Crisis Experience and the Deep Roots of COVID-19 Vaccination Preferences *

Ekaterina Borisova[†a,e], Klaus Gründler[b,c,d], Armin Hackenberger[b,c], Anina Harter[b,c], Niklas Potrafke[b,c,d], and Koen Schoors[e,a]

[a]HSE University, Moscow, [b]ifo Institute, Munich, [c]University of Munich (LMU), [d]CESifo, Munich, [e]Ghent University

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Abstract

We examine the deep roots of preferences for vaccination against COVID-19, moving beyond proximate factors which can only account for part of the observable heterogeneity in the willingness to get vaccinated. Our model on experience-based learning predicts that exposure to past disruptive crises increases individuals' willingness to acquire and take a promising remedy when new crises occur. Using micro-level data on vaccination preferences for individuals from 19 countries, we find strong evidence for our prediction. We investigate the role of competing vaccines exploiting original geocoded survey data from Russia. Consistent with our theory, past crisis experience decreases vaccination willingness when individuals have learned to distrust the effectiveness of government administered remedies.

Keywords: COVID-19 vaccination; vaccination preferences; crisis experience; experience effects; survey data; geocoded data

JEL Codes: H12; H51; I12; I15; I18

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†Corresponding author. National Research University Higher School of Economics and Ghent University. Myasnitskaya Str. 18, 101000 Moscow, Russia. E-Mail: eborisova@hse.ru

1 Introduction

"We are a significant step closer to providing people around the world with a much-needed breakthrough to help bring an end to this global health crisis."
— Dr. Albert Bourla, Chairman of Pfizer (9 November 2020)

Vaccines are widely recognized to be the most effective measure against the COVID-19 pandemic. Reaching sufficient immunization coverage to end the pandemic requires having widespread acceptance of COVID-19 vaccines among individuals. An empirical regularity reported by many previous studies, however, is that vaccination preferences vary substantially across individuals, with a considerable fraction of individuals being hesitant to get vaccinated (e.g. Arce et al., 2021; Aw et al., 2021; Khubchandani et al., 2021; Freeman et al., 2021; Rodriguez-Morales and Franco, 2021). Previous studies have examined proximate factors underlying vaccination preferences, showing that the willingness to get vaccinated correlates with socio-economic characteristics and exposure to the pandemic (e.g. Arce et al., 2021; Khubchandani et al., 2021). Another set of emerging stylized facts, which focuses on the strong heterogeneity in preferences across birth-cohorts within countries, has been harder to capture by these approaches.

In this paper, we move beyond the study of proximate factors underlying vaccination preferences, examining the deep roots of individuals' willingness to get vaccinated. We start by discussing stylized micro-level facts across 19 countries, showing that aside the well-documented variation across socio-economic characteristics, vaccination preferences vary across birth-year cohorts between and within countries. Most importantly, there are no clear cross-country trends in vaccination preferences across birth-cohorts. We develop a theoretical framework that is consistent with the observable stylized facts. Our main argument is that exposure to past disruptive crisis episodes increases individuals' willingness to acquire and take a promising remedy when new crises occur. Our analysis on experience-based preference formation follows the literature on experience effects, which shows that experiencing crises and shocks leaves a lasting imprint on individuals (Cogley and Sargent, 2008; Malmendier and Nagel, 2011; Malmendier and Nagel, 2016; Brown et al., 2018; Hanaoka et al., 2018 Malmendier et al., 2021). A key difference relative to other learning approaches is that experience-based learning initiates cohort-specific differences in preference formation after a common shock (Malmendier et al., 2021). Experienced-based learning rests on two pillars, including (i) the overweighing of observations that occurred during their own lifetime and (ii) a recency bias, assigning greater weight to more recent observations when forming preferences and beliefs.

We empirically test our theory using survey data that includes vaccination preferences along with socio-economic controls for 19 developing, emerging and advanced economies. Vaccination preferences were elicited in June 2020, months before the first vaccine against COVID-19 became available. This timing allows us to examine preference formation without distorting effects from the discussion about side effects of specific vaccine candidates, shortages in vaccine supply, and programs that prioritize the vulnerable and the elderly. We link the individuals in our sample to the crisis history of their countries, computing cohort-specific lifetime discounted crisis experience for all respondents in the sample. The literature on experience effects has shown that although different in nature, different types of crises trigger similar effects on preference formation, including natural disasters (Cassar et al., 2017; Hanaoka et al., 2018), epidemics (Gründler and Potrafke, 2020), conflicts (Voors et al., 2012), violent episodes (Callen et al., 2014), living under autocratic regimes (Alesina and Fuchs-Schündeln, 2007), terrorist attacks (Hetherington and Suhay, 2011), and many others (e.g. Malmendier and Nagel, 2011; Giuliano and Spilimbergo, 2014). Our measure of lifetime discounted crisis experience hence considers the full crisis history of countries to avoid false negatives in the control group. Given that the psychological literature offers little guidance on the exact functional form of the experienced-based learning algorithm, we apply three types of lifetime discounting following the suggestions of Malmendier et al. (2021). Our analysis reveals substantial heterogeneity in lifetime discounted crisis experience across individuals between and within countries, offering a rich source of variation that we exploit for causal identification.

Our cross-national results show that individuals with greater lifetime discounted crisis experience have a higher preference to get vaccinated against COVID-19. This result is robust across a series of model specifications that account for proximate factors underlying vaccination preferences (direct and indirect exposure to the pandemic and socio-economic characteristics), differential effects across geographic units, and birth-cohorts specific effects. The effect is also robust across weighting schemes applied to compute lifetime discounting of past events, appears consistently across survey questions designed to elicit individuals' vaccination preferences, and is not driven by the empirical strategy or individual countries in our sample.

