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The value of COVID-19 tests in Latin America

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Abstract

Testing is a crucial strategy to control the spread of a pandemic. Voluntary participation in this strategy will depend on individual preferences towards and willingness-to-pay (WTP) for test results. We distributed a web-based, contingent valuation survey to social-media users in 16 Latin American countries to evaluate regional attitudes towards the emerging COVID-19 outbreak and WTP for COVID-19 testing. We observe that the cost of the test and household income are important determinants of testing intentions. We find higher WTP among those reporting greater concern relative to the average respondent. Accounting for uncertainty, our results indicate a WTP of approximately $45 dollars or 4.2% of monthly income among respondents. These results, paired with our predicted participation rate of between 84–94% for a $1 test, suggest that local officials will be able to effectively recruit participation in this mitigation strategy given the appropriate subsidization structure.

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1. Introduction

Widespread testing is deemed essential for mitigating global health and economic crises resulting from a pandemic. Yet, little is known about individual preferences (i.e. willingness to pay and intended uptake) for diagnostic tests during these times of crisis. An improved understanding of those preferences may help design public policies aimed at increasing testing rates. We conducted a contingent valuation study to estimate the value that individuals assign to testing for COVID-19 in 16 Latin American countries. We also designed a split-sample treatment to investigate time preferences for test results. To the extent of our knowledge, this is the first study on individual preferences for COVID-19 testing in Latin America and elsewhere. Our study is policy relevant for a region that is in initial stages of the pandemic, and where testing strategies can help flatten the epidemic curve and prevent economic collapse. Our findings indicate that there is a latent demand for COVID-19 tests.

2. Materials and methods

Latin America provided a unique survey site, as one of the last regions in the world to have a confirmed case of coronavirus ([COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University, 2020]). Within our sample, the earliest detected cases were in Brazil (2/26/2020), Mexico (2/28/2020) and Ecuador (2/29/2020), and the latest, Nicaragua and El Salvador (3/18/2020). As shown in Table 1, over the course of two weeks when we collected data, the number of confirmed cases rose from a minimum of 5 additional cases reported in Nicaragua (a 500% increase relative to 3/19 baseline) to 10,509 (1692% increase) in Brazil.1 Detection strategies varied across countries. By mid-June 2020, Chile was conducting about 30,000 tests per million people, and Brazil 4000 tests per million people. Peru followed a different strategy based on rapid testing to improve detection (Ponchner, 2020). As of July 2020, out of the 16 countries in our sample, only Ecuador and El Salvador had an open public testing policy. Eight countries tested individuals with symptoms who met specific criteria (e.g. essential workers and returned from overseas), and six countries tested anyone with COVID-19 symptoms.

1 Appendix Fig. A1 plots the number of confirmed COVID-19 cases by country-day.
The procedure administered one, Table b/See a/
made J.M. Sources:
CSSE

Table 1
Evolution on COVID-19 in Selected Countries and Sample Share by Country.

| Index Case Date* | Confirmed Cases Over Sampling Period* | Testing Policy as of July 2020b | Unweighted Share of the Sample | Weighted Share of the Sample |
|------------------|---------------------------------------|-------------------------------|--------------------------------|-----------------------------|
|                  | Beginning (3/19/2020) | End (4/5/2020)               | Symptoms & Key Groups          |                             |
| Argentina        | 3–3–20                  | 97                           | 1451                          | Symptoms & Key Groups       | 0.213                      | 0.087                      |
| Bolivia          | 3–10–20                 | 12                           | 157                           | Symptoms & Key Groups       | 0.039                      | 0.021                      |
| Brazil           | 2–26–20                 | 621                          | 11,130                        | Anyone with Symptoms        | 0.070                      | 0.316                      |
| Chile            | 3–3–20                  | 238                          | 4471                          | Anyone with Symptoms        | 0.066                      | 0.039                      |
| Colombia         | 3–6–20                  | 102                          | 1485                          | Symptoms & Key Groups       | 0.141                      | 0.100                      |
| Costa Rica       | 3–6–20                  | 69                           | 454                           | Symptoms & Key Groups       | 0.020                      | 0.011                      |
| Dominican Rep.   | 3–1–20                  | 34                           | 1745                          | Symptoms & Key Groups       | 0.031                      | 0.031                      |
| Ecuador          | 2–29–20                 | 199                          | 3646                          | Open public testing         | 0.041                      | 0.031                      |
| El Salvador      | 3–18–20                 | 1                            | 62                            | Open public testing         | 0.054                      | 0.012                      |
| Guatemala        | 3–13–20                 | 9                            | 61                            | Anyone with Symptoms        | 0.037                      | 0.031                      |
| Honduras         | 3–11–20                 | 12                           | 268                           | Symptoms & Key Groups       | 0.048                      | 0.018                      |
| Mexico           | 2–28–20                 | 164                          | 2143                          | Symptoms & Key Groups       | 0.086                      | 0.220                      |
| Nicaragua        | 3–18–20                 | 1                            | 6                             | Symptoms & Key Groups       | 0.076                      | 0.012                      |
| Panama           | 3–10–20                 | 109                          | 1801                          | Anyone with Symptoms        | 0.011                      | 0.008                      |
| Peru             | 3–6–20                  | 234                          | 2281                          | Symptoms & Key Groups       | 0.033                      | 0.066                      |
| Uruguay          | 3–13–20                 | 94                           | 406                           | Symptoms & Key Groups       | 0.034                      | 0.007                      |

