 4.1 using the linear probability model, logistic regression, and the probit model. The results of the estimation are presented in Table 7.2. Due to the inherent heteroskedasticity in the linear probability model, confirmed by the Breusch-Pagan test rejecting the null hypothesis of homoskedasticity for all models, the standard errors for models (1) and (4) are the White's heteroskedasticity robust standard errors.

Marginal effects at the mean, together with their standard errors, are available in Table 7.3. Marginal effects at the mean denote the partial effect of each independent variable on the dependent variable, holding the independent variables at their sample means. For continuous variables, this means multiplying the respective density function evaluated at sample means with the parameter estimate. For dummy variables, we need to calculate the difference in probabilities that the dependent variable is equal to one when the dummy is equal to one and zero. The standard errors for logit and probit marginal effects are calculated according to the approach described by Greene (2012), which is implemented in the R package *erer*. The procedure goes as follows: for dummy variable $d$, and predicted probabilities $\hat{\mathbf{p}}$ we calculate the marginal effect as $\Delta\hat{\mathbf{p}} = (\hat{\mathbf{p}}|(d = 1)) - (\hat{\mathbf{p}}|(d = 0))$, other variables at sample means, and the asymptotic variance of the marginal effect is then $\tilde{Var} = (\partial\Delta\hat{\mathbf{p}}/\partial\hat{\boldsymbol{\beta}}\ )\mathbf{V}(\partial\Delta\hat{\mathbf{p}}/\partial\hat{\boldsymbol{\beta}})$,where $\mathbf{V}$ is the asymptotic variance-covariance matrix of the estimated parameters. For quantitative variables the procedure is similar, we just calculate the marginal effects as the product of the density function at the sample means and the estimated parameters. For a more detailed discussion, see Greene (2012). The standard errors for the linear probability model do not require any further calculation, since the marginal effects are simply the regression estimates. We also calculated the so-called average partial effects by calculating the partial effects across all observations and averaging them out. These results were very similar to the marginal effects at the mean for our data. This is in line with the theory that they are almost identical for large samples (Greene, 2012), and so, we do not report them here.

The results are generally consistent across models, indicating statistically significant and negative effects of the *Age*, *Republican*, *Independent*, and *Party_other* variables on both dependent variables. Conversely, the effects of *Education*, *Race_Hispanic*, and *Wave_2020* are positive and significant across models. The marginal effects suggest that, on average, holding all variables at their means, being a Republican decreases the probability that the respondent thinks that global warming is happening and that it is caused by humans by approximately 40-50 percentage points, compared to the baseline *Democrat* variable. The other effects are less pronounced, with the *Wave_2020* variable having marginal effects at the means around 0.04-0.05.

According to the estimates, *Wave_2020* positively affects the dependent variable across models, suggesting that people surveyed during the COVID-19 crisis had mildly increased beliefs about climate change. This contrasts with Kahn & Kotchen (2011), who found a negative significant effect of the financial crisis in 2011 on climate change concerns. However, there is no consensus in the literature. For example, Berazneva *et al.* (2023) found a slight increase in environmental concerns in Germany during the COVID-19 pandemic. It is for example possible, that the crises are of a different nature, or the attitudes towards climate change are changing in general. It should also be noted that R-squared in the linear

probability model of Kahn & Kotchen (2011) was 0.05 for the variable *Happening*, while we arrived at 0.18, suggesting a slight increase in the explained variation.
The negative estimated coefficient on *age* indicates that with increasing age the probability that the respondent thinks that climate change is happening and that is at least partially caused by humans decreases. This "generational gap" is not significant in the paper by Kahn & Kotchen (2011), but is in line with the results of Milfont *et al.* (2021), who study the beliefs that "Climate change is real" and "Climate change is caused by humans" for New Zealand. Conversely, the probability increases with years of education. This is in line with Kahn & Kotchen (2011). We also find a negative effect of all political party variables when compared to the baseline variable *Democrat*. Many papers show similar results, that those who consider themselves more conservative tend to have more sceptical beliefs about climate change (Whitmarsh, 2011; Hamilton *et al.*, 2015, for example).