In the second part of our paper, we conduct a case study for Russia to investigate the mechanisms underlying crisis-induced preference formation in greater detail. We ran a large-scale geocoded survey in November 2020, shortly before the Russian vaccination campaign started. Russia provides a uniquely suited laboratory to examine the effect of crisis experience on vaccination preferences. First, Russia was the first country that announced the development of a vaccine (Sputnik V) and started mass vaccination before most other industrialized countries. Despite this progress in vaccine development, vaccine hesitancy is widespread among individuals living in Russia and more prevalent than in most other countries (Arce et al., 2021). Second, Russia experienced many crises since World War II, and there is substantial geographic variation in crisis occurrence that we exploit for identification. Third, the Russian vaccine competes against widely-administered vaccines developed by international pharmaceutical firms. This setting allows us to test a fundamental building block of our theoretical model, which stipulates that the expected net payoff of the vaccine may be negative when individuals do not consider the vaccine to provide an effective crisis remedy. We elicit respondents' preferences to get vaccinated with the Russian vaccine vis-á-vis an imported vaccine. This allows us to disentangle effects from a crisis remedy in the sense of our theoretical model from potentially distorting effects coming from distrust towards the institutions and authorities that promote and organize the administration of the vaccine. The Russian vaccine was approved without large-scale testing or published results (Mahase, 2020), casting additional doubt on the vaccine's effectiveness and potentially contributing to Russia's high degree of vaccination hesitancy (Arce et al., 2021). Finally, the geocoded nature of our survey allows us to relax the assumption of synchronous crises within countries.

Replicating the empirical specifications of our cross-national setting, the results for Russia show that greater lifetime discounted crisis experience reduces preferences for COVID-19 vaccination. We interpret these results as reflecting scepticism towards the authorities that promote the vaccine and that may have provided insufficient remedies to previous crises experienced by individuals. Exploiting the unique setting of competing vaccines, we disentangle preferences towards a remedy to a crisis in the sense of our model and distorting effects coming from distrust in the government. Our results show that individuals with larger lifetime discounted crisis experience are *less* in favor of the Russian vaccine. Consistent with the results obtained in our cross-national setting, however, the willingness to take the *imported* vaccine increases with greater crisis experience.

Contribution to the literature: Our study is related to research on COVID-19 (for an overview see Brodeur et al., 2021), especially the literature on measures taken to tackle the COVID-19 pandemic (Goel and Nelson, 2021; Lokshin et al., 2020; Bjørnskov, 2021; Grewenig et al., 2021; Laliotis and Minos, 2021). Our paper is also related to studies that examine preferences for COVID-19 vaccination (Arce et al., 2021; Aw et al., 2021; Freeman et al., 2021; Galasso et al., 2021; Karlsson et al., 2021; Khubchandani et al., 2021; Lazarus et al., 2021; Rodriguez-Morales and Franco, 2021). We advance on these studies by examining the deep roots underlying preferences towards COVID-19 vaccination, complementing the evidence on proximate factors that correlate with vaccination preferences such as exposure to the pandemic and socio-economic characteristics.

A related strand of literature examines the consequences of COVID-19 specifically for Russia (e.g. Lancet, 2020). The most unique feature of the Russian case is the large degree of vaccination hesitancy, which is higher than in any other country for which granular survey data exists (see Arce et al., 2021 for a country comparison). Economic studies for Russia have theoretically predicted and empirically demonstrated that the reduction in mobility in response to COVID-19 was stronger in Russian regions with higher ethnic fractionalization (Egorov et al., 2021) and higher income levels (Dokhov and Topnikov, 2021). Some studies have investigated Russian vaccine hesitancy, finding that negative information on vaccine safety and efficacy reduces support for the anti-pandemic measures (Borisova et al., 2021). We contribute to these studies by showing that vaccine skepticism towards the Russian vaccine rises with higher crisis exposure, proposing mismanagement of previous crises as a possible channel. Our results also complement past analyses on the support for COVID-19 containment measures.

Our paper also connects to the literature on the determinants of vaccination against other diseases such as diphtheria, tetanus, pertussis (DTP) and measles across countries (Gauri and Khaleghian, 2002; de Figueiredo et al., 2016). In a previous study, Martinez-Bravo and Stegmann (2021) demonstrate that a political shock and subsequent propaganda campaign against the polio vaccine reduced vaccination rates in Pakistani districts. Our study adopts a similar line of reasoning but more broadly shows a general connection between the experience of past traumatic events and vaccination preferences. While our theory regarding crisis experience may also apply for regular vaccination against these known diseases, the COVID-19 pandemic provides an ideal testing ground for studying the role of experience effects for vaccination, given its unparalleled and unanticipated impact on health, living conditions, and wealth as well as the speed of vaccine development, distribution, and administration.

We also contribute to the burgeoning literature on experience effects and experience-based learning. This literature shows that experiencing crises and shocks leaves a lasting imprint on individuals (Cogley and Sargent, 2008; Malmendier and Nagel, 2011; Malmendier and Nagel, 2016; Malmendier et al., 2021) and changes their beliefs and preferences (Brown et al., 2018; Hanaoka et al., 2018). The core literature on experience effects focuses on financial topics, showing that personal experiences in the stock-market influences future willingness to invest (Malmendier and Nagel, 2011) and that macro-financial shocks shape investor behavior and market dynamics (Malmendier et al., 2020; see Malmendier, 2021a for an overview). A new strand of literature also focuses on experience effects in non-financial settings, offering great potential for future research in topics related to education, labor, and gender economics (see Malmendier, 2021b for a discussion). We contribute to this literature by providing evidence that experienced-based learning also shapes preferences in the field of health economics. Against the backdrop of the severe economic and humanitarian crisis caused by the COVID-19 pandemic, our results suggest that experience effects have tangible consequences beyond individual preference formation: In our setting, experience effects from past crises impact not only individuals' willingness to get vaccinated but directly translate into a larger collective action failure in ending the pandemic through mass immunization.

Organization: The remainder of this paper is organized as follows. Section (2) presents stylized cross-national facts on preferences towards COVID-19 vaccination. Section (3) presents our theoretical framework linking crisis experience to vaccination preferences. We test our theoretical predictions for individuals from 19 countries in Section (4) and provide case study evidence for Russia in Section (5). Section (6) concludes.

2 COVID-19 vaccination preferences: Stylized facts

We start by identifying micro-level stylized facts about preferences towards vaccination against COVID-19. Since the start of the global vaccination campaign in early December 2020, several research groups have collected fine-grained data about preferences towards COVID-19 vaccination (e.g. Arce et al., 2021; Jones, 2021 and country-specific selections). However, there are two major challenges in establishing stylized facts about vaccine preferences when we use data on COVID-19 vaccination rates or survey-based preferences reported after the beginning of the global vaccination campaign. First, many countries have vaccination programs in place that prioritize the vulnerable and the elderly. Inferring revealed preferences from realized vaccination rates is hence difficult. Also, such an analysis would mix "supply effects" (the availability of vaccine doses) with "demand effects" (individuals' willingness to take the vaccine). Second, reports on potential side effects of specific vaccine candidates came up early after the start of the global vaccination campaign and had a major impact on vaccination preferences of many individuals. We tackle these challenges by focusing on hypothetical vaccination preferences elicited in summer 2020, i.e. before COVID-19 vaccine candidates had become available.