Sources:
*CSSE COVID-19 Data Repository.
1/See Roser et al., 2020 https://ourworldindata.org/coronavirus-testing#testing-and-contact-tracing-policy (last accessed on July 11, 2020).

Table 2
Observations by Experimental Design.

| Cost | Waiting Time for Test Results |
|------|-------------------------------|
|      | 1 day | 2 days | 3 days | Total |
| $10  | 370   | 345    | 370    | 1085  |
| $20  | 394   | 365    | 367    | 1125  |
| $30  | 337   | 358    | 385    | 1080  |
| $40  | 393   | 376    | 352    | 1121  |
| $50  | 354   | 362    | 376    | 1092  |
| Total| 1848  | 1806   | 1850   | 5504  |

symptoms. Across the region, more testing is required to prevent the rapid spread of the virus in the region.

We designed a web-based survey to gather information regarding experiences, risk perceptions, and preferences for protective measures in the context of the COVID-19 pandemic. The survey had 28 questions, two of which had conditional follow up questions. We used a snowball sampling strategy to recruit respondents from 16 Latin American countries (see Table 1), with initial recruitment based on social media advertising.2 We administered the survey between March 19 and April 5, 2020. After applying data quality controls (e.g. outliers in sociodemographic variables and inconsistencies in household composition indicating survey inattentiveness or manipulation), our sampling procedure yielded 5504 completed surveys.

Following best practices (Boyle et al., 2017; Johnston et al., 2017), we designed a contingent valuation question to elicit the respondent’s uptake intentions and willingness to pay for a COVID-19 test. The time it would take to get test results could vary among one, two, and three days. The price of the proposed vaccine could take a value of $10 to $50 in increments of $10 (see our experimental design in Table 2).2 Before responding whether or not they would pay that amount, respondents were reminded of their budget constraint to imprint realism to their choice. The (translated) CV question presented in the survey read as follows:

For the following question, assume that you suspect that you or a member of your household is infected with COVID-19. Also assume that there is a test available in any clinic or laboratory that can detect in [1 day, 2 days, 3 days] whether someone is infected with COVID-19. That test would cost [$10, $20, $30, $40, $50]. Keep in mind that the money you spend on the test will not be available for other needs at your home (e.g. food, clothes). Would you pay for the test? (Yes/No)

Using a follow-up question, we elicited the certainty level of respondents regarding their answer to the contingent valuation question. The certainty question was based on a four-point scale varying from very unsure to very sure. We used these replies to reduce hypothetical biases related to the uncertainty of respondents regarding their decision to be tested (Blumschein et al., 2008), which may be particularly important in the initial stages of a disease outbreak. A number of hypothetical versus real comparisons using certainty corrections show that hypothetical bias can be mitigated by recoding favorable responses as negative ones when certainty levels are relatively low (Vossler et al., 2003). Recent contingent valuation studies have utilized similar certainty scales to reduce hypothetical biases (e.g. Ryan et al., 2017; van den Berg et al., 2017b; Vásquez and Rezende, 2019).