As a measure of goodness of fit, we report the R-squared for the linear probability model, and McFadden's likelihood ratio index and the maximized value of the log-likelihood for the logit and probit models. It is difficult to choose a preferred model between the logit and probit with some sound theoretical justification. In our case, they yield very similar results and hence we prefer them both to the linear probability model, mainly due to their advantage in predicting probabilities within the (0,1) interval. The fact that our ratio of 0s and 1s in the dependent variables is relatively balanced (70% and 61% of ones for *Happening* and *Human_cause*, respectively) also contributes to the similarity of the results. The R-squared values for the linear probability model range from 0.18 to 0.19, indicating that less than 20% of the variation in our data is explained by the model, suggesting the potential for further analysis to identify other influential variables. While the McFadden's likelihood ratio index does not have any direct interpretation and we cannot use it to choose between logit and probit due to the different likelihood functions, it still tells us that the models bring some new information as compared to the model containing only the constant term. Additionally, we report the p-value of the Wald test for the joint significance of all regressors, which leads to the rejection of the null hypothesis and the conclusion that the regressors are jointly significant in all specifications.

As we discussed in the methodology chapter, by the models' construction, we assume that the positive effect of *Wave_2020* is due to the COVID-19 crisis. If, for example, this increase reflects a broader trend in environmental awareness and concerns, we are unable to control for it. We attempt to partially address this issue by conducting a robustness check using survey data from April 2022, post-crisis, instead of April 2019. This analysis will show us, whether any of the effects appeared only temporarily during the Covid-19 crisis, and could thus indicate a shift in beliefs during the crisis period. The results, available in Table 7.4, show that while most variables' effects remain consistent, the significant effect of *Wave_2020* on the belief in climate change happening disappeared. For the *Human_Cause* models, however, *Wave_2020* remains positive and statistically significant at $\alpha = 0.05$ across all models, indicating a temporary increase in beliefs that climate change is partially caused by humans during the Covid-19 crisis.

Kahn & Kotchen (2011) who examined the crisis in the late 2000s continued their analysis by replacing the dummy indicating the wave of the survey with the regional seasonally adjusted unemployment rate, while also controlling for regional fixed effects. This allowed the authors to control for unobserved and time-invariant effects at the regional level, while relying on the within regional variation. In our case the average unemployment rate for the nine regions in the survey was 3.6% in April 2019 and 14.2% in April 2020. We ran only the linear probability model with the regional fixed effects and *Unemployment_rate* variable, since fixed effects estimation for logit and probit is less straightforward due to the non-linearity of the models; moreover, the incidental parameters problem arises (Greene, 2012). However, we also tested, whether there are significant regional fixed effects at all, by conducting the F test for individual effects for the linear probability model. We obtained p-value = 0.27 for the *Happening* linear probability model and p-value = 0.08 for the *Human_Cause* linear probability model, hence non-rejecting that there are no individual effects at $\alpha = 0.05$, suggesting the fixed effects estimation is not needed. When running all the models with the unemployment rate instead of the *Wave_2020* dummy, the results were akin to those using *Wave_2020*, with the *Unemployment_rate* variable being significant and positive for all specifications in April 2019 and April 2020, and significant for the *Human_Cause* models in the robustness check sample. The high correlation coefficient (0.96) between *Unemployment_rate* and *Wave_2020* explains the similarity in results.

The results are also robust to the precise definition of the dependent variable. We ran the analysis with only those observations that answered "Yes" or "No" to the question "Do you think that global warming is happening?". And one more analysis with those that answered the question "Assuming global warming is happening, do you think it is. . ." by "Caused mostly by natural changes in the environment" and "Caused mostly by human activities". While the precise numerical results changed a little bit, the significance of variables and the overall conclusions remained consistent. We also tried a completely different dependent variable *Worried* if the respondent is either "Very worried" or "Somewhat worried" about climate change. Again, we found a significant and positive effect during the Covid-19 crisis and consistent results for the other variables.

