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POLICY RESPONSES, SOCIAL NORMS, AND BEHAVIOR CHANGE IN THE TIME OF COVID-19

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SUSTAINABLE DEVELOPMENT GOALS
AND EXTERNAL SHOCKS IN THE MENA REGION:

FROM RESILIENCE TO CHANGE IN THE WAKE OF COVID-19

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Policy responses, social norms, and behavior change in the time of COVID-19

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Abstract

Inducing behavior change is a missing factor in the face of emerging viral threats. Beyond containment and closure policies, cognitive and social factors are key determinants of the public intention to adopt precautionary behavior, such as adjusting their mobility. Using a difference-in-differences fixed-effects framework, we estimate the effects of government containment, closure, and economic policy responses to COVID-19 on changes in human mobility behavior in 132 countries, while accounting for the actual disease risk and the public perception of that risk. We also indicate how social norms, including risk taking, patience, and trust, explain the heterogenous effects of policy responses on behavior change. Our estimates show that the stringency of containment and closure policies decreases human mobility; economic policies lead to a less significant decline. Stronger adjustment in the public mobility behavior originates from their risk perception rather than being policy induced. Examining the heterogeneity in behavior change, we find that risk averse populations and those who exhibit more patience pre-act and lower their mobility independent of public policies. Economic support triggers negative behavioral change in high time-preference settings, where increased mobility is reported, contrary to settings where populations are more patient. Risk communication elicits positive behavioral change among risk-averse and impatient populations, who reduced their mobility; the effect varies by trust in others, specifically politicians.

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1. Introduction and background

With accelerated globalization comes the threat that an infectious disease outbreak in one country will spread rapidly to another. The coronavirus disease (COVID-19) outbreak in the city of Wuhan of China in December 2019 is an example. The rapidly spreading virus, which infected over 100 million people and claimed above two million lives in 223 countries as of 29 January 2021, has deteriorated into one of the worst pandemics.[2] Unprecedented policy measures were enacted by governments to mitigate and contain the pandemic. In the absence of disease treatment and prevention, with more than 50 candidate vaccines in clinical trials, exploiting non-pharmaceutical interventions is paramount. Social distancing and other precautionary behaviors are the main mechanisms adopted by most countries (Anderson et al., 2020). The substantial variability in the individual adoption of precautionary behaviors warrants understanding the factors that motivate or inhibit adoption. In this paper, we examine the interplay between government policy responses to COVID-19 (including those inducing precautionary behavior and other health system and economic policies), cognitive factors (disease risk perception), and social factors (social norms for risk taking, patience, and trust); and the effect of this interplay on behavior change. Evidence on this subject is scattered across the economics and adjacent-fields literatures.

Theoretical models of determinants of behavior change during public health crises argue that *cognitive factors* especially those related to disease risk perception, such as the public perception of the likelihood of infection, severity of illness, personal impact, and coping efficacy, are central to the prediction of health behavior, and that addressing those factors can promote health-behavior change (e.g., Schwarzer, 2001). Empirical evidence confirms this: studies estimated significant effects of cognitive evaluations on adopting precautionary behaviors, especially *self-imposed* measures, during the influenza (H1N1) pandemic (e.g., Ibuka et al., 2010; Van Der Weerd et al., 2011). Against this backdrop, communicating with individuals about the risk of a disease can induce positive behavioral change (Renner & Schwarzer, 2003), especially as risk communication affects both the cognitive and emotional dimensions of risk perception (Oh et al., 2015). The relation between risk perception, communication, and management is conceptually established in the literature (Fischhoff, 1995); later studies reported that the adoption of precautionary behaviors during the 2003 outbreak of severe acute respiratory syndrome (SARS) was largely dependent on effective risk communication, which induced realistic risk perceptions (e.g., Brug et al., 2009). In this regard, the role of the mass media on risk communication in the context of SARS was emphasized (Smith, 2006). Its role was also stressed during the 2009 H1N1 pandemic in the U.S.: studying the dynamics of risk perception and precautionary behavior in response to the pandemic, Ibuka et al. (2010) concluded that the decline in interest in pharmaceutical interventions as well as engagement in precautionary behaviors was correlated with a decline in media attention to H1N1 which resulted in a decreased perceived likelihood of the disease infection. However, in general, it is important to

[2] According to the World Health Organization (WHO) statistics.

emphasize that the effectiveness of risk communication depends on the credibility of and trust in information sources (Williams & Noyes, 2007). This link became apparent during the 2014-15 Ebola viral disease (EVD) epidemic: Liberians with low trust in government were less likely to adopt precautionary behaviors or to comply with Ebola control policies (Blair et al., 2017). However, Van Der Weerd et al. (2011) reported that trust in the government had no effect on the intention of the public to adopt precautionary measures during the influenza (H1N1) pandemic in The Netherlands, but was positively linked to an intention to accept vaccination.

In parallel, several models of health behavior recognized *social factors* as key determinants of adoption of health-related behavior and behavior change (Dempsey et al., 2018). During public health crises, various aspects of the social context, such as social norms, social inequality, culture, and polarization affect the extent and speed of behavior change (Bavel et al., 2020). Latest evidence from COVID-19 indicates that social norms for risk taking, patience, reciprocity, altruism, and trust matter more than government stringency measures for facilitating positive behavior change. Studies reported interesting behavior patterns. First, in settings with risk-averse attitudes, individuals were more likely to adjust their mobility behavior in response to the World Health Organization (WHO) declaration of COVID-19 to be a pandemic before official government lockdowns (Chan et al., 2020; covering 58 countries). Second, stringency measures mattered less in settings where individuals are more patient, altruistic, and trusting, and exhibit less negative reciprocity; the pre-lockdown decrease in mobility in those settings was more significant. Third, trust, a social norm placed between pure altruism and reciprocity, muted mobility responses to government policies. Fourth, more patient, reciprocal, altruistic, and trusting individuals were less likely to increase their mobility again once the mitigation policies were relaxed (Alfaro et al., 2020; covering 45 countries). Fifth, in settings with high levels of political trust, mobility reduction was larger and the effect of policy stringency was more pronounced (Bargain & Aminjonov, 2020; covering 19 European countries and Brodeur et al., 2020; covering U.S. states). These findings may also suggest that individuals respond to other sources of information about disease prevalence and transmission.

Few studies hinted at the potential importance of *affective factors* for understanding health behavior and predicting compliance with precautionary measures during pandemics. For example, Prati et al. (2011) applied a social-cognitive model of pandemic influenza (H1N1) risk perception and behavioral response in Italy. They found that the affective response (feelings of worry about the pandemic) fully mediated the relation between both cognitive and social-contextual factors (except for exposure to media campaigns) and compliance with precautionary behaviors. The affective components of risk perceptions, reflecting worry or anxiety about a threat for example, also received some attention in the psychology literature (Ferrer & Klein, 2015).

As opposed to *self-imposed* measures, the effect of *government-imposed* measures, such as confinement and social distancing, on mitigating health crises has been recently acknowledged. Empirical evidence shows that social distancing, especially that with targeted designs, effectively mitigated the 2009 H1N1 influenza pandemic by interrupting disease transmission (Ahmed et al., 2018; Glass et al., 2006). Recent research on COVID-19 confirms this and shows that similar measures facilitated positive behavioral change measured by human mobility reductions, which helped control the transmission of the disease. For example, Kraemer et al. (2020) found that intensive control measures, including travel restrictions, mitigated the spread and reduced the local transmission of COVID-19 in China. Long-distance travel restrictions had greater impact in the early stage of the outbreak; while strict local control measures, such as social isolation and hygiene, were more effective afterwards. Consistent with this evidence, Flaxman et al. (2020) found that major non-pharmaceutical interventions, particularly lockdowns, had a significant effect on reducing COVID-19 transmission in 11 European countries. Fewer studies argue that, due to the epidemiological behavior of COVID-19, old-style public health measures, including isolation, quarantine, and social distancing, may not be sufficient to control the pandemic and that we need to await vaccines (e.g., Wilder-Smith & Freedman, 2020).

The complex dynamics of behavior change reflected by human mobility adjustment pose a challenge for the isolation of the effect of government responses to COVID-19, mostly large-scale containment and closure policies, on mobility behavior change. It remains unclear if the social distancing practice is the only factor that shapes mobility behavior. Also, the determinants of the heterogenous effects of government policies on changing such behavior remain under-identified. From the previous discussion, we expect cognitive evaluations and social norms to affect mobility behavior change, independent of government-imposed lockdown measures, as well as the magnitude of the response to these measures.

This paper addresses the gap in the literature by answering two main questions. First, what is the effect of government containment, closure, and economic policies versus that of the actual disease risk and the public perception of that risk on behavior change in the context of COVID-19 measured by human mobility adjustment? Second, how do the social norms for risk taking, patience, and trust determine the heterogenous effects of government policy responses to COVID-19 on mobility behavior change? To answer these questions, we use difference-in-differences (DiD) fixed-effects models around the time of policy announcements by governments worldwide between February and August 2020. We separately report the results of the Middle East and North Africa (MENA) region to compare the determinants of behavior change in this region relative to the rest of the world.

The novelty of this study is twofold. First, it is among the first to estimate the effects of cognitive and social factors on the public adoption of precautionary behavior during COVID-19. Importantly, we estimate the effectiveness in promoting positive behavioral change within a holistic framework that accommodates public policy responses and individual preference, among others. Second, this paper provides robust evidence on how social norms can be exploited by policy makers, aiming to influence individual behavior during health crises, to reinforce the effects of containment, closure, and economic policies. Complementing the growing body of research on 'norm-nudges' – nudges whose mechanism of action relies on social norms (for a recent discussion see Bicchieri & Dimant, 2019), we propose a way to exploit social norms to augment the effectiveness of public policy responses to health crises. Specifically, our findings will enable governments to tailor their various responses to the prevailing social norms for risk taking, patience, and trust. Such exercise is particularly relevant as individual behavior is crucial to control the spread of an infectious disease outbreak. In the early phases of a pandemic, compliance with precautionary behavior among the population at risk is the only means to prevent disease spread.

We conclude with a list of findings which include but are not limited to: the stringency of containment and closure policies being associated with positive behavioral change, reflected by a decrease in human mobility; economic support triggering negative behavioral change in high time-preference settings, reflected by an increase in mobility, unlike populations who are more patient; and risk communication eliciting positive behavioral change among risk-averse and impatient populations who reduced their mobility in response, with the effect varying by the level of trust in others, specifically politicians.

2. Conceptual framework

In this study, we hypothesize that cognitive aspects of COVID-19 risk perception contribute more than government measures, especially those imposing precautionary behavior, to positive behavioral change; and that prevailing social norms can explain the heterogenous effects of these measures on the estimated magnitude of change.

2.1 Risk perception

Risk perception – or an individual's perceived susceptibility to a threat – constitutes the cornerstone to many health behavior change theories (Becker, 1977; Waters et al., 2013). Behavior change during pandemics is hence presumed to be basically shaped by the public *perception* of infection risk and other risks associated with different consequences of that infection.

To estimate the effect of risk perception on individual decision making – or the public decision to change their mobility behavior, we explore the cognitive dimension of risk perception, specifically how risk perception is formed at the country level. Judgment about a number of aspects of a disease plays a critical role. Disease *controllability* and *dreadfulness* are highly relevant: the more uncontrollable and dreaded a health threat is regarded, the more pessimistic (i.e., high) is the associated risk perception (Ferrer & Klein, 2015; Slovic, 1987). Perception about the uncontrollability of a disease is exacerbated in the absence of protection or prevention measures (e.g., vaccines) as exposure to the risk of infection is hardly controlled (Smith, 2006).