3. Theoretical framework and econometric modeling

The CV method is based on a utility-theoretic framework (Boyle et al., 2017). In the context of this study, the indirect utility of a household (Y) is a function of household income (Y), information provided by the COVID-19 test (T), and prices of other goods (P), i.e. \(V(Y, T, P)\). The framework assumes that individuals derive utility from income and from knowing whether they are infected with COVID-19, as that information will allow them to proceed accordingly. The maximum amount that a person will pay to be tested (\(T_0 \rightarrow T_1\)) is equivalent to the income loss that would return their utility to the original level after the test (\(i.e. V(Y, T_0, P_0) = V(T_1, P_1)\)). This implies that WTP is related to the individual’s income, health information, and prices of other goods.

Given the binary format of our CV question (Yes/No), we indirectly identify the maximum WTP using the equivalence between the probability of being willing to pay for the proposed test and the probability that the respondent’s willingness to pay exceeds the cost of the test presented in the contingent scenario \(i.e., Pr(Yes) = Pr(WTP > COST) = Pr(LN(WTP > LN(COST))\). Consequently, the probability of a positive response (Pr) can be

2. We used paid Facebook advertisements and included ‘sharing’ buttons for
Linked-In and Twitter in-survey.
3. While we report US dollars in text, the cost of the test and income brackets were presented to respondents in terms of their national currency. All conversions were made using exchange rates from March 13, 2020.
modeled using the following logit specification:

$$\ln \left( \frac{Pr}{1-Pr} \right) = \alpha \text{ LNCOST } + X \delta + e$$  \hspace{1cm} (1)

where $X$ is the vector of covariates, $\alpha$ and $\delta$ are coefficients to be estimated, and the stochastic error term $e$ is assumed to follow a logistic distribution.

Table 3 presents the variables included in vector $X$. The variable LNCOST is included to investigate how the cost affects the likelihood of being tested. According to our theoretical framework, we expect this effect to be negative because such payment would reduce income available for other goods and services. Two indicators, WAITING2 and WAITING3, depict differentials among our split-sample treatments. Both indicators are expected to have negative effects assuming that individuals would prefer to have information sooner rather than later. We also included socio-demographic variables to control for the heterogeneity of respondents. Based on our theoretical framework, the likelihood of paying for the test increases with household income. The effect of other individual and household characteristics remains to be empirically estimated. All models include country fixed effects and a day-specific time trend to account for heterogeneity across nations and over time as disease burden and anxiety grew.

The amount that the median household is willing to pay for a COVID-19 test (median WTP) can be computed as the exponential of the linear combination of the average of covariates other than LNCOST and corresponding estimated logit coefficients scaled by the negative reciprocal of the logit coefficient of LNCOST:

$$\text{median WTP} = e^{-X / \alpha}$$  \hspace{1cm} (2)

where $X$ is a vector that includes the weighted sample means of covariates (as reported in Table 3) and the sample share of each country (as reported in Table 1), $\alpha$ is the coefficient of LNCOST, and $\delta$ is a vector of logit coefficients of the remaining covariates.

In addition to using the original responses of the full sample of respondents to estimate Eqs. 1 and 2 (Models 1 and 2 in Table 4), we used the follow-up certainty question to recode positive responses as negative if the respondent was uncertain about her decision to be tested for COVID-19 (Models 3 and 4). This approach produces more conservative and arguably more precise WTP estimates (Blumenschein et al., 2008), relevant during a time of substantial uncertainty. We also corrected for potential coverage biases that are typical in web-based surveys, following an iterative proportional fitting (raking) procedure to generate weights that estimate the total population by country of residence, sex, and age (Kolenikov, 2014). In total, we divided the population in the selected Latin American countries in 192 groups (16 countries x 2 sex groups x 6 age groups: 18–24, 25–34, 35–44, 45–54, 55–64, and 65+). In the next section, we present unweighted (Models 1 and 3) and weighted results (Models 2 and 4).

4 For a log-linear specification, the mean WTP can be computed as (median WTP) \* (exp [\(\alpha_X\)], where \(\alpha_X\) is the variance of the model’s error. As a result, model specification errors can directly lead to inflated estimates of the mean WTP (Huang and Smith, 1998). Therefore, we based our analysis on the median WTP, as a more conservative WTP estimate.