## 6 Conclusion

We estimate binary choice models to study the effects of the COVID-19 crisis on beliefs about climate change. The models provide consistent results, suggesting that, despite the COVID-19 crisis, we do not find evidence of decreased concern about climate change. Conversely, we find some limited evidence that beliefs about the existence of climate change and its anthropogenic causes increased during COVID-19, with the latter being more robust. This suggests a temporary, slight increase in the belief that human activities at least partially cause climate change. These results oppose those of the paper we built upon by Kahn & Kotchen (2011), who study the late 2000s crisis and find evidence of a significant decrease in climate concern during a crisis. We also find that age, education, and political party affiliation are significant determinants of these beliefs. In terms of policy implications, our results suggest that despite significant global disruptions like the COVID-19 pandemic, beliefs are more or less consistent, with limited disruptions. Hence, according to our results, the platform for proposing policies aimed at climate change mitigation appears to be quite stable in terms of crises like COVID-19. Several limitations are in order. First, the model assumes that the effect of the crisis is captured only by the variable *Wave_2020*. If there are other factors behind the changing beliefs, we are not able to control for them. Moreover, if we omitted some important variables, the estimator would not be consistent. In our analysis, we always only compared two periods, future research could thus take more longitudinal approach, or adapt a cross country perspective.

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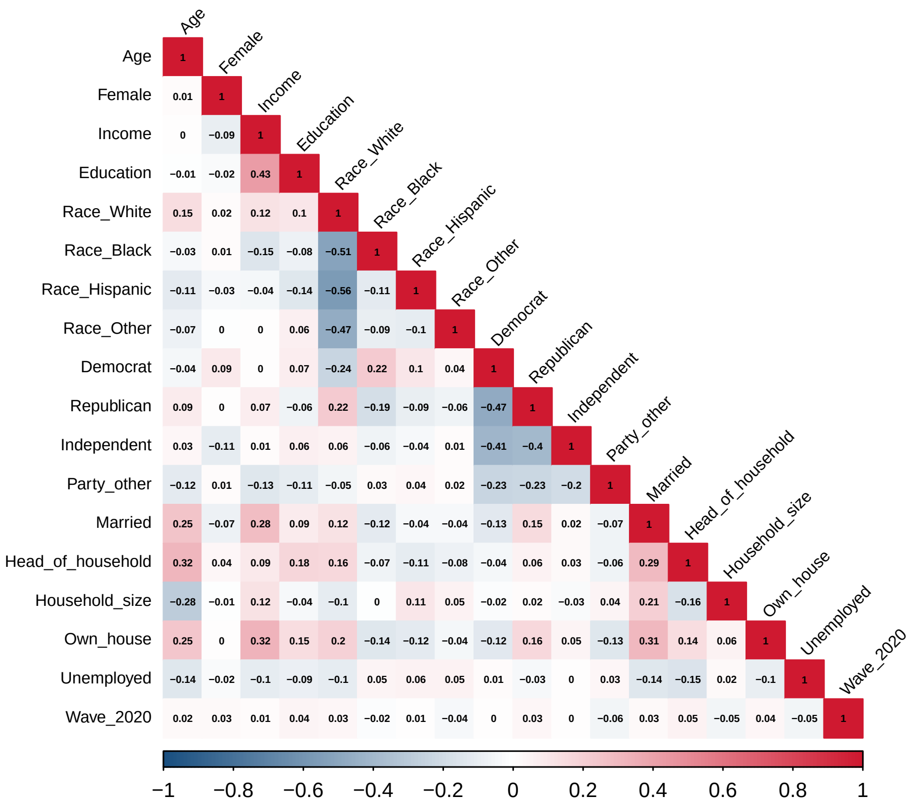
# 7 Appendix