Familiarity/unfamiliarity with a health threat is another pertinent aspect: the more familiar the risk, the lower the risk perception (Smith et al., 2011). A pessimistic bias is more likely for new health threats, especially those perceived as uncontrollable (Brug et al., 2009). The *immediacy of danger* can also be influential: as looming threats become more imminent, risk perception tends to be more pessimistic (Ferrer & Klein, 2015). One indication is outbreak reporting and spreading in one or more neighboring countries.

Higher *trust* in institutions managing the health threat can lower the public risk perception (Cori et al., 2020). In this context, the importance of *risk communication* – or communication of risk information – in inducing *realistic* risk perception and favorable health behavior is conceptualized in the literature (Brug et al., 2009; Fischhoff, 1995). The effectiveness of this communication depends on the credibility of and trust in information sources (Williams & Noyes, 2007). In this regard, the importance of the mass media in communicating public health threats and altering risk perception has been established (Smith et al., 2011).

Note that risk perception may as well be correlated to the best available determination of the *actual* risk, whose estimates reflect the "objective" probability of occurrence of a threat or danger (Leventhal et al., 1999).

2.2 Heterogeneity in behavior change

Several determinants are anticipated to drive heterogeneity in behavior change during a pandemic. Primary among these are social norms, including individual risk and time preferences as well as trust in others. If an individual is relatively more risk averse, it is likely that s/he adjusts her/his behavior toward "safer" options (Holt & Laury, 2002). In the context of a pandemic, this adjustment happens by relatively decreasing mobility in general or, at least, by reducing the frequency of visits to riskier and non-essential categories of places, such as retail and recreation, versus less risky places, such as residences. Such behavior change occurs even in the absence of knowledge or beliefs about the probability distribution of outcomes associated with alternative choices of action (Oyarzun & Sarin, 2013). If the decision-making process is at group- rather than individual-level, which is probably the case during a pandemic, "safer" options are more likely to be chosen (Masclet et al., 2009). In this sense, when individuals are more risk averse, government containment and closure policies are expected to be less significant; while social distancing measures, especially *stringent* ones, can be more effective in inducing mobility behavior change among risk-loving populations.

Besides risk preference, time preference is crucial to health-related decision making (Ferecatu & Ayse, 2016). Economic theory confirms that higher time preference is associated with less healthy behavior (e.g., Hunter et al., 2018). The intertemporal choices of impatient individuals tend to favor immediate payoffs associated with present mobility patterns over the (potential) health benefits of the preventive behavior of deferring mobility or reducing its frequency. In view of this, a higher time preference is presumed to be associated with a lower likelihood of modifying behavior with respect to mobility in the case of no enactment or, more importantly, no enforcement of containment and closure policies. We also hypothesize that economic policies, particularly those involving income support provision for poor

HHs, can partly offset the foregone economic payoffs of limiting present mobility, especially for patient individuals who are willing to defer consumption.

Finally, *trust in others* can play a tangible role in shaping individual responses to public policies or, generally, policy effectiveness. For the sake of this study, we are primarily concerned with the public trust in politicians, who typically develop public policies, rather than social or general trust.[3] Prior research shows that lower trust in government is associated with lower compliance with rules and regulations (e.g., Horodnic, 2018; Scholz & Lubell, 1998). Populations with higher levels of trust in their respective governments, or trust in politicians more broadly, typically exhibit higher levels of compliance with social distancing measures during a public health crisis.

3. Methods

As government policy responses to COVID-19 are staggered, we propose a DiD fixed effects model to estimate the effect of multiple determinants of the human mobility behavior response to the pandemic. In particular, we compare the daily changes in visits to various locations in countries that adopted COVID-19-related policies (treatment group) with those that did not (control group), before and after policy implementation between 15 February and 11 August 2020. Unlike the standard DiD estimator, with two time period and two groups, we use a general DiD design with multiple time periods and multiple groups to reflect the staggered treatment adoption, following Wooldridge (2012). Country- and time-fixed effects are included in all estimations.

Early adopters of COVID-19 related policies and relatively-late adopting countries presumably differ in observed characteristics, such as incomes and social protection, and unobserved ones too, such as culture and history. The DiD method controls for both observed and unobserved characteristics that are time invariant. By including *country* fixed effects, we eliminate any confounding that might be caused by country effects, whether observed or unobserved, which are constant over time within each country. We additionally account for *day* fixed effect. Time-varying unobserved country heterogeneity is not a concern in our context because our analysis covers a period of less than six months, which is exactly around the time of policy announcements. To further ensure the unbiasedness of our DiD estimates, we report the results of the parallel-trends test in Appendix A and provide evidence of the absence of any unobserved time-varying confounding.

For each country *i* at day *t*, we estimate the following model for each category of places:

$$Y_{it} = \alpha + \beta\, P_{it} + \gamma\, AR_{it} + \delta\, PR_{it} + \zeta\, W_{it} + \eta\, Z_{it} + \theta_i + \lambda_t + \epsilon_{it} \qquad (1)$$

[3] An individual's trust in social actors can differ. An individual, for instance, may have one level of trust in politicians, another in public authorities, and a third level of trust in a neighbor or colleague. Social or general trust, reflecting the degree to which people trust other people who they do not know, is often used in empirical research.

Y_{it} denotes the change in the frequency of visits to various categories of places, such as retail and recreation, groceries and pharmacies, parks, transit stations, workplaces, and residences in country i at day t. P_{it} is a matrix of COVID-19-related containment, closure, and economic policies introduced in country i at day t. AR_{it} denotes the actual risk of COVID-19 which is measured by the risk of illness captured by the (lagged) number of confirmed cases and the mortality risk captured by the (lagged) number of fatalities. PR_{it} is a matrix of factors that shape the public perception of the COVID-19 risk, including disease controllability, the neighborhood effect, disease dreadfulness, risk communication, and familiarity with the disease; these factors are captured by time-varying proxies (see section 5). W_{it} represents the weather effect measured by country-level mean daily temperature, precipitation amount, and mean wind speed. Z_{it} captures the seasonal weekend effect. θ_i and λ_t are sets of country and day fixed effects, respectively.

We cannot strictly refer to β, which captures the effects of government policies, as our DiD coefficient of interest as we are also interested in the effect of risk perception, which is captured by the coefficient δ. Our main hypothesis is that while containment and closure policies, imposing social distancing, and economic and health system policies can achieve positive behavioral change reflected by reducing human mobility, other factors can significantly contribute to this change, such as risk perception and actual illness and mortality risks.

Moreover, we hypothesize that the intensity of behavior change in terms of mobility varies by social norms, specifically risk preference, time preference, and trust in others. Hence, we re-estimate the DiD model and report the estimates by different levels of risk taking, patience, and trust in politicians. The thresholds that determine the constructed groups of each of the examined norms are discussed in section 5. We also separately report the results of MENA to identify what determines behavior change and the magnitude of this change in this region relative to the other regions.

As we expect changes in the frequency of visits within the same country to be serially correlated over time, standard errors are clustered at the country level (Bertrand et al., 2004).

4. Data

5.1 Dependent variables

We rely on human mobility patterns to measure behavior change in the time of COVID-19. We draw from the Google-released, anonymized daily location data on movement trends over time by country across 132 countries from 15 February to 11 August 2020[4]. The data is aggregated by Google from users who have enabled the Location History setting on their accounts. The dataset includes mobility trends for six categories of places: retail and recreation, grocery stores and pharmacies, parks, transit

[4] A comprehensive description of the data coverage, reporting, aggregation, and anonymization is provided online at https://www.google.com/covid19/mobility/.

stations, workplaces, and residences, all of which are useful to social distancing efforts. Daily change in mobility is reported by comparing each day to a baseline (median) value for the corresponding day of the week. Although this dataset does not include people without smartphones, people not carrying their phones to places, etc., it is unlikely that the COVID-19 policies affect such changes in recorded behavior.

5.2 Explanatory variables

Policy responses. We obtain information on COVID-19 government responses and their issue and effective dates for 180 countries from 1 January to 12 August 2020 from the Oxford COVID-19 Government Response Tracker (OxCGRT)[5].

We include seven indicators on containment and closure policies, which reflect closing of schools and universities, closing of workplaces, cancelling public events, limiting private gatherings, closing public transport, staying at home, and restricting internal movement between cities/regions. All indicators are reported on an ordinal scale that reflects the level of strictness of the policy. For example, the variable recording closings of schools and universities takes the discrete values "0" (no measures), "1" (recommend closing or all schools open with alterations), "2" (require closing (only some levels or categories, e.g., just high school, or just public schools), or "3" (require closing all levels).[6] Besides the containment and closure indicators, we include a health system policy indicator on the presence of COVID-19 public information campaigns. The latter takes the discrete values "0" (no Covid-19 public information campaign), "1" (public officials urging caution about Covid-19), or "2" (coordinated public information campaign (e.g., across traditional and social media). The data from the seven containment and closure indicators along with the health system policy indicator are aggregated into a continuous stringency index that takes a value between one and 100.

We also include two indicators on economic policies, which reflect income support and debt/contract relief for HHs. The former captures government provision of direct cash payments to those who lost their jobs or became unable to work as a result of COVID-19. The latter captures government freezing of financial obligations for HHs[7]. Both indicators are reported on an ordinal scale. The data from these two indicators are aggregated into an economic support index that takes a value between one and 100.[8]

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[5] The OxCGRT provides a systematic cross-national, cross-temporal measure to understand how government responses have evolved over the full period of the disease's spread. The project tracks governments' policies and interventions across a standardized series of indicators and creates a suite of composites indices (overall government response index, stringency index, containment and health index, economic support index) to measure the extent of these responses.

[6] A comprehensive description of the policy indicators and their meaning is provided by the *Codebook for the Oxford Covid-19 Government Response Tracker* online at https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/codebook.md

[7] E.g., stopping loan repayments, preventing services like water from stopping, or banning evictions.

[8] Further details on the stringency and economic support indices' construction and methodology are provided online at https://github.com/OxCGRT/covid-policy-tracker

Actual risk. To reflect the actual risk of illness or mortality from COVID-19 at the country level, we include the number of confirmed cases and the number of fatalities. One-day-lagged value is used as we presume that the actual risk impacts individuals' decisions of mobility on a *daily* basis but that the present day's values do not *instantaneously* affect their decisions. Information on confirmed cases and fatalities is availed by the European Centre for Disease Prevention and Control at the country level on a daily basis for the period from 1 January to 14 August 2020. The indicators reflect, more generally, the risk of further escalation of the pandemic.