2.1 Data on preferences towards COVID-19 vaccination

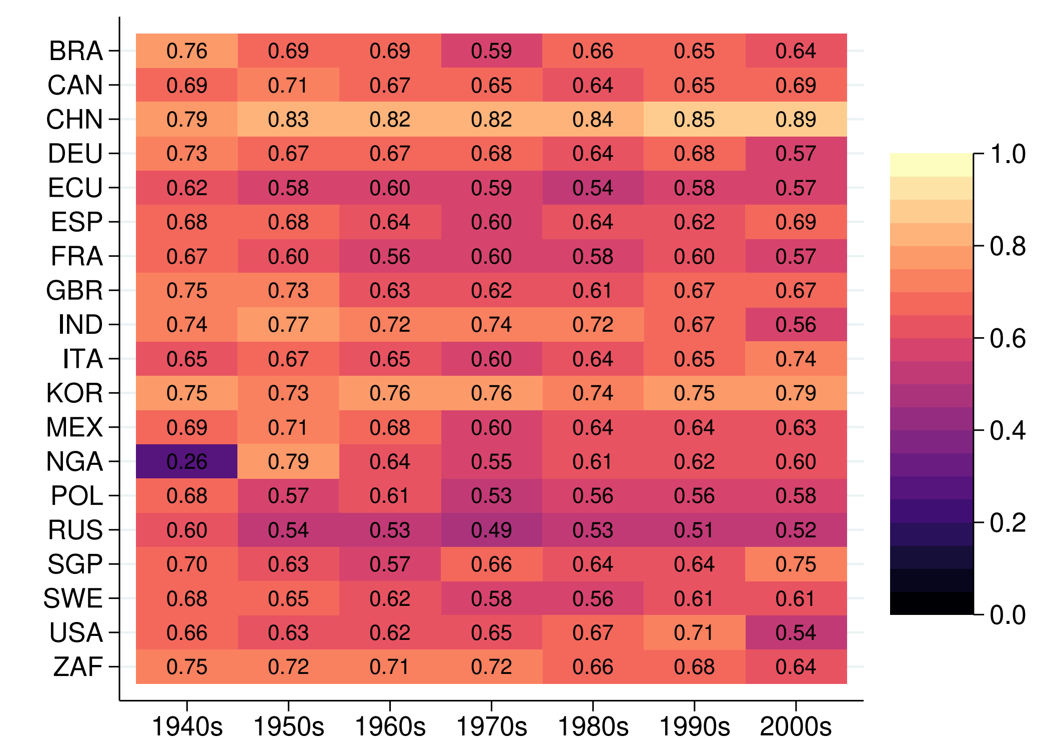
We use data compiled by Lazarus et al. (2021) who collected a cross-country survey on COVID-19 vaccination preferences of 13,426 individuals from 19 countries.[1] The survey was conducted between 16 June 2020 and 20 June 2020. An advantage of this timing is that the data reflects individuals' intention to get vaccinated without distorting effects from specific vaccine candidates, prioritization programs, or shortages in vaccine supply.[2] The survey elicits respondents' preferences for COVID-19 vaccination via two questions:

(Q1) "If a COVID-19 vaccine is proven safe and effective and is available to me, I will take it."

[1] These countries are Brazil, Canada, China, Ecuador, France, Germany, India, Italy, Mexico, Nigeria, Poland, Russia, Singapore, South Africa, South Korea, Spain, Sweden, the United Kingdom, and the United States.

[2] The public debate around varying efficacy rates amongst different COVID-19 vaccines as well as the suspension of vaccination due to concerns about cerebral venous sinus thrombosis in many countries in the spring of 2021 demonstrably influenced individuals' reported preferences.

Figure 1 HETEROGENEITY IN VACCINATION PREFERENCES: COUNTRIES AND BIRTH COHORTS



Notes: The figure shows the mean value of the standardized vaccination preference index by country and birth cohort. Higher scores indicate higher vaccination preferences. Vaccination preferences are based on own calculations using raw data on vaccination preferences taken from Lazarus et al. (2021).

(Q2) "I would follow my employer's recommendation to get a COVID-19 vaccine once the government has approved it as safe and effective."

The responses are coded on a Likert scale running from 1 ("completely disagree") to 5 ("completely agree").[3] For our benchmark specification, we exploit the full set of information by combining responses to both questions into an index reflecting individuals' preferences for COVID-19 vaccination that assumes values between 0 (no vaccination preference) and 1 (full vaccination preference).[4]

[3]The coding scheme is 1 ("completely disagree"), 2 ("somewhat disagree"), 3 ("neutral/no opinion"), 4 ("somewhat agree"), 5 ("completely agree").

[4]We create a composite measure of individuals' vaccination preferences by combining the answers to both Q1 and Q2 of each survey respondents via Principal Component Analysis (PCA). We standardize the first component for ease of comparison.

2.2 Stylized facts about vaccination preferences

Figure (B-7) shows how our combined measure of COVID-19 vaccination preferences is distributed across countries and birth cohorts. Figure (B-1) in the appendix provides complementary information on vaccination preferences across socio-economic characteristics. These statistics reveal a set of stylized facts about COVID-19 vaccination preferences:

(A) There is substantial heterogeneity in vaccination preferences across countries.

(B) There is substantial heterogeneity in vaccination preferences across birth-cohorts.

(C) Birth-cohort specific preferences also vary considerably *within* countries.

(D) There is no clear cross-country trend in vaccination preferences across birth-cohorts.

(E) Vaccination preferences also vary across socio-economic characteristics.

These observable stylized facts are in line with findings of prior studies for single countries (e.g. Khubchandani et al., 2021 for the United States) and lay the foundation for studies that aim to explain micro-level preferences for COVID-19 vaccination. A startling empirical regularity that cannot be described by proximate factors influencing vaccination preferences (such as local exposure to COVID-19 or socio-economic and socio-demographic characteristics) is that preferences vary substantially across birth-year cohorts, but this variation does not seem to be *systematic* across countries. Similar cross-cohort differences can also be observed in realized vaccination rates across industrialized countries (B-2).