5 See Kolenikov (2014) for a theoretical discussion of the iterative proportional fitting method and Stata application, and Lusk and Marette (2010); Ward et al. (2011); Alemi et al. (2018); Huang et al. (2019), and Yu et al. (2019) for recent applications.

6 In robustness tests (available upon request), we substitute the day-specific time trend with a control for lagged confirmed positive cases at the country-day level, to capture local severity and mounting anxiety of the pandemic. The lagged cases variable is insignificant, and the results are unchanged, suggesting that the ‘concern’ indicator captures this relevant information. We also substitute the day-specific time trend with fixed effects to assess the robustness of our results when time effects are modeled using a non-linear specification. Once again, the results are unchanged. Additionally, we find our results to be robust to the wild-cluster bootstrap method.

### Table 3

| Variables       | Definition                                                                 | Unweighted Mean | Weighted Mean |
|-----------------|---------------------------------------------------------------------------|-----------------|---------------|
| LNCOST          | Natural logarithm of the out-of-pocket cost of the test presented in the contingent scenario | 3.262           | 3.262         |
| WAITING2        | If the time to get results is 2 days in the contingent scenario (1=Yes; 0=Otherwise) | 0.328           | 0.333         |
| WAITING3        | If the time to get results is 3 days in the contingent scenario (1=Yes; 0=Otherwise) | 0.336           | 0.334         |
| CONCERNED       | If the respondent is very concerned about COVID-19 (1=Yes; 0=Otherwise)    | 0.578           | 0.546         |
| FEMALE          | Respondent’s sex (1=female; 0=male)                                        | 0.765           | 0.584         |
| AGE             | Respondent’s age (in years)                                               | 36.209          | 39.992        |
| EDUCATION       | Respondent’s education (in schooling years)                               | 15.363          | 16.382        |
| HOUSEHOLD       | Number of household members                                               | 4.567           | 4.175         |
| INCOME          | Monthly household income (in 1000s US$)                                   | 0.777           | 1.074         |

4 For a log-linear specification, the mean WTP can be computed as (median WTP) \* (exp [\(\alpha_X\)], where \(\alpha_X\) is the variance of the model’s error. As a result, model specification errors can directly lead to inflated estimates of the mean WTP (Huang and Smith, 1998). Therefore, we based our analysis on the median WTP, as a more conservative WTP estimate.

5 See Kolenikov (2014) for a theoretical discussion of the iterative proportional fitting method and Stata application, and Lusk and Marette (2010); Ward et al. (2011); Alemi et al. (2018); Huang et al. (2019), and Yu et al. (2019) for recent applications.

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Table 4
Logit Models of Willingness to Pay for a COVID-19 Test (Marginal Effects).

|                | Model 1: Raw Data | Model 2: Raw Data | Model 3: Corrected for Uncertainty | Model 4: Corrected for Uncertainty |
|----------------|-------------------|-------------------|-----------------------------------|-----------------------------------|
| LNCOST         | −0.109 (0.008)*** | −0.106 (0.016)***| −0.103 (0.012)***                 | −0.117 (0.017)***                 |
| WAITING2       | 0.013 (0.011)    | 0.039 (0.012)*** | −0.001 (0.013)                    | 0.015 (0.010)                     |
| WAITING3       | 0.007 (0.009)    | 0.030 (0.013)**  | −0.026 (0.012)                    | −0.025 (0.017)                    |
| CONCERNED      | 0.051 (0.012)**  | 0.058 (0.013)**  | 0.048 (0.011)**                   | 0.043 (0.012)**                   |
| FEMALE         | 0.038 (0.012)**  | 0.027 (0.016)*   | 0.014 (0.014)                     | 0.020 (0.017)                     |
| AGE            | 0.000 (0.000)    | 0.000 (0.000)    | 0.001 (0.000)**                   | 0.001 (0.001)                     |
| EDUCATION      | −0.001 (0.002)   | 0.001 (0.002)    | −0.001 (0.002)                    | 0.001 (0.002)                     |
| HOUSEHOLD      | −0.000 (0.002)   | 0.000 (0.003)    | −0.002 (0.002)                    | 0.001 (0.003)                     |
| INCOME         | 0.149 (0.025)**  | 0.086 (0.022)**  | 0.141 (0.018)**                   | 0.091 (0.019)**                   |
| Pseudo R²      | 0.0645           | 0.0596           | 0.0733                            | 0.0756                            |
| Weights        | No                | Yes              | No                                | Yes                               |

Notes: Observations = 5,504. Standard errors, clustered by country, are reported in parentheses. ***, **, and * imply statistical significance at 1%, 5% and 10% level, respectively. All models include country-fixed effects, and a variable representing the day the survey was completed to depict effects of the growth in reported cases.