Risk perception. We include five time-varying indicators to represent cognitive factors that can shape how the public perceives the COVID-19 risk daily at the country level. To reflect the COVID-19 disease controllability, a dummy variable is constructed for the time period starting post the day the WHO announced that "COVID-19 can be characterized as a pandemic" and that "we have never before seen a pandemic that can be controlled" (11 March 2020). To capture the neighborhood effect, we construct a country-level categorical variable that equals "1" if at least one COVID-19 case was confirmed in *one* neighboring country, "2" if at least one case was confirmed in *two* neighboring countries, or "3" if at least one case was confirmed in *three or more* neighboring countries. To reflect COVID-19 dreadfulness, a country-level dummy variable is constructed for the time period post the day the cumulative number of confirmed fatalities reached the concerning 100-fatality threshold.[9] Studies show that individuals are sensitive to health threats that kill the number of people similar to the size of a typical human social circle of about 100 people. Risks threatening a larger number of people (e.g., 1,000) are not perceived to be dreaded more than those killing 100 people (Galesic & Garcia-Retamero, 2012). To capture risk communication, we include a categorical variable that reflects the presence of a COVID-19 public information campaign in a country. As noted, on an ordinal scale, the variable equals "0" if there is no campaign, "1" if public officials are urging caution about COVID-19, or "2" if there is a coordinated COVID-19 public information campaign[10]. To reflect familiarity with the COVID-19 disease, we construct a sequence variable for the days since the first documented death related to COVID-19 by country.

Weather and seasonal effects. To control for the effect of weather variation on human mobility, we extract country daily summaries of mean temperature, precipitation amount, and mean wind speed from over 9,000 weather stations worldwide. This information is obtained for the period from 1 January to 11 August 2020 from the National Oceanic and Atmospheric Administration. A dummy variable is also constructed to control for the seasonal effect of different weekend days across countries on human mobility.[11]

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[9] This naturally covers the time period post the day the cumulative number of confirmed cases reached the concerning 1,000-case threshold.
[10] E.g., across traditional and social media.
[11] A table showing the days of the work week by country is available online at https://en.wikipedia.org/wiki/Workweek_and_weekend.

5.3 Social norms

Risk taking and patience. To explore how behavior change during COVID-19 varies by prevailing social norms, specifically social norms for risk taking and patience, we extract data from the Global Preference Survey on country-level *risk* and *time* preferences (Falk et al., 2016; Falk et al., 2018).[12] A sequence of five quantitative questions and one qualitative question were used to measure *risk* preference. Quantitative questions were binary: a participant had to decide between a fixed lottery, where s/he wins a fixed amount or loses and receives nothing, and varying sure payments, where s/he receives varying *sure* payments. If the participant chose the fixed lottery, the *sure* payment offered by the second option was increased in the subsequent question, and vice versa, to precisely identify her/his certainty equivalent. Responding to the qualitative question, the participant self-rated her/his willingness to take risk on an 11-point Likert scale. Outcomes of the two question formats were finally combined with equal weights (Falk et al., 2016). The constructed variable takes on values within the interval (-0.8, 1). To reflect variation in risk preference, we recode the obtained variable into three equally ranged groups: risk-averse populations have a risk-taking value between -0.8 and -0.2; risk-neutral populations have a risk-taking value between -0.2 and 0.4; and risk-loving populations have a risk-taking value between 0.4 and 1.0. Each group has exactly the same value range.

Similarly, the social norm of patience, also referred to as *time* preference, was measured through a sequence of five quantitative questions and one qualitative question. The former questions were binary: a participant had to make a trade-off between a payment today and higher payments in 12 months. Responding to the qualitative question, the participant self-assessed her/his willingness to wait on an 11-point scale. Outcomes of the two question formats were finally combined with equal weights (Falk et al., 2016). The constructed variable takes on values within the interval (-0.7, 1.1). We recode the variable into three equally ranged groups to reflect variation in time preference: impatient populations have a patience value between -0.7 and -0.1; moderately patient populations have a patience value between -0.1 and 0.5; and patient populations have a patience value between 0.5 and 1.1. Each group has exactly the same value range.

These risk and time preference measures are available at the country level for 76 geographically and culturally diverse countries.

Trust. We explore the heterogenous effects of public policy responses, especially risk communication, on mobility behavior change by the level of trust in others. We obtain the public trust in politicians index for 151 countries from the World Economic Forum Global Competitiveness Index database for the latest available year. The index is constructed based on individual assessments of the ethical standards of politicians in their country. Ranging from "1" (extremely low) to "7" (extremely high), the

[12] A comprehensive description of the data coverage, survey methodology, and questions is provided online at https://www.briq-institute.org/global-preferences/home.

obtained variable is recoded into five equally ranged groups to reflect variation in public trust in politicians: extremely low (1.32, 2.34), low (2.34, 3.36), medium (3.36, 4.38), high (4.38, 5.40), and extremely high (5.40, 6.42). Each group has exactly the same value range.

5. Results and discussion

Tables 1-5 list the DiD fixed effects estimates of our pooled sample. Tables B.1-B.4 in Appendix B list the estimates of the MENA region. We include all relevant regressors in each respective estimation, but we only report the coefficients that are relevant to the discussion in the tables to preserve space and readability.

6.1 Estimated effects on behavior change

Table 1 presents the effects of various determinants of human mobility behavior change during COVID-19. Our results show that the level of strictness of containment and closure policies, captured by the stringency index, is associated with positive behavioral change measured by significant reductions in the frequency of visits to places classified as retail and recreation, grocery and pharmacy, parks, transit stations, and workplaces by 0.54 percentage points (ppts), 0.31 ppts, 0.65 ppts, 0.46 ppts, and 0.35 ppts, respectively. We estimate a significant increase in the stay-at-home response by 0.18 ppts in parallel. Except for parks, the economic support index, reflecting income support and debt/contract relief for HHs, is associated with a slight decrease in the frequency of visits to all places (less than 0.10 ppts) and a slighter significant increase in the stay-at-home response (0.02 ppts).

However, stronger significant adjustment in the public mobility behavior basically originated from their perceptions and feelings, even more than that driven by the actual disease risk (see Table 1). We find that disease uncontrollability, reflected by the WHO declaration of COVID-19 as a pandemic, has a significant effect on mobility change; this effect has higher magnitude than that of actual disease risk (COVID-19 confirmed cases and deaths). Uncontrollability is associated with a significant decline in the frequency of visits to places classified as retail and recreation (18 ppts), grocery and pharmacy (12 ppts), parks (18 ppts), transit stations (26 ppts), and workplaces (29 ppts), with a significant increase in the stay-at-home response (8 ppts). Disease dreadfulness and the immediacy of danger, captured by the neighborhood effect, significantly reduced mobility to non-essential places, such as parks; the magnitude of the reduction induced by the latter is larger, the more the neighboring countries confirming at least one COVID-19 case. The reported coefficients of familiarity with the disease, reflected by the days since first COVID-19 confirmed death, show significant but slight reductions in the frequency of visits to places classified as retail and recreation and parks, providing evidence of how populations become unresponsive as time passes.

In MENA, Table B.1 shows that the level of strictness of containment and closure policies is similarly associated with significant reductions in the frequency of visits to places classified as retail and recreation (0.56 ppts), transit stations (0.32 ppts), and workplaces (0.46 ppts), but had no effect on the frequency of visits to grocery and pharmacy and parks. Moreover, inconsistent with the results of the pooled sample, we find that economic support had no effect on mobility behavior but for residential places (+0.12 ppts); and that risk perception proxied by disease uncontrollability and dreadfulness had no effect on mobility behavior but for transit stations (-32 ppts) and residential places (+2 ppts), respectively. MENA populations also appear to be less responsive to the actual disease risk.

TABLE 1

Estimated effects on mobility behavior change

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
Policy responses						
Stringency index	-0.543***	-0.306***	-0.649***	-0.459***	-0.351***	0.182***
	(0.044)	(0.046)	(0.195)	(0.036)	(0.042)	(0.016)
Economic support index	-0.056*	-0.043*	-0.011	-0.053**	-0.053**	0.021*
	(0.028)	(0.026)	(0.100)	(0.025)	(0.025)	(0.012)
Actual risk						
Lagged (log) COVID-19 cases	-0.741***	-0.256	-0.977	-0.434*	-0.033	0.345***
	(0.248)	(0.229)	(1.072)	(0.221)	(0.240)	(0.103)
Lagged (log) COVID-19 deaths	-1.455**	0.335	-5.644***	-0.492	0.113	0.058
	(0.553)	(0.523)	(1.347)	(0.450)	(0.445)	(0.243)
Risk perception						
COVID-19 disease uncontrollability	-17.688***	-11.938***	18.434	-25.925***	-28.936***	8.448***
	(3.642)	(3.488)	(11.370)	(3.636)	(3.175)	(1.474)
Neighborhood effect (Ref: 0 - No cases in neighbors)						
1 - 1st case in 1 neighboring country	5.621*	0.320	-20.335**	3.458	6.912**	0.952
	(2.850)	(5.193)	(9.779)	(4.491)	(2.815)	(1.914)
2 - 1st case in 2 neighboring countries	3.345	-0.064	-29.495**	-0.040	1.939	3.398
	(4.161)	(5.530)	(12.934)	(6.108)	(3.531)	(2.082)
3 - 1st case in 3+ neighboring countries	5.624	1.037	-31.311*	-0.372	3.804	1.386
	(3.934)	(4.354)	(16.815)	(6.458)	(3.521)	(2.031)
COVID-19 disease dreadfulness	-1.086	0.762	-10.803***	-1.148	-1.767	0.638
	(1.635)	(1.715)	(3.644)	(1.488)	(1.512)	(0.603)
Days since 1st COVID-19 confirmed death	0.121**	0.006	0.559***	0.061	0.026	-0.030
	(0.046)	(0.044)	(0.116)	(0.048)	(0.046)	(0.029)
Weather effect						
Temperature	0.284***	0.132**	1.404***	0.196***	0.064	-0.095***
	(0.053)	(0.057)	(0.339)	(0.062)	(0.051)	(0.019)
Precipitation amount	-0.004	-0.012	-0.086	-0.008	0.008	0.005
	(0.025)	(0.029)	(0.054)	(0.022)	(0.028)	(0.009)
Wind speed	-0.012***	-0.006	-0.020	-0.008**	-0.005	0.004***
	(0.003)	(0.004)	(0.018)	(0.003)	(0.004)	(0.001)
Seasonal effect						
Weekend (Y=1)	-6.223***	-6.310***	-6.714***	-2.888***		-3.698***
	(1.157)	(1.426)	(1.861)	(0.876)		(0.393)
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No of observations	12,427	12,422	12,427	12,427	12,427	12,399

Clustered standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Country fixed effects are included in all estimations.

6.2 Heterogeneity in behavior change

In this section, we estimate how social norms for risk taking, patience, and trust drive the heterogeneity of policy effects on behavior change. We start by disentangling the effects of policy responses, among other mobility determinants, on human mobility change by *risk* preference. Our results in Table 2 show that government containment and closure policy responses to COVID-19, especially that related to restrictions on gatherings and stay-at-home requirements, do not facilitate behavior change among *risk-averse* populations, being associated with an *insignificant* decline in the frequency of visits to all categories of places other than workplaces. This result suggests that *risk-averse* populations are more likely to pre-act and adjust their mobility behavior significantly prior to the enactment of government policies and confirms that individuals typically respond to other sources of information about disease prevalence and transmission. Supporting this argument, we find that the WHO declaration of COVID-19 as a pandemic, reflecting the disease uncontrollability – a key factor in the formation of risk perception, has a higher effect on mobility change among *risk-averse* than *risk-loving* populations. In *risk-averse* settings, the declaration is associated with significant drops in visits to places classified as retail and recreation, grocery and pharmacy, transit stations, and workplaces by 30 ppts, 24 ppts, 33 ppts, and 36 ppts, respectively. In this regard, it is important to note that the WHO pandemic declaration preceded the imposition of lockdown measures of most governments.