3 Crisis experience and vaccination preferences

How can we explain the stylized facts on preferences towards COVID-19 vaccination? We develop a theoretical framework that is in line with the observable patterns reported in Section (2). The key argument of our model is that exposure to past traumatic crisis episodes increases individuals' willingness to acquire and take a promising remedy when new crises occur. Our analysis on crisis experience and vaccination preferences is based on the literature of experience effects, which shows that experiencing crises and shocks leaves a lasting imprint on individuals (Cogley and Sargent, 2008; Malmendier and Nagel, 2011; Malmendier and Nagel, 2016; Malmendier et al., 2021) and changes their beliefs and preferences (Brown et al., 2018; Hanaoka et al., 2018).

We argue that experience-based learning matches the stylized facts reported in Section (2). Other forms of learning procedures, such as natural expectation formation (e.g. Fuster et al., 2010) and over-extrapolation (e.g. Barberis et al., 2018) are able to capture some of the stylized facts, but other observable patterns are harder for these approaches to capture, particularly the large cross-sectional heterogeneity across cohorts (see also Malmendier et al., 2020; Malmendier, 2021b for a discussion on experience-based learning and differential within-country trends across cohorts). We develop a simple model in the spirit of this literature, particularly borrowing from Malmendier et al. (2020).

3.1 The basic model set-up

Consider an economy i that has been hit by a pandemic. At time t, a new vaccine against the virus has been developed. Societies need to decide about the quantity of the vaccine, x_{it}, they want to purchase and administer. We assume a political economy framework in which politicians are election-motivated and hence follow the will of the median voter. Suppose that the entire government budget needs to be spent to tackle the pandemic. The budget constraint of the government is

$$W_{it} = x_{it}p_t + H_{it}, \tag{1}$$

where W_{it} is the wealth of country i at time t, p_t is the price of one unit of the vaccine, and H_{it} describes all other health expenditure spent to fight the pandemic, e.g. for hospitals, workers in the medical sector, drugs, etc. When the vaccine is more effective in fighting the pandemic than other health expenditure, it pays a dividend d on a country's wealth in $t+1$. This dividend can be thought of as a direct economic return when better health allows for a more effective production of output, but it may also reflect societal gains in the form of better living conditions, health, and life satisfaction that indirectly manifest in economic returns. Hence, wealth in $t+1$ can be expressed as

$$W_{it+1} = x_{it}(d_{t+1}) + H_{it}R = x_{it}(d_{t+1} - p_tR) + W_{it}R, \tag{2}$$

where R is the payoff of traditional health spending H_{it}. The excess payoff obtained by buying and taking one unit of the vaccine therefore is

$$s_{it+1} = d_{t+1} - p_t R, \tag{3}$$

where $p_t R$ is the opportunity cost of buying the vaccine. We assume that every unit of the vaccine that is purchased will also be administered.[5]

3.2 Crisis experience and vaccination preferences of individuals

At time t, the excess payoff is unknown. Societies want to maximize W_{it+1}, and hence the decision on the allocation of resources between x_{it} and H_{it} depends on expectations about the excess payoff, $\mathrm{E}_{it}[s_{it+1}]$. When expectations about s_{it+1} are evenly distributed across the members of a society, then the allocation between x_{it} and H_{it} can easily be derived and is representative for all agents j, i.e. $\mathrm{E}_{ijt}[s_{ijt+1}] = \mathrm{E}_{it}[s_{it+1}]$. However, this assumption is at stark contrast with the stylized facts about COVID-19 vaccination preferences reported in Section (2), suggesting that there is substantial heterogeneity regarding $\mathrm{E}_{ijt}[s_{ijt+1}]$ across members of a society. The heterogeneity is consistent with realized preferences observable for the industrialized countries: Empirically, we observe large within-country heterogeneity in vaccination rates across age cohorts (see Figure (B-2)). Experience-based learning offers a convincing approach to capture these stylized facts.

A large body of literature has shown that individuals often over-weigh personal experiences when forming expectations and beliefs (e.g. Malmendier and Nagel, 2011; Malmendier and Nagel, 2016; Malmendier et al., 2021). This heuristic reflects a pervasive and robust psychological phenomenon in human behavior related to availability bias first studied by Tversky and Kahneman (1974). The theory on "experience effects" rests on two pillars. First, agents over-weigh events that they experienced over their lifetime. Second, they assign greater weights to the most recent events.[6] Heterogeneity in expectations results in expected payoffs that differ across agents, with society's collective expectation about d_{t+1} reflecting mean expectations across all agents.

[5] This assumption essentially reflects the argument that the number of purchased vaccines can be thought of as the aggregate of vaccine preferences over all members of a society.

[6] This class of models is based on further assumptions, e.g. that agents only consider events observed during their lifetime even though they may have knowledge about prior events and that agents' actions do not influence the information they receive ("passive learning model").

Our key argument is that the vaccine can essentially be thought of as a potential remedy for a severe crisis. Hence, the experience of past crisis episodes should be a key driver underlying $\mathrm{E}_{ijt}[s_{ijt+1}]$. This line of reasoning is consistent with two strands of the literature on preference formation. First, empirical studies found that disruptive events have strong effects of individuals' preferences (e.g. Cogley and Sargent, 2008). Second, the exhaustive evidence on crisis-induced preference formation appears to suggest that the effect of crises on preferences does not differ much across types of crises (e.g. Voors et al., 2012; Callen et al., 2014 Cassar et al., 2017; Hanaoka et al., 2018).