Fig. 1. Test Uptake Rates.

Notes: Results based on the raw reported data (certainty-adjusted data) are presented in gray (black), and the weighted estimates are shown with a dashed line. Model 1 – Raw Data, Unweighted; Model 2 – Raw Data, Weighted; Model 3 – Data Corrected for Uncertainty, Unweighted; Model 4 – Data Corrected for Uncertainty, Weighted.

Table 5 shows median WTP estimates for each model, by the time it would take to receive test results. Based on the weighted model with original responses (Model 2), the median person would pay between 142 and 204 US dollars for a COVID-19 test. Conservative estimates indicate that the median person would pay at least 45 US dollars for a COVID-19 test, even of the longest wait time (see Model 3, waiting time = 3 days).

Finally, we consider whether the price elasticity of testing intentions varies with any individual and household-level controls by incorporating interaction terms with LNCOST. Table 6 reports the marginal effects of LNCOST by AGE and CONCERN. We find that concerned and younger respondents’ testing intentions are less responsive to higher fees. For example, we observe a decrease of 6.7 (8.5) percentage points in the probability of testing associated with a 1% increase in cost for concerned (unconcerned) 20-year-olds (Model 6), consistent with the belief that concerned individuals likely want confirmation on disease-status. If we compare by age, we find that while older respondents are more likely to test, they are more price sensitive, i.e. compare the decrease in the probability of testing of 6.7, 11.1, and 15 percentage points for concerned 20, 40 and 60-year-olds, respectively. In contrast, we find no significant differential effects by education, household income, or household size.

5. Discussion and conclusions

We implemented a web-based survey to investigate individual preferences for COVID-19 tests. Our findings suggest that there is a latent demand for COVID-19 tests in the Latin American countries included in this study. The median person would be willing to pay at least 4.2% of the average monthly income for a COVID-19 test (or $45). Our WTP estimates are consistent with charges made by private labs at the beginning of the pandemic (March 2020), of up to $70 in Brazil, $140 in Chile, $80 in Colombia, $300 in Ecuador, $420 in Mexico, and $137 in Uruguay. Policymakers can use these estimates to design subsidization schemes that allow reaching a targeted level of testing, while preventing rent-seeking behaviors amid the pandemic. Our findings also indicate that constituents would support the extension of testing as a strategy to mitigate health and economic consequences of the COVID-19 pandemic.

While our study provides timely and policy relevant information on preferences for COVID-19 testing, more research on this topic is still needed. Future studies can be conducted with more representative samples of respondents at the country level, and consider new tests for antibodies for those not tested during an active infection. Another logical extension to this study would be the analysis of preferences for test accuracy, mode of specimen gathering (e.g. nasopharyngeal, blood samples), and the time it takes for results beyond 1–3 days used in this study, given that respondents were not impatient to receive test results in that window of time. This could have been associated with

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7 Models 5 and 6 build on Models 3 and 4, respectively, adding interaction terms LNCOST*CONCERN and LNCOST*AGE. Due to multicollinearity, CONCERN was omitted from these models. The logit estimates are available in Appendix Table A1.

8 See https://mundo.sputniknews.com/america-latina/202003311090965827-cuanto-cuesta-saber-si-tienes-coronavirus-en-america-latina/ (last accessed on July 11, 2020).
the widespread belief (shared by more than 90% of respondents) that the number of tests available is insufficient to face such an unprecedented pandemic. However, we leave the evolution of such preferences over the course of a pandemic to future investigations.

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**Note:** WTP estimates reported are evaluated at the averages listed in Table 2.