In contrast, our results provide evidence that containment and closure policies, imposing precautionary behaviors, are indispensable to induce mobility behavior change among *risk-loving* populations during a pandemic. While COVID-19 uncontrollability and dreadfulness appear to have no effect, restrictions on 10-people-or-less-gatherings or 11-100 people gatherings are associated with significant 36-ppt, 34-ppt, and 41-ppt drops on average in the frequency of visits of *risk-loving* populations to parks, transit stations, and workplaces. Stay-at-home requirements also have highly significant effects on reducing the mobility of *risk-loving* populations; the reported coefficients indicate that the magnitude of the effect is higher the more stringent are the imposed requirements. Most stringently, requiring the public not to leave house with minimal exceptions[13] is associated with the strongest effects in terms of mobility reduction to all places other than residences: retail and recreation (29 ppts), grocery and pharmacy (23 ppts), parks (15 ppts), transit stations (16 ppts), and workplaces (17 ppts) (Table 2).

Moreover, Table 2 shows that risk communication through COVID-19 public information campaigns seems to significantly curb the mobility of *risk-averse* populations to non-essential categories of places, such as parks. This effect occurs regardless of the stringency of risk communication – whether it is in the form of public officials urging caution about COVID-19 (38 ppts) or coordinated COVID-19 public information campaigns (32 ppts). No effects are reported for *risk-loving* populations.

[13] E.g., allowing to leave once a week, allowing only one person to leave at a time

TABLE 2

Estimated effects of policy responses on mobility behavior change *by risk preference*

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
			Risk-averse populations			
Restrictions on gatherings						
(Ref: 0 - No restrictions)						
1 - Restrictions on very large gatherings	-2.093 (2.706)	0.702 (2.925)	27.353** (11.979)	-4.549 (2.517)	-5.806*** (1.659)	-0.690 (1.242)
2 - Restrictions on 101-1,000 people gatherings	-2.356 (2.924)	-3.916 (2.558)	-1.566 (10.757)	-4.062 (2.427)	-4.935** (1.756)	1.370 (0.873)
3 - Restrictions on 11-100 people gatherings	-5.999 (4.667)	-1.108 (3.877)	-5.927 (5.798)	-2.019 (3.719)	-7.344** (3.261)	0.367 (1.455)
4 - Restrictions on 10 people or less gatherings	0.396 (3.476)	-1.623 (2.654)	10.645 (9.724)	1.235 (1.939)	-4.017* (1.969)	0.171 (0.833)
Stay @home requirements						
(Ref: 0 - No measures)						
1 - Recommend not leaving house	-4.042* (1.875)	0.512 (2.819)	-4.043 (10.386)	-4.133 (2.508)	-0.139 (2.808)	-0.014 (0.567)
2 - Require not leaving house but for 'essentials'	-5.929 (3.406)	-1.920 (4.671)	-2.933 (9.498)	-5.176 (4.456)	0.252 (3.979)	0.564 (1.161)
3 - Require not leaving house w/ min exceptions	-8.430 (5.885)	-16.128 (9.904)	-6.996 (12.754)	-13.439 (7.454)	-10.186* (4.949)	4.815 (3.050)
Public info campaigns						
(Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19	4.981** (1.918)	3.742 (3.009)	-37.530* (20.156)	6.635* (3.069)	2.682 (2.219)	-1.548 (1.058)
2 - Coordinated public info campaign	-1.883 (2.793)	-1.902 (2.991)	-31.671* (17.166)	2.158 (3.318)	2.276 (2.349)	0.249 (1.190)
COVID-19 disease uncontrollability	-29.988*** (9.320)	-24.386** (8.381)	-17.069 (10.992)	-32.674*** (8.515)	-35.696*** (9.235)	10.700*** (3.090)
COVID-19 disease dreadfulness	-3.706 (2.925)	-4.909 (2.818)	1.829 (5.197)	-3.142 (2.744)	-5.639** (2.520)	1.373 (0.989)
No of observations	1,773	1,773	1,773	1,773	1,773	1,773
			Risk-loving populations			
Restrictions on gatherings						
(Ref: 0 - No restrictions)						
1 - Restrictions on very large gatherings	-22.740 (11.844)	-4.530 (16.581)	-30.971 (14.878)	-37.152* (13.898)	-53.723** (11.071)	12.139 (7.194)
2 - Restrictions on 101-1,000 people gatherings						
3 - Restrictions on 11-100 people gatherings	-18.950 (11.884)	-4.910 (15.530)	-37.125* (14.525)	-34.027* (13.691)	-42.030** (10.955)	10.653 (7.327)
4 - Restrictions on 10 people or less gatherings	-11.419 (11.651)	-3.389 (15.105)	-34.951* (14.552)	-33.686* (13.774)	-40.704** (10.978)	9.426 (7.104)
Stay @home requirements						
(Ref: 0 - No measures)						
1 - Recommend not leaving house	-12.695** (3.963)	-13.448* (4.887)	-1.870 (5.278)	-7.581 (7.313)	-5.859* (2.350)	3.282 (2.379)
2 - Require not leaving house but for 'essentials'	-19.230** (4.919)	-18.107* (6.456)	-4.661 (4.231)	-11.927 (6.383)	-10.650** (2.638)	5.245* (2.074)
3 - Require not leaving house w/ min exceptions	-29.133*** (2.871)	-23.027*** (2.753)	-15.003** (3.831)	-15.545** (4.539)	-16.977** (3.876)	9.329** (2.032)
Public info campaigns						
(Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19	-3.351 (8.400)	-2.347 (10.598)	4.580 (6.240)	3.731 (6.789)	-0.640 (5.668)	-2.027 (3.803)
2 - Coordinated public info campaign	-0.867 (7.408)	-3.769 (10.106)	5.646 (6.993)	4.364 (7.115)	-0.493 (5.281)	-2.766 (3.667)

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
COVID-19 disease	2.279	12.125**	-6.073	-13.726***	-13.589*	0.419
uncontrollability	(3.864)	(2.102)	(4.509)	(1.857)	(5.615)	(1.591)
COVID-19 disease	1.162	-4.140	-2.437	-1.360	-2.647	-0.520
dreadfulness	(2.184)	(1.988)	(3.377)	(2.671)	(1.189)	(0.818)
No of observations	583	583	583	583	583	583

Clustered standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. On a scale from -0.8 to 1.0, risk-averse populations have a risk-taking value between -0.8 and -0.2; risk-loving populations have a risk-taking value between 0.4 and 1.0. Non-reported explanatory variables include additional five policy indicators on containment and closure policies, two policy indicators on economic policies, and the rest of the actual risk, risk perception, weather effect, and seasonal effect variables listed in Table 1. Country fixed effects are included in all estimations.

In MENA, information on risk preferences is available for nine countries[14], out of which only one has a risk-averse population and only one has a risk-loving population. So, due to insufficient observations, we cannot re-generate Table 2 for the region. Alternatively, we compare mobility behavior change among risk-neutral populations in MENA to that of risk-neutral populations elsewhere (see Table B.2). Our estimates show that containment and closure policies imposing restrictions on 11-100 people gatherings helped achieve positive behavior change among risk-neutral populations in MENA, being associated with significant 30-ppt, 16-ppt, 5-ppt, and 18-ppt drops on average in the frequency of visits to groceries and pharmacies, parks, transit stations, and workplaces. Surprisingly, we observe no effects of any level of restrictions on gatherings among risk-neutral populations elsewhere. Contrary to the other regions, stay-at-home requirements appear to have induced negative behavior change in MENA: recommending not leaving house or requiring not leaving house but for 'essentials' are associated with significant increases in the frequency of visits to parks by 4 ppts and 3 ppts, respectively. We also observe that risk perception and communication through public information campaigns appear to have stronger effects among risk-neutral populations in regions other than MENA.

Next, we disentangle the effects of policy responses, among other determinants, on mobility behavior change by the social norm of patience or *time* preference. Table 3 shows that individuals who are more patient are more likely to lower their mobility to most categories of places independent of government containment and closure policies. Nonetheless, in countries with higher aggregate time preference, these policies appear to have highly significant effects that are larger in magnitude when the imposed policies become more stringent. While *partial* workplace closing, or requiring closing (or working from home) for *some* sectors or categories of workers, is associated with 7-ppt, 11-ppt, and 6-ppt reductions in the frequency of visits of impatient individuals to places classified as retail and recreation, parks, and transit stations, respectively; *full* workplace closing, or requiring closing for *all-but-essential* workplaces[15], is

[14] Algeria, Egypt, Iran, Iraq, Israel, Jordan, Morocco, Saudi Arabia, and United Arab Emirates
[15] E.g., grocery stores, doctors

associated with 9-ppt, 13-ppt, and 10-ppt respective reductions. We also observe that only in the case of *full* workplace closing do we observe a significant decrease in the frequency of visits to workplaces.

Similar behavior change is reported in response to stay-at-home requirements. In high time-preference settings, requiring not leaving house with exceptions for ‘essential’ trips[16] only reduces the frequency of visits significantly to transit stations (6 ppts). However, more stringently, requiring not leaving house with minimal exceptions is associated with significant reductions in the frequency of visits to grocery stores and pharmacies (12 ppts), transit stations (10 ppts), and workplaces (10 ppts) (Table 3).

Interestingly, Table 3 indicates that some economic policies can have an adverse effect on the behavior of impatient populations, inducing more mobility. We find that *stringent* income support for HHs, where the government is replacing 50% or more of lost salary, increases the frequency of visits to non-essential categories of places, such as parks, by 15 ppts, and decreases that to residential places by 4 ppts. It can be that those with high time preference decide to use the provided income support to enjoy the parks – or outdoor lifestyle in general – while it is still possible before it is banned. An opposing behavior is reported for populations who are more patient: *stringent* income support is associated with significant declines in the frequency of visits to places classified as retail and recreation (6 ppts), grocery and pharmacy (6 ppts), parks (42 ppts), and transit stations (4 ppts). Other economic policies, such as broad debt/contract relief, are as well associated with a drop in the mobility of patient populations, especially to transit stations (12 ppts).

These findings align with our hypothesis that although containment and closure policies, imposing precautionary behavior, are crucial to facilitate positive behavioral change in high time-preference settings, economic policies appear to be more influential in low time-preference settings where these policies help offset the foregone economic payoffs of limiting present mobility for patient individuals who are more willing to defer consumption. In this context, it is imperative to note that, besides social norms, the effectiveness of economic policies on the public mobility change can vary by economic endowment (see Table 4).[17] We find that income support for HHs is effective in *low-income* countries: government replacing less than 50% of lost salary has been associated with significant reductions in the frequency of visits to grocery stores and pharmacies (4 ppts), transit stations (7 ppts), and workplaces (7 ppts), with debt/contract relief for HHs being ineffective at all. However, in *middle-* and *high-income*

[16] E.g., daily exercise, grocery shopping

[17] Since compliance with government policy measures, specifically that related to containment and closure, is individually costly; populations with lower-income level can find it harder to adhere as opposed to their counterparts in settings with higher economic endowments (Wright et al., 2020). Also, in view of the enormous increase in economic uncertainty in the time of pandemics (Baker et al., 2020), we anticipate the effectiveness of different economic policies to vary by economic endowment. Our intuition is that extending *direct* income support for poorer population, for example, in the form of cash payments to individuals who lost their jobs during a pandemic, can be more effective in limiting their mobility than less *explicit* policies, such as debt relief in the form of freezing financial obligations. Our rationale is that high-income individuals tend to have higher debt liabilities (Mason, 2018). To explore the heterogenous effects of economic support policies on mobility behavior change by the economic endowment level, we rely on the latest income classification of economies by the World Bank, grouping countries into low-income, middle-income, and high-income countries.

countries, debt/contract relief seems to be the effective economic policy: government *broadly* freezing the financial obligations for HHs is associated with significant declines in the frequency of visits to grocery stores and pharmacies (4 ppts), transit stations (3 ppts), and workplaces (3 ppts). One explanation is that, given the high economic uncertainty during the COVID-19 pandemic, providing *direct* cash payments to individuals with lower incomes can be more reassuring and thus effective in reducing their mobility than less *explicit* policies, such as debt relief that is typically more customized for higher-income individuals with higher debt liabilities. Table 4 further shows that stay-at-home requirements appear to be costly in all income settings but are more perceived to be so in low-income countries, entailing more stringent requirements and enforcement. Most stringently, requiring not leaving house with minimal exceptions is associated with a significant drop of 16 ppts in the mobility of individuals in low-income countries to workplaces, which is double the magnitude reported for middle- or high-income countries.