We consider the experience-based learning process of an individual j to follow the empirical patterns reported in Malmendier and Nagel (2011) and Malmendier et al. (2020)

$$\mathrm{E}_{ijt}[s_{ijt+1}] = \sum_{k=0}^{\text{age}} \omega(k, \lambda, \text{age})\, d_{ijt-k}, \tag{4}$$

where age $= t - n$ and $\omega(k, \lambda, \text{age})$ denotes the weight individuals assign to the payoff of tackling similar events observed k periods earlier. As individuals only consider events observed during their lifetime, it holds that $\omega(\cdot) \equiv 0\, \forall k >$ age. At this stage, we make two simplifying assumption. First, we study the case of a remedy that is able to fully alleviate the consequences of a crisis, and hence the economic value of the remedy equals the economic value of the damage caused by the crisis. We therefore use crises and their remedies as synonyms. Second, we assume that d_{t+1} captures the full spectrum of possible favorable and unfavorable payoffs, including (i) the potential to mitigate the crisis θ and (ii) potential medical side effects from taking the vaccine ρ (see Black and Rappuoli, 2010), i.e.

$$d_{t-1} = \theta_{t-1} - \rho_{t-1}, \tag{5}$$

where d_{t-1} reflects the net payoff that may also be negative.

To measure lifetime discounted crisis experience, past events are discounted by a parameter λ that regulates the recency bias via (see Malmendier et al., 2020)

$$\omega(k, \lambda, \text{age}) = \frac{(\text{age} + 1 - k)^{\lambda}}{\sum_{k'=0}^{\text{age}} (\text{age} + 1 - k')^{\lambda}} \tag{6}$$

where the denominator works as a normalizing constant depending on agents' age cohort and the regulating parameter λ. For $\lambda = 1$, the weights assigned to past crises decay linearly. For $\lambda > 1$ the relative weight assigned to more recent observations increases. For the special case of $\lambda = 0$, each lifetime observation is equally weighted.[7]

3.3 The central mechanism

The key argument underlying the learning process modeled in equations (4)–(6) is that individuals who experienced incisive events in the past have greater knowledge about the excess payoff provided by the vaccine because they have observed some d_{t-k} in the past or experienced the costs in the absence of a crisis remedy. We may also expect crisis-experienced individuals to put less weight on potential adverse side effects; but even if not, the expected net payoff (the remedy to the crisis less potential side effects) is higher for individuals with greater lifetime crisis experience. As a consequence, crisis-experienced individuals put greater value on a potential remedy than individuals who experienced less drastic events during their lifetime.[8]

Our central mechanism is consistent with the stylized facts showing that there are substantial cohort-specific differences in vaccination preferences within countries. Such differences may be explained by cohort-specific differentials in lifetime crises and the following experience effects. Second, the heterogeneity across age cohorts does not seem to vary systematically across countries, suggesting that preferences are not shaped by a collective memory or a period-specific zeitgeist.

Our central learning mechanism essentially reflects a demand-side argument. Higher exposure to past crises makes individuals more willing to get vaccinated. However, when the perceived payoff is large, higher willingness of crisis-experienced individuals to pay for the vaccine may eventually also translate into greater effort that is put into acquiring it, in which case crisis experience may also affect the supply side.

As d_{t-k} reflects the perceived net excess payoff of the vaccine, the expected willingness to get vaccinated increases with $\mathrm{E}_{ijt}[s_{ijt+1}]$. Hence, a simple representation of our central mechanisms regarding crisis experience and vaccination preferences is

$$\mathrm{Vacc}_{ijh} = f(C^o_{ih}, \mathbf{S}_{ij}), \quad \frac{\partial \mathrm{Vacc}_{ijh}}{\partial C^o_{ih}} > 0, \tag{7}$$

[7] For a negative value of the regulatory parameter, i.d. $\lambda < 0$, more recent observations receive relatively fewer weight, which however violates the fundamental assumption underlying experience-based learning.

[8] Anecdotal evidence for our central mechanism comes from the observation that many countries that were heavily hit by the SARS crisis of 2002/03 have much higher vaccination rates against SARS-CoV-2 than other less crisis-experienced countries (Lin and Meissner, 2020).

where Vacc_{ijh} denotes j's vaccination preferences and C^o_{ih} is lifetime discounted crisis experience of cohort h living in country i. The vector $\mathbf{S}_{ij}$ accounts for any other non-crisis related factor that affects j's vaccination preferences.

4 Micro-economic evidence across countries

4.1 Empirical strategy

We transfer our theoretical prediction of Equation (7) into an empirically estimable model. We assume that lifetime discounted crisis experience and non-crises related factors are linearly linked to vaccination preferences, i.e.

$$\text{Vacc}_{ijh} = \psi C^o_{ih} + \mathbf{S}_{ij}\boldsymbol{\beta}. \tag{8}$$

Non-crisis related factors can be divided into variables that are observable with data and unobserved factors. We account for observable factors that may influence preferences towards COVID-19 vaccination via

$$\text{Vacc}_{ijh} = \psi C^o_{ih} + \mathbf{A}_i\boldsymbol{\alpha} + \mathbf{B}_j\boldsymbol{\rho} + \mathbf{X}_i\boldsymbol{\gamma} + \eta_r + \zeta_h + \varepsilon_{ijh}. \tag{9}$$

The model accounts for indirect exposure to COVID-19 by including country-specific COVID-19 controls $\mathbf{A}_j$, i.e. the number of COVID-19 cases and deaths in a citizens' country at the time the survey was conducted. We also include individual-specific COVID-19 controls for direct exposure to COVID-19 via dummy variables $\mathbf{B}_i$ that assume a value of 1 if the respondent or a family member had fallen sick with COVID-19. To address the proximate factors of vaccination preferences reported in previous studies (e.g. Arce et al., 2021, see also the stylized facts in Section (2) that document differentials in vaccination preferences across socio-economic characteristics, we include individual-level factors $\mathbf{X}_j$ that account for respondents' gender, income, and education. To account for systematic cross-country differences in the management of the COVID-19 crisis and time-invariant heterogeneity regarding medical infrastructure, cultural socialization, institutions, geography, and ex ante vulnerability to crises, the model also includes fixed effects η_r for geographic regions r. To address changes in preferences over the life-cycle (i.e. that citizens may become more risk-averse when they get older), we also account for birth-cohort fixed effects ζ_h. All unobserved factors that influence vaccination preferences are absorbed by the idiosyncratic error term ε_{ijh}.

Identification: The key identifying assumption of our model requires that past crises are exogenous to individuals and do not correlate with other factors that are related to individuals' vaccination preferences. This assumption would be fulfilled if countries were randomly treated by crises. However, the exposure to crises may differ heavily across geographic units and hence lifetime discounted crisis experience may depend on a region's ex ante vulnerability to crises. Conditional on fixed effects for the geographic region, however, the literature usually treats large sudden natural disasters (e.g. Cavallo et al., 2013) and episodes of civil conflict (e.g. Rohner et al., 2013) as exogenous events. A violation of the identifying assumption by unobserved factors that correlate with past crises and vaccination preferences would require that such factors do not vary across the multiple types of crises that constitute an individuals' lifetime discounted crisis experience.