Table 7.1: Descriptions and summary statistics of the variables

| Variable | Description | Mean | SD | Median | Min | Max |
|---|---|---|---|---|---|---|
| *Dependent variables* | | | | | | |
| Happening | The respondent thinks that global warming is happening | 0.70 | 0.46 | 1.00 | 0.00 | 1.00 |
| Human_Cause | The respondent thinks global warming is caused at least partially by humans | 0.61 | 0.49 | 1.00 | 0.00 | 1.00 |
| *Independent variables* | | | | | | |
| Age | Age of the respondent | 52.41 | 16.65 | 55.0 | 18.0 | 93.0 |
| Female | = 1 if the respondent's sex is female | 0.48 | 0.50 | 0.00 | 0.00 | 1.00 |
| Income | Annual income in $10,000 | 9.43 | 6.49 | 8.00 | 0.50 | 25.0 |
| Education | Years of education obtained by the respondent | 14.5 | 2.69 | 14.0 | 0.0 | 21.0 |
| Race_White | = 1 if the race of the respondent is white *(reference category)* | 0.72 | 0.45 | 1.00 | 0.00 | 1.00 |
| Race_Black | = 1 if the race of the respondent is black | 0.09 | 0.29 | 0.00 | 0.00 | 1.00 |
| Race_Hispanic | = 1 if the race of the respondent is Hispanic | 0.11 | 0.31 | 0.00 | 0.00 | 1.00 |
| Race_Other | = 1 if the race of the respondent is neither of the above | 0.08 | 0.27 | 0.00 | 0.00 | 1.00 |
| Democrat | = 1 if the respondent considers themselves a democrat *(reference category)* | 0.33 | 0.47 | 0.00 | 0.00 | 1.00 |
| Republican | = 1 if the respondent considers themselves a republican | 0.31 | 0.46 | 0.00 | 0.00 | 1.00 |
| Independent | = 1 if the respondent considers themselves an independent | 0.26 | 0.44 | 0.00 | 0.00 | 1.00 |
| Party_other | = 1 if the respondent considers themselves neither of the above | 0.10 | 0.30 | 0.00 | 0.00 | 1.00 |
| Married | = 1 if the respondent is married | 0.60 | 0.49 | 1.00 | 0.00 | 1.00 |
| Head_of_household | = 1 if the respondent's home is in their name | 0.82 | 0.38 | 1.00 | 0.00 | 1.00 |
| Household_size | Number of people living with the respondent | 2.59 | 1.46 | 2.00 | 1.00 | 12.0 |
| Own_house | =1 if the house is owned by respondent or someone in their household | 0.74 | 0.44 | 1.00 | 0.00 | 1.00 |
| Unemployed | =1 if the respondent is either "Not working –looking for work" or "Not working–on temporary layoff from a job | 0.04 | 0.20 | 0.00 | 0.00 | 1.00 |
| Wave_2020 | = 1 if the observation is from April 2020 | 0.44 | 0.50 | 0.00 | 0.00 | 1.00 |

*Note:* This table presents the variables and summary statistics. SD = Standard Deviation

Figure 7.1: Correlations among independent variables




*Note:* The figure presents Pearson correlation coefficients for independent variables in the pooled data for survey waves Apr 2019 and Apr 2020. Definitions and descriptions of those variables are available in Table 7.1.