In parallel, our results in Table 3 emphasize the importance of risk communication policies, for example through public information campaigns, for achieving positive behavioral change during public health crises in settings with higher aggregate time preference. However, our estimates show that this change has been attained in the context of COVID-19 only when public campaigns are coordinated ones and not in the simple form of public officials urging caution about COVID-19. The former is associated with a significant drop in the frequency of visits to parks by 12 ppts.

In MENA, information on time preferences is available for nine countries[18], out of which five have impatient populations, four have moderately patient populations, while no country has a patient population. We cannot re-generate Table 3 for the region and, instead, compare mobility behavior change among impatient and moderately patient populations in the region (see Table B.3). Inconsistent with the results of the pooled sample, individuals who are more patient in MENA are *not* more likely to lower their mobility independent of government containment and closure policies. In fact, Table B.3 provides evidence that if workplace closing is not stringent, it induces negative behavior change in the region, being associated with significant increases in the frequency of visits of impatient populations to places classified as retail and recreation (33 ppts), grocery and pharmacy (19 ppts), and parks (28 ppts), and even a decline in the frequency of visits to residences (8 ppts). Even among moderately patient MENA populations, we still observe significant (but lower) increases in the mobility to places classified as retail and recreation (13 ppts) and parks (19 ppts). however, stay-at-home requirements are associated with positive mobility behavior change among the two types of populations in the region.

[18] Algeria, Egypt, Iran, Iraq, Israel, Jordan, Morocco, Saudi Arabia, and United Arab Emirates

TABLE 3

Estimated effects of policy responses on mobility behavior change *by time preference*

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplace s	Residential
			Impatient populations			
Workplace closing (Ref: 0 - No measures)						
1 - Recommend closing/work from home	2.737	8.349**	6.632	3.687**	3.276	-2.759***
	(3.438)	(3.296)	(5.926)	(1.782)	(2.562)	(0.987)
2 - Require partial closing/work from home	-6.537*	-2.983	-11.132*	-5.568**	-2.906	1.226
	(3.391)	(3.035)	(5.482)	(2.241)	(3.038)	(1.116)
3 - Require full closing/work from home	-8.520**	-4.594	-13.395**	-10.122***	-5.738*	2.707**
	(3.895)	(3.615)	(5.832)	(3.057)	(3.208)	(1.190)
Stay @home requirements (Ref: 0 - No measures)						
1 - Recommend not leaving house	-3.684	-2.557	6.335	-6.259**	-1.018	0.345
	(3.294)	(2.350)	(4.169)	(2.535)	(1.923)	(0.881)
2 - Require not leaving house but for 'essentials'	-4.697	-3.153	4.145	-5.650**	-2.283	0.805
	(3.753)	(3.075)	(5.670)	(2.086)	(2.621)	(1.044)
3 - Require not leaving house w/ min exceptions	-7.233	-12.034***	4.456	-9.585***	-10.219***	3.665**
	(4.237)	(3.998)	(7.429)	(3.204)	(3.309)	(1.413)
Income support for HHs (Ref: 0 - No support)						
1 - Government replacing <50% of lost salary	-2.595	0.410	-1.867	-1.228	-0.687	-0.160
	(3.204)	(2.310)	(3.519)	(2.409)	(2.590)	(0.881)
2 - Government replacing >=50% of lost salary	8.319*	1.774	15.221***	4.124	6.033*	-3.888***
	(4.448)	(4.095)	(4.356)	(3.263)	(3.252)	(1.052)
Debt/contract relief for HHs (Ref: 0 - No relief)						
1 - Narrow relief, specific to one kind of contract	2.063	4.888**	1.648	4.038	1.977	-1.960*
	(3.330)	(2.368)	(4.835)	(2.461)	(2.536)	(1.034)
2 - Broad debt/contract relief	-2.195	-2.032	-3.737	0.364	-1.805	0.374
	(2.742)	(3.041)	(3.818)	(2.626)	(2.558)	(1.004)
Public info campaigns (Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19	4.400	6.435	-5.941	4.342	3.425	-1.344
	(5.210)	(3.996)	(5.917)	(4.503)	(4.320)	(1.975)
2 - Coordinated public info campaign	-3.049	0.974	-11.702***	-1.884	-1.951	0.485
	(2.737)	(2.551)	(4.170)	(2.283)	(2.798)	(1.257)
No of observations	3,962	3,962	3,962	3,962	3,962	3,962
			Patient populations			
Workplace closing (Ref: 0 - No measures)						
1 - Recommend closing/work from home	0.021	-0.175	9.896	-0.976	-0.039	-0.512
	(2.427)	(5.029)	(16.156)	(2.204)	(2.123)	(0.780)
2 - Require partial closing/work from home	-4.173	-1.506	5.591	-4.420**	-2.020	0.592
	(2.329)	(4.521)	(18.018)	(1.716)	(2.373)	(0.500)
3 - Require full closing/work from home	-7.223	-4.874	-5.279	-8.471***	-5.267	2.047*
	(4.708)	(5.220)	(21.004)	(2.296)	(4.039)	(0.989)
Stay @home requirements (Ref: 0 - No measures)						
1 - Recommend not leaving house	-5.114*	-2.405*	-13.366	-6.227**	-0.069	2.291**
	(2.432)	(1.067)	(18.024)	(2.025)	(3.008)	(0.813)
2 - Require not leaving house but for 'essentials'	0.189	-2.402	1.968	-3.946	-2.888	1.681
	(5.337)	(2.225)	(21.936)	(2.568)	(4.245)	(1.073)
3 - Require not leaving house w/ min exceptions	3.789	-2.950*	-50.637	-3.088	3.084	1.289
	(6.954)	(1.555)	(28.254)	(3.627)	(3.994)	(1.202)

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
Income support for HHs (Ref: 0 - No support)						
1 - Government replacing <50% of lost salary	11.656***	5.159	-28.180	3.042	13.130***	-3.755***
	(2.769)	(4.139)	(25.878)	(3.805)	(2.621)	(0.990)
2 - Government replacing >=50% of lost salary	-6.036**	-5.995***	-41.981*	-3.704**	-3.888	1.297**
	(1.880)	(1.645)	(19.993)	(1.284)	(2.450)	(0.469)
Debt/contract relief for HHs (Ref: 0 - No relief)						
1 - Narrow relief, specific to one kind of contract	4.478**	2.928	30.199**	-0.893	0.412	-0.311
	(1.578)	(1.658)	(11.890)	(1.229)	(1.177)	(0.396)
2 - Broad debt/contract relief	-11.705*	-8.707	-16.458	-12.287***	-7.912	3.679**
	(5.024)	(4.739)	(19.405)	(3.434)	(4.308)	(1.093)
Public info campaigns (Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19	6.803	3.099	-17.674	-7.168*	-1.477	1.005
	(4.546)	(3.126)	(15.793)	(3.166)	(3.799)	(1.287)
2 - Coordinated public info campaign	3.465	1.768	0.571	-2.243	-0.639	0.260
	(2.343)	(2.572)	(5.010)	(2.275)	(2.761)	(0.772)
No of observations	1,408	1,408	1,408	1,408	1,408	1,408

Clustered standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. On a scale from -0.7 to 1.1, impatient populations have a patience value between -0.7 and -0.1; patient populations have a patience value between 0.5 and 1.1. Non-reported explanatory variables include additional five policy indicators on containment and closure policies and the rest of the actual risk, risk perception, weather effect, and seasonal effect variables listed in Table 1. Country fixed effects are included in all estimations.

Contrary to the findings of the pooled sample, income support appears to help achieve positive behavior change in MENA even among impatient populations: government replacing less than 50% of lost salary has been associated with significant reductions in the frequency of visits to grocery stores and pharmacies (11 ppts) and workplaces (7 ppts). As in the rest of the world, risk communication through coordinated public information campaigns seem to have a greater effect on impatient than moderately patient populations in MENA. The estimated effect on the reduction in the mobility of impatient populations in MENA is higher in magnitude and more significant compared to impatient populations elsewhere. Specifically, coordinated public information campaigns are associated with 11-ppt, 7-ppt, and 7-ppt drops in the frequency of MENA impatient populations visits to parks, transit stations, and workplaces, respectively; in addition to a significant 3-ppt increase in the mobility to residential places.

TABLE 4

Estimated effects of economic support on mobility behavior change *by economic endowment*

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
			Low-income countries			
Income support for HHs (Ref: 0 - No support)						
1 - Government replacing <50% of lost salary	-2.341	-4.262**	1.012	-7.222**	-7.145***	0.378
	(1.258)	(1.308)	(1.511)	(1.952)	(1.671)	(0.427)
2 - Government replacing >=50% of lost salary						
Debt/contract relief for HHs (Ref: 0 - No relief)						
1 - Narrow relief, specific to one kind of contract	0.570	3.387	-1.396	-0.679	2.651	0.193
	(2.630)	(2.780)	(2.908)	(2.121)	(2.390)	(1.671)
2 - Broad debt/contract relief	-4.482	-2.386	-6.967	-0.758	2.025	3.101
	(5.739)	(6.738)	(5.398)	(2.667)	(5.080)	(3.723)
Stay @home requirements (Ref: 0 - No measures)						
1 - Recommend not leaving house	-11.747***	-13.512***	-6.621**	-4.403*	-14.732***	6.401***
	(1.930)	(2.721)	(2.068)	(2.025)	(3.906)	(1.154)
2 - Require not leaving house but for 'essentials'	-9.743**	-12.480***	-3.994*	-1.477	-10.831*	4.543**
	(3.186)	(2.854)	(1.941)	(1.486)	(4.749)	(1.440)
3 - Require not leaving house w/ min exceptions	-12.930***	-16.094***	-7.817**	-4.647	-16.410**	6.038**
	(3.226)	(3.943)	(2.428)	(3.296)	(5.362)	(1.728)
No of observations	958	958	958	958	958	958
			Rest of countries (Middle/high-income)			
Income support for HHs (Ref: 0 - No support)						
1 - Government replacing <50% of lost salary	-1.066	0.436	-7.830	-0.201	-1.288	-0.111
	(1.570)	(1.475)	(5.026)	(1.431)	(1.329)	(0.597)
2 - Government replacing >=50% of lost salary	3.115	3.261	12.993*	1.643	0.280	-1.027
	(2.584)	(2.550)	(7.617)	(2.297)	(1.975)	(0.986)
Debt/contract relief for HHs (Ref: 0 - No relief)						
1 - Narrow relief, specific to one kind of contract	1.263	1.425	15.434**	0.511	0.044	-0.707
	(1.763)	(1.607)	(5.921)	(1.651)	(1.522)	(0.634)
2 - Broad debt/contract relief	-3.127	-3.803**	-3.143	-3.367**	-2.604*	1.136
	(1.898)	(1.585)	(5.517)	(1.475)	(1.497)	(0.712)
Stay @home requirements (Ref: 0 - No measures)						
1 - Recommend not leaving house	-4.488**	-3.017*	-8.920	-4.726**	-0.728	1.371*
	(2.030)	(1.613)	(6.094)	(1.867)	(1.468)	(0.791)
2 - Require not leaving house but for 'essentials'	-8.325***	-5.551***	-8.273	-8.159***	-5.231***	2.900***
	(2.449)	(2.073)	(6.698)	(1.977)	(1.889)	(0.818)
3 - Require not leaving house w/ min exceptions	-10.860***	-12.373***	-2.780	-11.853***	-8.104***	4.827***
	(2.791)	(2.453)	(7.244)	(2.331)	(2.334)	(1.010)
No of observations	11,467	11,462	11,467	11,467	11,467	11,439

Clustered standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Non-reported explanatory variables include additional six policy indicators on containment and closure policies, one policy indicator on public information campaigns, and all the actual risk, risk perception, weather effect, and seasonal effect variables listed in Table 1. Country fixed effects are included in all estimations. The latest income classification of economies by the World Bank is used, grouping countries into low-income, middle-income, and high-income countries.