4.2 Measuring individual crisis experience across countries

We develop a composite measure that captures individuals' lifetime discounted crisis experience C^o_{ih}. Our measure is built on the argument that various types of crises may initiate the central mechanism described in Section (3). Creating such an index is a three-step problem (Munck and Verkuilen, 2002; Gründler and Krieger, 2021b,a). In the first step, the we define the "crises" we want to measure (*"conceptualization"*). Second, we choose observable components that reflect the chosen definition (*"operationalization"*). Finally, we design a rule to transform the observable components into a uni-dimensional index (*"aggregation"*) using a dimensionality reduction approach. We next describe these three steps taken to create the aggregate crisis index in greater detail. We proceed to describe how we construct the lifetime discounted crisis experience for individuals in our survey from the index.

4.2.1 Multidimensional nature of crisis experience

The fundamental building block of our theory on crisis-induced vaccination preferences is that although different in nature, different types of crises may have similarly devastating consequences on individuals' lives. Hence, the effect on individuals' value of a crisis remedy are likely to be similar. This argument is consistent with the empirical literature that finds similar effects on preferences across different types of crises (e.g. Voors et al., 2012; Callen et al., 2014 Cassar et al., 2017; Hanaoka et al., 2018). Therefore, empirically examining our theory by focusing on single types of past crises would bias our estimates with unobserved confounding events when unobserved crises are included in the non-treated units ("false negatives"). The key challenge is to derive a metric that comprehensively reflects past crisis experience.

4.2.2 Conceptualization

The question of how to best define the term "crisis" is afflicted with two key challenges: (i) the selection of features that are associated with crises and (ii) the specification of how these features interact with one another (Gründler and Krieger, 2021a). Regarding the first challenge, we may define crisis in a minimalist or maximalist concept of crises. From a conceptual perspective, both concepts are equally valid, because there is no objective guideline for when a situation may be sufficiently disruptive in order to justify the label "crisis". From an empirical perspective, however, maximalist definitions may be unfavourable because they often overlap with other economic and societal circumstances and it is hence unclear how a parameter estimate for a broad concept should be interpreted (Gründler and Krieger, 2021a). Regarding the second challenge, the main question is whether the aspects underlying the definition of crises are necessary conditions for crises or whether they are (partial) substitutes.

For our definition of crises, we aim to strike a good balance between minimalist and maximalist concepts of crises. We define crises as plausibly exogenous non-economic events that have profound influence on a country's living conditions and health situation. Our definition of crises rests on two pillars: (i) natural and technical disasters including previous epidemics and (ii) conflict and war. Our aspects are substitutes because they do not need to occur at the same time in order to constitute a crisis.

4.2.3 Operationalization

We use data for natural and technical disasters and conflict from two main sources in order to operationalize our definition of crises.

For natural and technical disasters, we take data from the EM-DAT database (Centre for Research on the Epidemiology of Disasters, 2021). EM-DAT covers a variety of natural and technical disasters such as floods, droughts, storms, and epidemics with over 20,000 observations between 1900 and 2020. For multi-year events, we average the number of deaths over all disaster-year observations. Disasters are defined as events which leave ten or more people dead; affect 100 or more people; cause the declaration of a state of emergency, or a call for international assistance. Entries include information inter alia on the type of disaster, the location, and a death count estimate. As the coverage of the death count variable becomes less reliable in earlier years of the data, we take both the estimated number of deaths from a disaster and construct a count variable of the number of disasters in a given country-year.

For conflict, we use the UCDP/PRIO Armed Conflict Dataset collected by Gleditsch et al. (2002) in its updated 21.1 version (Pettersson et al., 2021).[9] The Armed Conflict Dataset spans the years 1946 to 2020. The data includes conflict observations where at least one actor is a state and the use of armed force resulted in at least 25 battle-related deaths per year and actor-dyad. We use the "location" of a conflict to obtain the most accurate measure of a country's affectedness: For intrastate and internationalized intrastate as well as extrasystemic conflicts, this refers to the geographic location, for interstate conflicts to the state actors. From the individual conflict observations we construct a count variable on the number of conflicts in a given country-year.

4.2.4 Aggregation

Data aggregation requires finding a function f that maps our set of observable characteristics ($\mathbf{z}$) onto the level of crises

$$C_{it} = f(\mathbf{z}_{it}) \,\forall\, \mathbf{z}_{it} = z_{1t}, z_{2t}, z_{3t}, \tag{10}$$

where i denotes countries and the characteristics $\mathbf{z}_{it}$ are observed over $t \in T$ periods. The specification of the aggregation scheme is the most fundamental step in computing the index and has been shown to substantially influence the results in empirical models (Gründler and Krieger, 2021a). The main challenges involved in specifying the function of Equation (10) are (i) the selection of a scale for C_{it} and (ii) the selection of an aggregation rule. Regarding (i), we use a continuous scale, which has been shown to provide greater discrimination power in empirical studies. It also allows for a fine-grained investigation of our main hypothesis, as coding errors are particularly severe for dichotomous scales. Regarding (ii), we obtain weights that reflect the relative importance of the aspects entering our index by running a PCA. The transformation of the PCA is defined by weights $\mathbf{w}_k$ that map each vector of $\mathbf{z}_i$ to a new vector of

[9] For conflict data, the challenge is to achieve data coverage for the lifetime of the all survey participants in our sample, i.e. starting in the 1940s and ending in 2020. The other commonly used source for historic data on conflict is the Correlates of War Database (see Sarkees (2010) for details). However, the dataset spans the years 1817 to 2007 and hence does not provide suitable time coverage.

principal component scores $\rho_i = (\rho_1, \rho_2, \rho_3)$ so that the ρ_i's successively inherit the maximum possible variance from the data. The first weight vector satisfies

$$\mathbf{w}_1 = \arg\max_{||\mathbf{w}||=1} \left\{ \sum_i (\rho_1)_i^2 \right\} = \arg\max_{||\mathbf{w}||=1} \left\{ \sum_i (\mathbf{z}_i \times \mathbf{w})^2 \right\}.$$

Based on these weights, the principal components can be computed via $\rho_1 = \mathbf{x}_i \times \mathbf{w}_1$. Aggregation obtained by PCA fulfills our conceptual requirement that different aspects of crises are partial substitutes.