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### Table 5

Median Willingness to Pay Estimates (95% Confidence Intervals).

| Waiting | Model 1: Raw Data | Model 2: Raw Data | Model 3: Corrected for Uncertainty | Model 4: Corrected for Uncertainty |
|---------|-------------------|-------------------|-----------------------------------|-----------------------------------|
| 1 day   | 166.47            | 142.31            | 57.72                             | 70.56                             |
|         | 114.24            | 70.78             | 45.81                             | 51.56                             |
|         | 218.69            | 213.85            | 69.63                             | 89.56                             |
| 2 day   | 187.30            | 204.23            | 57.09                             | 80.10                             |
|         | 126.81            | 62.30             | 46.35                             | 50.60                             |
|         | 247.80            | 346.16            | 67.84                             | 109.60                            |
| 3 day   | 177.35            | 188.05            | 45.04                             | 57.20                             |
|         | 121.88            | 53.02             | 33.58                             | 36.05                             |
|         | 232.82            | 323.09            | 56.50                             | 78.36                             |

### Table 6

Marginal Effects on LNCOST on the Probability of Being Willing to Pay for a COVID-19 Test by Age and Level of Concern.

| AGE | CONCERNED | 20 | 30 | 40 | 50 | 60 | 70 |
|-----|-----------|----|----|----|----|----|----|
| 0   | Based on Model 5: Raw Data | -0.086 (0.012)** | -0.106 (0.014)** | -0.126 (0.021)** | -0.145 (0.029)** | -0.163 (0.038)** | -0.181 (0.046)** |
|     | Yes (1)   | -0.058 (0.007)** | -0.076 (0.008)** | -0.093 (0.016)** | -0.111 (0.024)** | -0.127 (0.032)** | -0.143 (0.041)** |
| 1   | Based on Model 6: Corrected Uncertainty | -0.085 (0.018)** | -0.108 (0.014)** | -0.130 (0.019)** | -0.151 (0.028)** | -0.172 (0.038)** | -0.191 (0.048)** |
|     | Yes (1)   | -0.067 (0.014)** | -0.089 (0.011)** | -0.111 (0.018)** | -0.131 (0.028)** | -0.150 (0.039)** | -0.169 (0.049)** |

**Notes:** Observations = 5,504. Standard errors, clustered by country, are reported in parentheses. ***, ** and * imply statistical significance at 1%, 5% and 10% level, respectively. These marginal effects were estimated based on Models 5 and 6 reported in Appendix Table A1.

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**CRediT authorship contribution statement**

**Jennifer M. Trudeau:** Investigation, Data curation, Writing - original draft. **Jessica Alicea-Planas:** Writing - review & editing. **William F. Vásquez:** Methodology, Formal analysis, Writing - original draft.

**Declaration of Competing Interest**

None.

**Appendix A.**

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**Fig. A1.** Confirmed Cases of COVID-19 by Country-Day.

Note: The legend lists the Latin American countries in rank order of highest to lowest number of cases as of the end date of our survey, 4/5/2020. The number reported in square brackets next to the country name indicates their rank order at the start of the survey on 3/19/2020.
Table A1: Logit Model of Willingness to Pay for a COVID-19 Test with Interaction Terms (Coefficients).

|                | Model 5: Raw Data | Model 6: Corrected for Uncertainty |
|----------------|-------------------|-----------------------------------|
| LNCOST         | -0.216 (0.140)    | -0.165 (0.181)                    |
| LNCOST x CONCERNED | 0.101 (0.021)**   | 0.070 (0.020)**                   |
| AGE            | 0.037 (0.038)**   | 0.040 (0.018)**                   |
| LINCOST x AGE  | -0.011 (0.005)**  | -0.011 (0.006)*                   |
| WAITING2       | 0.202 (0.064)**   | 0.064 (0.044)                     |
| WAITING3       | 0.149 (0.071)**   | -0.126 (0.082)                    |
| FEMALE         | 0.140 (0.084)*    | 0.087 (0.079)                     |
| EDUCATION      | 0.005 (0.012)     | 0.002 (0.008)                     |
| HOUSEHOLD      | -0.001 (0.017)    | 0.005 (0.015)                     |
| INCOME         | 0.466 (0.126)**   | 0.425 (0.094)**                   |
| Pseudo R²      | 0.0613            | 0.0756                            |

Notes: Observations = 5,504. Standard errors, clustered by country, are reported in parentheses. ***, ** and * imply statistical significance at 1 %, 5 % and 10 % level, respectively. Both models include country fixed effects, a variable representing the day the survey was completed to depict effects of the growth in reported cases. Sampling weights are used to estimate both models.

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