Our results of the pooled sample confirm that the effectiveness of risk communication in promoting behavior change during a pandemic depends on trust in others, specifically politicians (see Table 5). Only in countries with extremely high trust in politicians do we observe significant decreases in the public mobility irrespective of the form of related public information campaigns. Interestingly, less organized campaigns can be sufficient or even more influential in changing the behavior of the public in these countries. Public officials urging caution about COVID-19 is associated with 15-ppt, 10-ppt, and 9-ppt significant reductions in the frequency of visits to places classified as grocery and pharmacy, transit stations, and workplaces, respectively. These magnitudes are larger than those reported for *coordinated* COVID-19 public information campaigns: grocery and pharmacy (14 ppts), transit stations (7 ppts), and workplaces (4 ppts).

Table 5 reveals another behavioral pattern: in settings with extremely low trust in politicians, urging caution about COVID-19 by public officials appears to have stimulated irrational or unfavorable behaviors, such as panic buying or stockpiling. Such behaviors are captured by the reported significant increase in the frequency of visits to grocery stores and pharmacies by 16 ppts. Our justification is that the delivery of caution messages by public officials in these settings provoked high levels of anxiety and fear that have been aggravated by the public lack of trust in their government and its capability to manage the looming health crisis.

Finally, Table 5 shows that compliance with stay-at-home requirements was not strictly influenced by the level of the public trust in politicians. It can be that higher trust in politicians ensures voluntary compliance with stay-at-home and other lockdown rules. In countries with lower trust, lockdown *enforcement* can play a more pivotal role in public compliance.

As for MENA, information on trust in others, specifically politicians, is available for 18 countries[19], out of which three have extremely low trust, five have low trust, five have medium trust, three have high trust, and two have extremely high trust in politicians. Since we cannot re-generate the exact Table 5 for the region due to insufficient observations, we report the joint estimates of three groups of countries: (1) extremely low and low trust, (2) medium trust, and (3) high and extremely high trust in politicians (see Table B.4). Similar to the other world regions, in MENA, the effectiveness of risk communication in promoting behavior change depends on the level of trust in others, specifically politicians. Only among MENA populations with high trust in politicians do we observe significant reductions in the mobility to places classified as retail an recreation (8 ppts), parks (16 ppts), transit stations (12 ppts), and workplaces (10 ppts) in association with coordinated public information campaigns.

[19] Algeria, Bahrain, Egypt, Iran, Israel, Jordan, Kuwait, Lebanon, Libya, Malta, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, United Arab Emirates, and Yemen

TABLE 5

Estimated effects of risk communication on mobility behavior change *by level of trust*

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
(Extremely) low trust in politicians						
Stay @home requirements						
(Ref: 0 - No measures)						
1 - Recommend not leaving house	-0.722	-3.049	-3.509	-0.255	1.045	-1.117
	(2.950)	(2.490)	(6.486)	(1.945)	(2.225)	(1.135)
2 - Require not leaving house but for 'essentials'	-7.676**	-7.677**	-6.384	-4.903*	-2.914	1.169
	(3.237)	(2.912)	(7.263)	(2.650)	(2.796)	(1.290)
3 - Require not leaving house w/ min exceptions	-11.428***	-13.420***	-6.345	-7.272**	-7.087**	3.560**
	(3.895)	(3.294)	(6.808)	(3.049)	(3.373)	(1.520)
Public info campaigns						
(Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19	11.711**	16.491***	26.400**	12.770***	9.364**	-3.601*
	(4.511)	(4.384)	(10.264)	(3.785)	(4.535)	(1.814)
2 - Coordinated public info campaign	6.025	10.678***	13.087*	4.606*	4.748	-1.589
	(3.850)	(3.503)	(7.685)	(2.590)	(3.745)	(1.274)
No of observations	4,433	4,432	4,433	4,433	4,433	4,433
Medium trust in politicians						
Stay @home requirements						
(Ref: 0 - No measures)						
1 - Recommend not leaving house	-4.810	-3.121	-5.727	-8.607**	-1.710	2.490
	(3.765)	(2.557)	(5.726)	(2.870)	(2.923)	(1.573)
2 - Require not leaving house but for 'essentials'	-6.189	-2.301	-1.012	-7.156**	-4.494	2.641*
	(4.622)	(3.532)	(4.551)	(2.895)	(2.961)	(1.249)
3 - Require not leaving house w/ min exceptions	-10.864**	-11.500	-1.571	-14.050**	-8.541**	4.506**
	(4.412)	(6.507)	(6.131)	(5.769)	(3.917)	(2.084)
Public info campaigns						
(Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19	-2.761	1.702	-14.225	-10.491**	-5.035*	1.237
	(10.096)	(5.799)	(16.513)	(4.468)	(2.765)	(2.893)
2 - Coordinated public info campaign	-8.251	-5.154	-10.955	-11.511***	-11.102***	2.333
	(8.157)	(4.838)	(9.818)	(3.229)	(2.330)	(2.451)
No of observations	2,171	2,171	2,171	2,171	2,171	2,145
(Extremely) high trust in politicians						
Stay @home requirements						
(Ref: 0 - No measures)						
1 - Recommend not leaving house	-3.241	3.008	-25.251**	-1.195	3.071	1.882**
	(2.774)	(3.677)	(10.462)	(2.255)	(3.362)	(0.775)
2 - Require not leaving house but for 'essentials'	-1.624	4.207	-28.293**	-2.154	-1.647	3.251**
	(4.835)	(2.638)	(10.642)	(2.708)	(2.669)	(1.203)
3 - Require not leaving house w/ min exceptions	3.992	4.322	-0.146	1.891	-5.067	1.521
	(5.472)	(3.120)	(12.257)	(3.630)	(3.516)	(1.741)
Public info campaigns						
(Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19	-7.189	-15.487**	14.129	-10.113*	-8.989*	1.681
	(5.277)	(4.956)	(30.167)	(4.709)	(4.644)	(1.468)
2 - Coordinated public info campaign	-4.801	-14.156***	-6.464	-6.525	-3.598	1.826
	(4.169)	(4.241)	(20.767)	(4.084)	(3.503)	(1.221)
No of observations	1,706	1,702	1,706	1,706	1,706	1,704

Clustered standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. On a scale from 1 (= extremely low) to 7 (= extremely high), a value between 1.32 and 2.34 denotes extremely low trust; a value between 3.36 and 4.38 denotes medium trust; and a value between 5.40 and 6.42 denotes extremely high trust in politicians. Non-reported explanatory variables include seven policy indicators on containment and closure policies, two policy indicators on economic policies, and all the actual risk, risk perception, weather effect, and seasonal effect variables listed in Table 1. Country fixed effects are included in all estimations.

However, dissimilar to the rest of the world, it appears that high trust in politicians in MENA is associated with negative mobility behavioral responses to the stay-at-home requirements, possibly due to the stronger trust in the government capability of crises management.

Study limitations. The study has a number of limitations. Although the constructed dataset covers both developed and developing countries, which is an attractive feature of the analysis, this brings its own concerns: the possibility of missing country-specific details. One example is averaging weather at the country level. We also realize that exposure to COVID-19 and the risks associated with the infection are not the same for different health statuses, for younger and older individuals, for women and men, etc., which can affect mobility change within a country. However, we trust this disturbance to be very small or inexistent in a country-level analysis because such socio-demographic characteristics are not expected to change within a country in a period of less than six months, which is the case in this study. Country fixed effects are included to account for time-invariant country characteristics.

6. Conclusion

Our findings provide pertinent information regarding how government containment, closure, and even economic support policies affect the public intention to adopt precautionary behavior by changing their mobility behavior for example, resulting in the effective control of COVID-19 at the early stages. We show that the stringency of these policies is associated with a significant decline in human mobility. However, we find that other cognitive factors especially those related to the public perception of the COVID-19 risk are critical determinants of behavior change during the pandemic.

Examining how social norms affect behavior change, our results indicate that risk-averse populations and populations who are more patient are more likely to pre-act and lower their mobility independent of containment and closure policies. These policies are yet essential to achieve positive behavioral change during public health crises among risk-loving and impatient. Our results also indicate that while containment and closure policies are crucial to induce mobility behavior change among impatient populations, economic support policies appear to have greater impact in low time-preference settings. Income support is the effective economic policy response in low-income countries and debt relief is the effective one in higher-income countries. Effective risk communication through public information campaigns plays a pivotal role among risk-averse and, importantly, impatient populations. Nonetheless, its effectiveness in promoting behavior change varies by trust levels, specifically trust in politicians.

Comparing mobility behavior change in the MENA region to the rest of the world, our estimates show that MENA populations are less responsive to the level of strictness of containment and closure policy responses to COVID-19 as well as the actual disease risk. Risk perception also appears to play a less significant role in inducing behavior change in the region. Comparing behavioral responses of risk-neutral populations in the MENA to elsewhere, we find that while containment and closure policies imposing restrictions on gatherings helped achieve positive behavior in MENA with no effects being observed elsewhere, stay-at-home requirements appear to have induced negative behavior change in the region, facilitating the public mobility to parks. Risk perception and communication appear to have stronger effects among risk-neutral populations in other world regions. We also provide evidence that, in settings with high time preference, workplace closing can result in a negative behavior change. Imposition of stay-at-home requirements and risk communication are central to curb the public mobility in these settings. Similar to the other world regions, in MENA, the effectiveness of risk communication in promoting behavior change depends on the level of trust in politicians. However, high trust in politicians is associated with negative mobility behavioral responses to the stay-at-home requirements, possibly due to the stronger trust in the government capability of crises management.