Based on our choices on the conceptualization, operationalization, and aggregation for the crisis index, we run a PCA using three variables reflecting the intensity of disasters and conflict. Summary statistics are reported in Table (A-3). Figure (B-3) in the appendix shows the scree-plot of eigenvalues that we obtain after running our PCA. The figure shows that the eigenvalue of the first principal component is significantly greater than 1, whereas the eigenvalues of all other components are considerably and significantly smaller than 1. Furthermore, the first component captures more than two thirds of the variation in the variables. We can hence conclude that the first principle component describes the information in the data sufficiently well to use it as an index C_{it} on crisis episodes in i at t. To facilitate the interpretation of our results, we re-scale our indicator for all country-year observations $\langle i, t \rangle$ so that $C_{it} \in (0,\ 1)$.

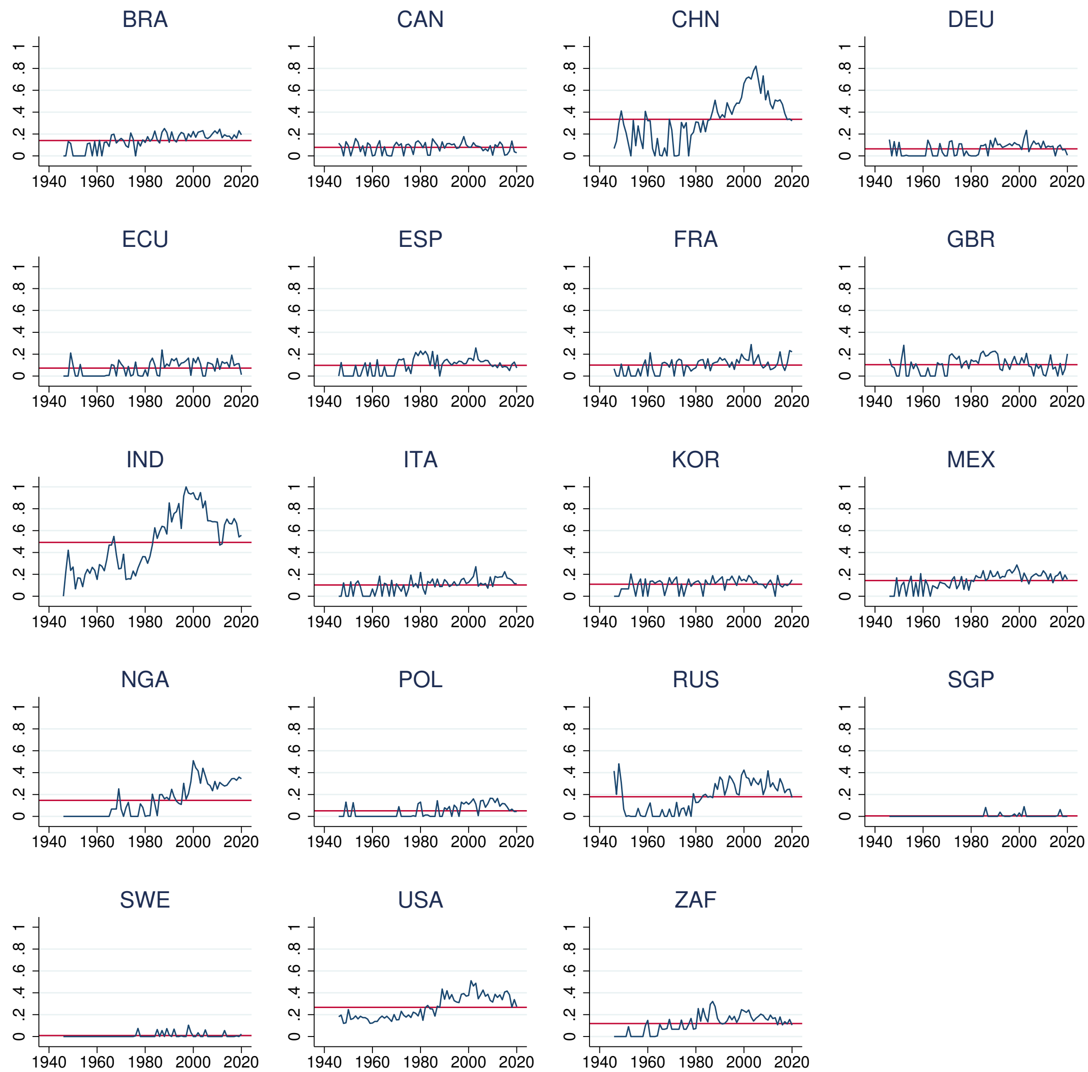
4.2.5 Crisis indices across countries

Our procedure yields a comparative measure of crisis experience across countries and years. Figure (2) shows how the country-specific crisis indices have developed over time. The figure suggests that there is substantial between-country variation in the extent of crisis experience. The figure also shows that countries differ substantially in the extent of within-variation. While some countries such as Sweden, Canada, or Germany have experienced few crises over the sample period, we observe considerable temporal variation in crisis experience in China, Russia, Nigeria, and India.

4.2.6 Lifetime discounted crisis experience

To measure crisis experience of individuals, we construct a lifetime discounted crisis experience measure for each respondent in our survey. To reflect lifetime crisis experience, we aggregate the yearly crisis experience measured by our index C_{it} which individual j born in country i in birth-year cohort h has observed over her lifetime. Do-

Figure 2 CRISIS INDICES ACROSS COUNTRIES AND YEARS



Notes: The figure shows how the country-specific crisis index has developed over time. The sample consists of the 19 countries in the survey on vaccination preferences (see 2.1). The index accounts for natural and technical disasters as well as conflict in a given country-year (see 4.2 for details on the construction). It covers the years 1946–2020 and is standardized to take values between 0 and 1. The sample average of crisis experience across time in a given country is represented by red lines.

ing so, we discount crisis experience to reflect recency bias in experience based learning (see Equation 4). We use the weighting function $\omega(k, \lambda, \text{age})$ to construct the lifetime discounted crisis experience measure C^o_{ih} for each surveyed individual via

$$C^o_{ih} = \sum_{k=0}^{\text{age}} \left(\frac{(\text{age} + 1 - k)^\lambda}{\sum_{k'=0}^{\text{age}} (\text{age} + 1 - k')^\lambda} \right) \mathrm{C}_{ik} \tag{11}$$

An important parameter for our measure of lifetime discounted crisis experience is the parameter λ, which regulates the relative weight that individuals assign to more recent crisis episodes. The psychological literature offers little guidance on the exact functional form of the weighting scheme and the relative weights may also differ across agents. We hence proceed with three variants of temporal discounting, including our preferred specification of linearly declining weights ($\lambda = 1$), progressively declining weights with heavy recency bias ($\lambda = 3$), and equal weights ($\lambda = 0$).