Table 7.2: Regression Results for Happening and Human Cause

| | Happening | | | Human_Cause | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | LPM | Probit | Logit | LPM | Probit | Logit |
| Intercept | 0.689*** | 0.630** | 1.104** | 0.716*** | 0.650** | 1.083** |
| | (0.070) | (0.242) | (0.417) | (0.073) | (0.229) | (0.384) |
| Age | −0.002** | −0.007** | −0.011** | −0.003*** | −0.009*** | −0.015*** |
| | (0.001) | (0.002) | (0.004) | (0.001) | (0.002) | (0.003) |
| Female | 0.032· | 0.102· | 0.188· | 0.006 | 0.014 | 0.026 |
| | (0.018) | (0.060) | (0.102) | (0.019) | (0.058) | (0.096) |
| Income | 0.002 | 0.008 | 0.013 | 0.003 | 0.010· | 0.015 |
| | (0.002) | (0.006) | (0.009) | (0.002) | (0.005) | (0.009) |
| Education | 0.017*** | 0.063*** | 0.106*** | 0.018*** | 0.057*** | 0.095*** |
| | (0.004) | (0.013) | (0.022) | (0.004) | (0.012) | (0.021) |
| Race_Black | 0.017 | −0.013 | 0.014 | −0.083* | −0.298** | −0.489** |
| | (0.029) | (0.118) | (0.208) | (0.036) | (0.104) | (0.175) |
| Race_Hispanic | 0.087** | 0.308** | 0.553** | 0.089** | 0.280** | 0.503** |
| | (0.028) | (0.108) | (0.187) | (0.030) | (0.101) | (0.172) |
| Race_Other | −0.023 | −0.083 | −0.119 | −0.005 | −0.009 | −0.012 |
| | (0.033) | (0.116) | (0.196) | (0.033) | (0.111) | (0.187) |
| Republican | −0.418*** | −1.453*** | −2.483*** | −0.472*** | −1.401*** | −2.303*** |
| | (0.022) | (0.088) | (0.163) | (0.023) | (0.079) | (0.138) |
| Independent | −0.181*** | −0.808*** | −1.430*** | −0.204*** | −0.695*** | −1.160*** |
| | (0.021) | (0.091) | (0.168) | (0.024) | (0.080) | (0.139) |
| Party_other | −0.292*** | −1.104*** | −1.924*** | −0.230*** | −0.754*** | −1.260*** |
| | (0.035) | (0.110) | (0.194) | (0.036) | (0.103) | (0.173) |
| Married | −0.026 | −0.080 | −0.149 | −0.025 | −0.076 | −0.123 |
| | (0.021) | (0.072) | (0.123) | (0.022) | (0.069) | (0.115) |
| Head_of_household | 0.011 | 0.030 | 0.056 | −0.022 | −0.069 | −0.119 |
| | (0.026) | (0.087) | (0.148) | (0.027) | (0.084) | (0.140) |
| Household_size | −0.010 | −0.040· | −0.065· | −0.008 | −0.029 | −0.047 |
| | (0.007) | (0.023) | (0.038) | (0.008) | (0.022) | (0.036) |
| Own_house | 0.047* | 0.159* | 0.268* | 0.018 | 0.052 | 0.089 |
| | (0.022) | (0.078) | (0.133) | (0.023) | (0.075) | (0.125) |
| Unemployed | 0.017 | 0.026 | 0.076 | −0.014 | −0.040 | −0.069 |
| | (0.047) | (0.152) | (0.259) | (0.046) | (0.146) | (0.244) |
| Wave_2020 | 0.049** | 0.171** | 0.293** | 0.038* | 0.126* | 0.207* |
| | (0.017) | (0.060) | (0.102) | (0.018) | (0.058) | (0.096) |
| Observations | 2320 | 2320 | 2320 | 2320 | 2320 | 2320 |
| $R^2$ | 0.18 | - | - | 0.19 | | |
| LRI | - | 0.16 | 0.16 | - | 0.16 | 0.15 |
| LnL | - | -1191 | -1192 | - | -1315 | -1317 |
| Wald test p-value | - | 0.000 | 0.000 | - | 0.000 | 0.000 |

*Note:* Standard errors are in parentheses (For LPM heteroskedasticity robust SE). Significance levels: · = p < 0.1,* = p < 0.05, ** = p < 0.01, *** = p < 0.001., LPM = Linear Probability Model, LRI = McFadden's likelihood ratio index.