The findings of this paper provide timely implications for enhancing the effectiveness of precautionary activities against the global spread of future viral threats while harnessing the power of social norms to facilitate positive behavioral change during public health crises. Risk management strategies aiming at the rapid adjustment of individual behavior will continue to be one of the frontline policy responses available to governments in the face of new viral threats. Besides confinement and social distancing interventions, policy makers should navigate policy options that seek to engage and change public risk perceptions. A relevant policy option is risk communication or, broadly, information dissemination and media reporting. Our findings also suggest that, to augment the effectiveness of public policy responses during public health crises, governments should tailor them to the prevailing social norms for risk taking, patience, and trust.

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Appendix A: Robustness checks

The key identifying assumption of DiD application in this study is parallel trends in the human mobility of early and relatively-late adopters of policy responses to COVID-19 in the absence of the pandemic and related responses. As noted earlier, government policy responses (treatment) are staggered in days (time) across countries (groups). To test for pre-treatment parallel trends in this setting, we allow for "leads" and "lags" of the treatment and then check the coefficients on all leads of the treatment, following Angrist and Pischke (2009) and Autor (2003). The model becomes

$$Y_{it} = \theta_i + \lambda_t + \sum_{\tau=1}^{q=7} \beta_{+\tau}\, P_{i,t+\tau} + \sum_{\tau=0}^{m=7} \beta_{-\tau}\, P_{i,t-\tau} + X_{it}\xi + \epsilon_{it} \qquad (A.1)$$

Instead of a single treatment effect, we also include seven q leads and seven m lags of the treatment effect. The coefficients on the former (β_{+1}, β_{+2}, …, β_{+7}) capture a one-week anticipatory effects; and the coefficients on the latter (β_{-1}, β_{-2}, …, β_{-7}) capture a one-week post-treatment effects. The policy variable of interest, $P_{i,t}$, denotes the enactment of stay-at-home requirements in country i at day t. X_{it} is a vector of country- and day-varying covariates, including other determinants of human mobility (see equation (1)). The definitions of Y_{it}, θ_i, λ_t are as before.

Conditional on country and day effects and other mobility determinants, past $P_{i,t}$ should predict Y_{it} while future $P_{i,t}$ should not. Accordingly, one test of the DiD assumption is $\beta_{+\tau} = 0 \; \forall \tau > 0$; i.e., the coefficients on the leads should be equal (or close) to zero and insignificant.

Table A.1 depicts the estimated anticipated and post-treatment effects of stay-at-home requirements on mobility to seven categories of places, as in the main estimation results. The reported leads and lags run from seven days ahead to seven days behind – a total window of 15 days. The pattern of the coefficients on the adoption leads show no effects in the seven days before the countries adopted any stay-at-home requirement, with sharply increasing effects on the day of adoption and the day after, which then appear to fade over the subsequent six days. This pattern provides robust evidence that adoption of stay-at-home requirements led the decline in mobility rather than vice versa, indicating that the DiD strategy is successful in our context. As almost all countries worldwide adopted policies in response to COVID-19, a "never-treated" group of countries is almost not available or "too small." To accommodate this, our approach to test the DiD identification strategy allows us to exploit more groups of countries as valid comparison units, potentially leading to more informative inference procedures.

TABLE A.1

Estimated anticipated and post-treatment effects of stay-at-home requirements

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
Stay @home requirements						
(Ref: 0 - No measures)						
$P_{i,t+7}$	-1.120	0.696	-4.220	-0.958	-1.299	0.032
	(1.247)	(1.418)	(3.320)	(1.128)	(1.311)	(0.476)
$P_{i,t+6}$	0.475	2.135	-0.876	0.619	1.417	0.133
	(1.715)	(1.950)	(4.564)	(1.551)	(1.803)	(0.654)
$P_{i,t+5}$	-1.800	-2.231	-1.672	-1.430	-0.901	0.241
	(1.692)	(1.924)	(4.504)	(1.531)	(1.779)	(0.645)
$P_{i,t+4}$	-0.897	1.504	1.835	-0.273	-1.068	0.064
	(1.655)	(1.882)	(4.406)	(1.497)	(1.740)	(0.631)
$P_{i,t+3}$	0.575	-0.834	1.597	1.311	1.776	-0.410
	(1.645)	(1.870)	(4.378)	(1.488)	(1.729)	(0.627)
$P_{i,t+2}$	-0.354	1.103	0.044	-0.439	-0.694	0.126
	(1.612)	(1.833)	(4.290)	(1.458)	(1.694)	(0.614)
$P_{i,t+1}$	0.561	2.644	-2.004	-0.571	-0.570	0.194
	(1.578)	(1.794)	(4.199)	(1.427)	(1.659)	(0.602)
$\boldsymbol{P_{i,t0}}$	**-5.944*** **	**-6.160*** **	**-1.453**	**-4.496*** **	**-4.230** **	**2.091*** **
	(1.576)	**(1.792)**	**(4.194)**	**(1.426)**	**(1.657)**	**(0.601)**
$P_{i,t-1}$	-3.692**	-3.426*	-5.787	-3.567**	-1.559	1.547***
	(1.567)	(1.782)	(4.171)	(1.418)	(1.648)	(0.598)
$P_{i,t-2}$	-0.945	-1.043	-3.254	-1.643	-1.063	0.776
	(1.547)	(1.759)	(4.117)	(1.399)	(1.626)	(0.591)
$P_{i,t-3}$	-0.182	-0.475	1.655	-0.073	0.132	-0.274
	(1.531)	(1.741)	(4.074)	(1.385)	(1.609)	(0.585)
$P_{i,t-4}$	-0.722	-0.810	-0.613	0.522	-0.699	-0.111
	(1.511)	(1.719)	(4.023)	(1.367)	(1.589)	(0.576)
$P_{i,t-5}$	-1.196	-1.206	-2.504	-1.437	-0.617	0.024
	(1.507)	(1.713)	(4.011)	(1.363)	(1.584)	(0.576)
$P_{i,t-6}$	0.828	1.698	0.749	0.725	0.501	0.065
	(1.510)	(1.717)	(4.020)	(1.366)	(1.588)	(0.577)
$P_{i,t-7}$	-1.220	-0.536	-9.551***	-0.858	1.200	0.295
	(1.098)	(1.249)	(2.923)	(0.993)	(1.154)	(0.419)
Other covariates						
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Mobility determinants	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.772	0.529	0.493	0.764	0.665	0.743
No of observations	11,876	11,871	11,876	11,876	11,876	11,849

Standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix B: MENA estimated results

TABLE B.1

Estimated effects on mobility behavior change in MENA

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
Policy responses						
Stringency index	-0.559**	-0.255	-0.446	-0.316*	-0.424**	0.200**
	(0.205)	(0.246)	(0.266)	(0.147)	(0.160)	(0.059)
Economic support index	-0.192	-0.262	-0.237	-0.054	-0.141	0.115*
	(0.138)	(0.139)	(0.155)	(0.097)	(0.123)	(0.055)
Actual risk						
Lagged (log) COVID-19 cases	-1.281	-1.614	-1.992**	-1.162	-1.843**	0.560**
	(0.759)	(0.876)	(0.612)	(0.649)	(0.598)	(0.205)
Lagged (log) COVID-19 deaths	0.683	0.766	2.469	0.837	0.198	-0.303
	(1.565)	(2.035)	(2.329)	(1.060)	(0.662)	(0.194)
Risk perception						
COVID-19 disease uncontrollability	-4.661	-10.408	-15.318	-31.711**	-10.172	3.649
	(11.702)	(15.629)	(14.416)	(13.196)	(7.434)	(3.429)
Neighborhood effect (Ref: 0 - No cases in neighbors)						
1 - 1st case in 1 neighboring country	-7.498*	-5.365	-14.879**	-12.278**	-5.523	0.102
	(3.933)	(4.972)	(5.786)	(4.382)	(5.053)	(1.427)
2 - 1st case in 2 neighboring countries	-8.339	-6.518	-19.817	-18.994*	-6.839	-0.385
	(5.794)	(8.508)	(12.446)	(8.840)	(6.922)	(2.388)
3 - 1st case in 3+ neighboring countries	-13.510	-4.044	-25.392*	-26.330*	-8.507	-1.996
	(9.568)	(13.821)	(12.355)	(11.942)	(12.226)	(3.923)
COVID-19 disease dreadfulness	-1.671	2.629	1.533	-3.810	-0.764	1.631*
	(2.756)	(3.390)	(3.643)	(2.156)	(1.806)	(0.731)
Days since 1st COVID-19 confirmed death	-0.086	0.222	0.387	0.366	0.019	-0.213
	(0.495)	(0.659)	(0.718)	(0.560)	(0.407)	(0.168)
Weather effect						
Temperature	-0.032	0.075	-0.109	-0.159	0.002	-0.008
	(0.329)	(0.448)	(0.416)	(0.242)	(0.277)	(0.107)
Precipitation amount	-0.080	-0.086	-0.013	-0.024	-0.073	0.052
	(0.108)	(0.136)	(0.121)	(0.071)	(0.100)	(0.043)
Wind speed	0.092***	0.132**	0.078*	0.071**	0.044	-0.039***
	(0.025)	(0.044)	(0.034)	(0.021)	(0.024)	(0.009)
Seasonal effect						
Weekend (Y=1)	-8.075***	-9.211***	-9.600***	-5.546***		-3.194***
	(1.293)	(1.687)	(2.267)	(0.738)		(0.359)
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No of observations	1,209	1,209	1,209	1,209	1,209	1,209

Clustered standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. Country fixed effects are included in all estimations.

TABLE B.2

Estimated effects of policy responses on mobility behavior change *in risk-neutral settings*

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
Risk-neutral populations in MENA						
Restrictions on gatherings						
(Ref: 0 - No restrictions)						
1 - Restrictions on very large gatherings						
2 - Restrictions on 101-1,000 people gatherings						
3 - Restrictions on 11-100	-18.934	-29.915*	-15.626**	-4.945*	-17.747*	7.410**
people gatherings	(7.286)	(9.429)	(1.767)	(1.600)	(4.383)	(1.460)
4 - Restrictions on 10	-40.097	24.632	-39.375	30.060	18.488	-3.677
people or less gatherings	(14.411)	(17.918)	(14.366)	(12.442)	(37.045)	(12.920)
Stay @home requirements						
(Ref: 0 - No measures)						
1 - Recommend not	1.177	3.130	4.485*	-3.357	4.868	-2.511
leaving house	(3.573)	(4.733)	(1.448)	(2.436)	(2.472)	(1.790)
2 - Require not leaving	0.670	4.901	3.280*	-1.503	2.207**	-0.409
house but for 'essentials'	(1.337)	(2.938)	(0.831)	(0.739)	(0.412)	(0.516)
3 - Require not leaving	-7.159	4.108	0.038	3.012	-5.823	1.485
house w/ min exceptions	(5.370)	(7.509)	(4.336)	(4.232)	(4.705)	(1.097)
Public info campaigns						
(Ref: 0 - No campaign)						
1 - Public officials urging	8.162	53.633	-31.919**	-6.604	9.601	-0.911
caution about Covid-19	(19.744)	(27.417)	(3.516)	(9.733)	(26.094)	(9.564)
2 - Coordinated public	-43.886*	-43.387	-18.335	6.961	-5.356	4.935
info campaign	(12.061)	(18.361)	(7.392)	(4.657)	(8.936)	(3.201)
COVID-19 disease	2.916	46.680	-23.605**	-0.534	9.604	-0.746
uncontrollability	(13.452)	(18.952)	(4.706)	(9.082)	(27.023)	(8.417)
COVID-19 disease	-3.419*	-0.890	-0.495	-0.833	-1.254	1.369
dreadfulness	(1.082)	(1.137)	(0.943)	(0.896)	(1.592)	(0.542)
No of observations	468	468	468	468	468	468
Risk-neutral populations elsewhere						
Restrictions on gatherings						
(Ref: 0 - No restrictions)						
1 - Restrictions on very large gatherings						
2 - Restrictions on 101-	-1.146	-3.491	-10.885	-4.489	-2.381	0.249
1,000 people gatherings	(3.784)	(3.634)	(24.090)	(3.629)	(3.089)	(1.311)
3 - Restrictions on 11-100	0.557	-0.524	3.018	-0.172	-1.029	-0.276
people gatherings	(3.599)	(3.205)	(17.467)	(3.054)	(2.819)	(1.308)
4 - Restrictions on 10	-3.726	-1.318	-3.564	-3.663	-3.065	1.070
people or less gatherings	(3.583)	(2.874)	(15.328)	(2.929)	(2.176)	(1.247)
Stay @home requirements						
(Ref: 0 - No measures)						
1 - Recommend not	-7.626**	-5.256**	-15.677*	-4.833*	-2.689	1.548
leaving house	(3.301)	(2.327)	(8.171)	(2.761)	(2.452)	(1.172)
2 - Require not leaving	-5.944	-4.795*	-11.579	-4.376	-2.874	1.549
house but for 'essentials'	(3.638)	(2.740)	(10.474)	(2.657)	(2.845)	(1.212)
3 - Require not leaving	-6.705	-9.623***	0.394	-9.321***	-6.553*	3.399**
house w/ min exceptions	(3.992)	(2.716)	(12.167)	(2.867)	(3.332)	(1.295)
Public info campaigns						
(Ref: 0 - No campaign)						
1 - Public officials urging	12.539***	12.255***	67.730**	4.517	0.445	-2.083
caution about Covid-19	(4.059)	(3.286)	(27.478)	(4.113)	(3.997)	(1.571)
2 - Coordinated public	5.662	9.260***	11.125	0.457	2.175	-0.393
info campaign	(3.546)	(2.597)	(12.023)	(3.601)	(3.006)	(1.235)

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
COVID-19 disease	-23.016***	-12.644**	9.194	-22.190***	-29.305***	9.172***
uncontrollability	(6.867)	(5.313)	(23.940)	(6.126)	(6.814)	(2.751)
COVID-19 disease	2.233	4.327***	-6.131	1.386	1.842	-0.207
dreadfulness	(1.597)	(1.557)	(5.844)	(1.245)	(1.391)	(0.537)
No of observations	4,997	4,997	4,997	4,997	4,997	4,997

Clustered standard errors are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. On a scale from -0.8 to 1.0, risk-neutral populations have a risk-taking value between -0.2 and 0.4. Non-reported explanatory variables include additional five policy indicators on containment and closure policies, two policy indicators on economic policies, and the rest of the actual risk, risk perception, weather effect, and seasonal effect variables listed in Table 1. Country fixed effects are included in all estimations.

TABLE B.3

Estimated effects of policy responses on mobility behavior change in MENA *by time preference*

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
			Impatient populations			
Workplace closing (Ref: 0 - No measures)						
1 - Recommend closing/work from home	32.921***	19.484**	28.095**	4.944	4.321	-8.486**
	(1.961)	(4.129)	(4.744)	(6.444)	(4.730)	(1.228)
2 - Require partial closing/work from home	13.947	15.270	9.929*	7.512	12.110	-4.220
	(5.875)	(5.617)	(3.389)	(5.236)	(6.436)	(1.776)
3 - Require full closing/work from home	6.015	16.029	1.576	13.783	11.429	-3.708
	(7.330)	(11.510)	(4.670)	(10.045)	(9.151)	(3.421)
Stay @home requirements (Ref: 0 - No measures)						
1 - Recommend not leaving house	4.323	-18.835*	5.237	-24.323**	-12.444***	2.240**
	(2.853)	(5.773)	(4.403)	(4.076)	(0.743)	(0.277)
2 - Require not leaving house but for 'essentials'	0.614	-4.549	5.260*	-12.495*	-15.681***	1.088*
	(0.832)	(2.100)	(1.599)	(3.209)	(0.702)	(0.258)
3 - Require not leaving house w/ min exceptions	-8.239***	-14.515*	3.086	-15.194**	-24.752**	4.166***
	(0.621)	(4.053)	(1.193)	(3.155)	(3.315)	(0.319)
Income support for HHs (Ref: 0 - No support)						
1 - Government replacing <50% of lost salary	-5.537	-10.592*	-5.144	-4.598	-6.622**	3.026*
	(2.777)	(3.597)	(4.385)	(1.831)	(1.208)	(0.932)
2 - Government replacing >=50% of lost salary						
Debt/contract relief for HHs (Ref: 0 - No relief)						
1 - Narrow relief, specific to one kind of contract	1.448	-4.209	-5.595	-0.809	-3.462	1.717**
	(2.824)	(4.371)	(3.495)	(2.308)	(4.304)	(0.370)
2 - Broad debt/contract relief	0.867	-15.544	-9.543	-4.933	-8.458	4.387
	(8.066)	(9.227)	(7.492)	(6.804)	(9.161)	(2.094)
Public info campaigns (Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19						
2 - Coordinated public info campaign	1.800	5.131	-10.874***	-6.596**	-6.731**	2.785*
	(5.255)	(9.369)	(0.436)	(0.910)	(1.551)	(0.925)
No of observations	471	471	471	471	471	471
			Moderately patient populations			
Workplace closing (Ref: 0 - No measures)						
1 - Recommend closing/work from home	12.672**	6.541	19.454***	-2.485	-3.417	-2.229
	(5.523)	(7.727)	(5.626)	(2.837)	(5.344)	(1.783)
2 - Require partial closing/work from home	-2.165	-2.374	6.226	-0.410	-7.598*	0.295
	(4.438)	(6.209)	(4.521)	(2.280)	(4.294)	(1.432)
3 - Require full closing/work from home						
Stay @home requirements (Ref: 0 - No measures)						
1 - Recommend not leaving house	-4.959	-4.657	4.165	-0.582	-6.862**	0.320
	(3.290)	(4.603)	(3.351)	(1.690)	(3.183)	(1.062)
2 - Require not leaving house but for 'essentials'	-7.408***	-7.015**	-2.816	-4.700***	-6.624***	2.449***
	(2.459)	(3.440)	(2.505)	(1.263)	(2.379)	(0.794)
3 - Require not leaving house w/ min exceptions	-18.836***	-15.509***	-11.160***	-6.502***	-13.523***	4.538***
	(4.080)	(5.708)	(4.156)	(2.096)	(3.948)	(1.317)

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
Income support for HHs (Ref: 0 - No support)						
1 - Government replacing <50% of lost salary						
2 - Government replacing >=50% of lost salary						
Debt/contract relief for HHs (Ref: 0 - No relief)						
1 - Narrow relief, specific to one kind of contract	-2.561	-2.838	7.350**	-1.402	-4.704	1.364
	(3.364)	(4.706)	(3.427)	(1.728)	(3.255)	(1.086)
2 - Broad debt/contract relief	6.795	14.655**	9.203*	2.085	6.517	-1.532
	(5.223)	(7.307)	(5.320)	(2.683)	(5.054)	(1.686)
Public info campaigns (Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19						
2 - Coordinated public info campaign	-1.565	5.250	-0.471	-1.817	-0.989	-0.449
	(7.508)	(10.504)	(7.648)	(3.857)	(7.265)	(2.423)
No of observations	329	329	329	329	329	329

(Clustered) standard errors are reported in parentheses (first row panel). *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. On a scale from -0.7 to 1.1, impatient populations have a patience value between -0.7 and -0.1; moderately patient populations have a patience value between -0.1 and 0.5. Non-reported explanatory variables include additional five policy indicators on containment and closure policies and the rest of the actual risk, risk perception, weather effect, and seasonal effect variables listed in Table 1. Country fixed effects are included in all estimations.

TABLE B.4

Estimated effects of risk communication on mobility behavior change in MENA *by level of trust*

	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
			Low trust in politicians			
Stay @home requirements						
(Ref: 0 - No measures)						
1 - Recommend not leaving house						
2 - Require not leaving	6.455	4.737	-6.534	-0.266	4.984	-2.113
house but for 'essentials'	(7.295)	(7.670)	(7.174)	(6.158)	(7.419)	(2.489)
3 - Require not leaving house w/ min exceptions						
Public info campaigns						
(Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19						
2 - Coordinated public	-0.813	3.028	-1.212	0.732	-5.401	1.330
info campaign	(8.895)	(9.352)	(8.747)	(7.508)	(9.046)	(3.034)
No of observations	231	231	231	231	231	231
			Medium trust in politicians			
Stay @home requirements						
(Ref: 0 - No measures)						
1 - Recommend not	3.641	-3.232	12.748	-14.220**	-12.195	5.226
leaving house	(16.464)	(22.539)	(16.458)	(5.822)	(12.327)	(4.488)
2 - Require not leaving	4.204	0.640	12.098	-5.950	-13.634*	2.141
house but for 'essentials'	(10.946)	(14.985)	(10.941)	(3.870)	(8.203)	(2.984)
3 - Require not leaving	-5.726	-6.756	7.796	-6.927	-24.950**	4.794
house w/ min exceptions	(13.690)	(18.741)	(13.684)	(4.841)	(10.261)	(3.732)
Public info campaigns						
(Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19						
2 - Coordinated public	-15.770	-19.475	-15.301	-8.146	-1.251	-2.164
info campaign	(22.060)	(30.200)	(22.051)	(7.801)	(16.470)	(6.014)
No of observations	296	296	296	296	296	296
			High trust in politicians			
Stay @home requirements						
(Ref: 0 - No measures)						
1 - Recommend not	1.542	-1.330	9.275**	5.414**	-1.354	-0.089
leaving house	(2.440)	(4.606)	(2.466)	(1.322)	(1.834)	(0.741)
2 - Require not leaving	3.305	7.578	10.075*	-0.571	-2.158	0.782
house but for 'essentials'	(3.076)	(6.013)	(3.908)	(2.200)	(2.130)	(0.899)
3 - Require not leaving	-5.518	1.558	5.691	0.445	-10.202*	3.638
house w/ min exceptions	(5.347)	(10.622)	(5.836)	(4.349)	(4.250)	(1.552)
Public info campaigns						
(Ref: 0 - No campaign)						
1 - Public officials urging caution about Covid-19						
2 - Coordinated public	-8.267**	-2.743	-16.390***	-12.360**	-9.677**	3.389*
info campaign	(1.988)	(3.667)	(1.566)	(2.438)	(2.925)	(1.265)
No of observations	682	682	682	682	682	682

(Clustered) standard errors are reported in parentheses (third row panel). *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. On a scale from 1 (= extremely low) to 7 (= extremely high), a value between 1.32 and 3.36 denotes extremely low or low trust; a value between 3.36 and 4.38 denotes medium trust; and a value between 4.38 and 6.42 denotes high or extremely high trust in politicians. Non-reported explanatory variables include seven policy indicators on containment and closure policies, two policy indicators on economic policies, and all the actual risk, risk perception, weather effect, and seasonal effect variables listed in Table 1. Country fixed effects are included in all estimations.