Table 7.3: Marginal Effects at Means for Different Models

| | Happening | | | Human_Cause | | |
|---|---|---|---|---|---|---|
| | LPM | Probit | Logit | LPM | Probit | Logit |
| Age | -0.002** | -0.002** | -0.002** | -0.003*** | -0.003*** | -0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Female | 0.032 | 0.033 | 0.035 | 0.006 | 0.005 | 0.006 |
| | (0.018) | (0.020) | (0.019) | (0.019) | (0.022) | (0.022) |
| Income | 0.002 | 0.003 | 0.002 | 0.003 | 0.004 | 0.003 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Education | 0.017*** | 0.020*** | 0.020*** | 0.018*** | 0.022*** | 0.022*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.005) | (0.005) |
| Race_Black | 0.017 | -0.004 | 0.003 | -0.083* | -0.116** | -0.118** |
| | (0.029) | (0.038) | (0.039) | (0.036) | (0.041) | (0.043) |
| Race_Hispanic | 0.087** | 0.092** | 0.092** | 0.089** | 0.101** | 0.109** |
| | (0.028) | (0.029) | (0.027) | (0.030) | (0.034) | (0.035) |
| Race_Other | -0.023 | -0.028 | -0.023 | -0.005 | -0.003 | -0.003 |
| | (0.033) | (0.039) | (0.039) | (0.033) | (0.042) | (0.044) |
| Republican | -0.418*** | -0.502*** | -0.514*** | -0.472*** | -0.515*** | -0.518*** |
| | (0.022) | (0.028) | (0.029) | (0.023) | (0.025) | (0.025) |
| Independent | -0.181*** | -0.285*** | -0.304*** | -0.204*** | -0.268*** | -0.278*** |
| | (0.021) | (0.033) | (0.036) | (0.024) | (0.030) | (0.032) |
| Party_other | -0.292*** | -0.411*** | -0.437*** | -0.230*** | -0.294*** | -0.305*** |
| | (0.035) | (0.040) | (0.042) | (0.036) | (0.039) | (0.040) |
| Married | -0.026 | -0.026 | -0.028 | -0.025 | -0.029 | -0.028 |
| | (0.021) | (0.023) | (0.023) | (0.022) | (0.026) | (0.027) |
| Head_of_household | 0.011 | 0.010 | 0.011 | -0.022 | -0.026 | -0.027 |
| | (0.026) | (0.029) | (0.028) | (0.027) | (0.031) | (0.032) |
| Household_size | -0.010 | -0.013 | -0.012 | -0.008 | -0.011 | -0.011 |
| | (0.007) | (0.007) | (0.007) | (0.008) | (0.008) | (0.008) |
| Own_house | 0.047* | 0.053* | 0.052 | 0.018 | 0.020 | 0.021 |
| | (0.022) | (0.027) | (0.027) | (0.023) | (0.028) | (0.029) |
| Unemployed | 0.017 | 0.008 | 0.014 | -0.014 | -0.015 | -0.016 |
| | (0.047) | (0.049) | (0.047) | (0.046) | (0.056) | (0.058) |
| Wave_2020 | 0.049** | 0.055** | 0.055** | 0.038* | 0.048* | 0.048* |
| | (0.017) | (0.019) | (0.019) | (0.018) | (0.022) | (0.022) |

*Note:* This table presents the marginal effects at means for all the models with standard errors in parentheses. Significance levels are denoted as * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.

Table 7.4: Regression Results for Happening and Human_Cause - April 2020 and April 2022

| | Happening | | | Human_Cause | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | LPM | Probit | Logit | LPM | Probit | Logit |
| Intercept | 0.800*** | 1.037*** | 1.834*** | 0.752*** | 0.755** | 1.284** |
| | (0.078) | (0.266) | (0.461) | (0.078) | (0.245) | (0.411) |
| Age | −0.002*** | −0.008*** | −0.015*** | −0.003*** | −0.010*** | −0.017*** |
| | (0.001) | (0.002) | (0.004) | (0.001) | (0.002) | (0.003) |
| Female | 0.039* | 0.145* | 0.245* | 0.011 | 0.031 | 0.060 |
| | (0.020) | (0.065) | (0.110) | (0.020) | (0.061) | (0.101) |
| Income | 0.003 | 0.010 | 0.017 | 0.005* | 0.015** | 0.023* |
| | (0.002) | (0.006) | (0.010) | (0.002) | (0.006) | (0.009) |
| Education | 0.013** | 0.051** | 0.084*** | 0.009* | 0.029* | 0.048* |
| | (0.004) | (0.014) | (0.023) | (0.004) | (0.013) | (0.021) |
| Race_Black | 0.001 | −0.071 | −0.099 | −0.032 | −0.141 | −0.218 |
| | (0.039) | (0.128) | (0.227) | (0.039) | (0.113) | (0.189) |
| Race_Hispanic | 0.065* | 0.237* | 0.426* | 0.099** | 0.306** | 0.514** |
| | (0.032) | (0.112) | (0.195) | (0.032) | (0.102) | (0.171) |
| Race_Other | 0.030 | 0.130 | 0.242 | 0.061 | 0.211 | 0.348 |
| | (0.039) | (0.130) | (0.223) | (0.039) | (0.121) | (0.203) |
| Republican | −0.410*** | −1.463*** | −2.521*** | −0.493*** | −1.432*** | −2.359*** |
| | (0.025) | (0.097) | (0.182) | (0.025) | (0.085) | (0.147) |
| Independent | −0.165*** | −0.790*** | −1.414*** | −0.277*** | −0.866*** | −1.435*** |
| | (0.025) | (0.099) | (0.187) | (0.025) | (0.083) | (0.142) |
| Party_other | −0.251*** | −1.042*** | −1.843*** | −0.294*** | −0.904*** | −1.506*** |
| | (0.039) | (0.123) | (0.220) | (0.039) | (0.111) | (0.185) |
| Married | −0.009 | −0.036 | −0.068 | −0.028 | −0.094 | −0.153 |
| | (0.031) | (0.105) | (0.180) | (0.031) | (0.097) | (0.163) |
| Head_of_household | −0.015 | −0.054 | −0.095 | −0.038 | −0.136 | −0.238 |
| | (0.039) | (0.139) | (0.238) | (0.039) | (0.129) | (0.217) |
| Household_size | −0.019* | −0.072** | −0.120** | −0.006 | −0.018 | −0.031 |
| | (0.008) | (0.025) | (0.043) | (0.008) | (0.024) | (0.040) |
| Own_house | 0.042 | 0.144 | 0.249 | 0.046· | 0.142· | 0.232 |
| | (0.025) | (0.084) | (0.143) | (0.025) | (0.078) | (0.131) |
| Unemployed | −0.063 | −0.254 | −0.424 | 0.057 | 0.178 | 0.252 |
| | (0.085) | (0.259) | (0.433) | (0.085) | (0.261) | (0.433) |
| Wave_2020 | 0.036 | 0.135 | 0.243 | 0.087* | 0.290* | 0.494* |
| | (0.040) | (0.140) | (0.242) | (0.040) | (0.131) | (0.221) |
| Observations | 2047 | 2047 | 2047 | 2047 | 2047 | 2047 |
| $R^2$ | 0.17 | - | - | 0.20 | | |
| LRI | - | 0.16 | 0.16 | - | 0.16 | 0.16 |
| LnL | - | -1026 | -1028 | - | -1180 | -1181 |
| Wald test p-value | - | 0.000 | 0.000 | - | 0.000 | 0.000 |

*Note:* This table presents the results of regression analyses. Standard errors are in parentheses. Significance levels: * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$., LRI = McFadden's likelihood ratio index.