Figure (B-4) in the appendix shows how the choices for λ influence our measure of lifetime discounted crisis experience. We observe that the choice particularly influences crisis experience of individuals born in early cohorts, while the effect on younger cohorts and cohorts born in the middle of our sample is smaller.

Our lifetime discounted crisis experience measure is constructed so that all individuals of a given birth-year cohort in a country have the same lifetime discounted crisis experience. Variation stems from citizens born in the same country but in different years; born the same year but in different countries; or both. We then match this index by country and birth-year to the participants included in the survey collected by Lazarus et al. (2021) (see Section 2).

4.3 Empirical results

Our benchmark results on lifetime discounted crisis-experience and COVID-19 vaccination preferences are reported in Table (1). The results are obtained using our preferred regulation parameter $\lambda = 1$ to model individuals' lifetime discounted crisis experience. For our benchmark results, we estimate Equation (9) by OLS using standard errors that are robust to arbitrary heteroskedasticity.[10]

The main result of Table (1) is that higher lifetime discounted crisis experience in-

[10]We cannot model standard errors to be nested within countries, as the number of included countries is not sufficiently large to cluster standard errors on the country-level (see, e.g., Cameron and Miller, 2015).

creases the willingness to get vaccinated against COVID-19. In the most parsimonious specification reported in Column (I), we regress vaccination preferences on our measure of crisis experience, neglecting any source of confounding effects from other variables. The estimated parameter has a positive sign and is statistically significant at the 1% level ($t = 12.78$).

In Columns (II)–(VII), we gradually add observable factors that may correlate simultaneously with crisis experience and vaccination preferences (see Equation 9). In all specifications, the parameter estimate remains positive and statistically significant at the 1%. In the most extended empirical specification shown in Column (VII), the estimated coefficient on lifetime discounted crisis experience increases by a factor of 2.6 compared to the parsimonious model presented in Column (I). Numerically, the parameter estimates suggest that a one standard deviation increase in lifetime discounted crisis experience raises preferences for COVID-19 vaccination by between 0.1 and 0.3 standard deviations.

Robustness of the benchmark results: We run a battery of robustness analyses to asses the sensitivity of our results to changes in the empirical specification.

First, we examine whether different weights used to discount past crisis experience change the inferences regarding crisis experience. We present results for two alternative weighting schemes in the appendix, where we discount past crises using equal weights ($\lambda = 0$) and progressively declining weights ($\lambda = 3$). The results, shown in Tables (A-5) and (A-6), are comparable to those of our benchmark specifications.

Second, we also disentangle the components underlying preferences for COVID-19 vaccination. For our benchmark model, we combine the two questions on vaccination preferences collected in the Lazarus et al. (2021) survey. In the next step, we re-run the benchmark specifications separately for each survey question. Given that these variables are coded on a Likert scale running from 1 to 5, we re-estimate our empirical specifications using an ordered probit model. This strategy also accounts for non-linearity in the relationship between crisis experience and COVID-19 vaccination preferences, i.e. when a change from, say, 1 to 2 has a different meaning than a change from 2 to 3. We report the results for both questions on vaccination preferences separately for our three types of discounting schemes in Tables (A-7)–(A-12) in the appendix. In each model, the coefficients on crisis experience are positive and statistically significant at the 1% level. These complementary analyses show that the

Table 1 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — BENCHMARK RESULTS ($\lambda = 1$)

Dependent variable: Covid 19-Vaccination Preference, continuous indicator, Vacc_{ijh}

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^o_{ih}	0.161***	0.374***	0.195***	0.135***	0.121***	0.309***	0.417***
	(0.0126)	(0.0238)	(0.0129)	(0.0210)	(0.0210)	(0.0321)	(0.0241)
Obs. (# of Ind.)	13197	13197	13197	13197	13197	13197	13197
R-Squared (adj.)	0.013	0.035	0.037	0.069	0.082	0.089	0.070
Pers. C19 Cont.	-	X	-	-	-	X	X
Count. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (9). Lifetime discounted crisis experience is measured via our composite measure described in Section (4.2), using a regulating parameter of $\lambda = 1$ (linearly declining weights assigned to recently observed crises episodes) to account for the recency bias. Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if the respondent or a family member had fallen sick with COVID 19. Country COVID-19 controls ("Count. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (June 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed effects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

results are not driven by (i) a specific question of the Lazarus et al. (2021) survey, (ii) our procedure to combine both questions and (iii) the estimation technique employed to obtain the benchmark results.

Third, a threat to the identification may be that the results are driven by individuals from specific countries. We examine this potential threat in Figure (B-5) in the appendix, presenting results from jack-knife analyses that replicate our benchmark regressions in a "leave-one-out" setting, in which we consecutively leave out all respondents from one specific country. This analysis shows that the results are not driven by individual countries in our sample.

5 A Case study for Russia

Our theoretical model predicts that greater exposure to past crisis events increases individuals' willingness to get vaccinated against COVID-19. An important building block of our model is that individuals weigh the expected benefits of the vaccine against possible adverse side effects when forming their preferences (see Equation 5). The key factor that influences individuals' perceptions about both parameters is their belief in the vaccine to effectively tackle the crisis. When individuals observed ineffective crisis management in the past or distrust the ruling government that promotes taking the remedy, we expect them to become sceptical about the effectiveness of a new remedy. This argument is in line with previous studies showing that successful crisis management increases long-run trust (Andrabi and Das, 2017) and that political manipulation may undermine trust in health services and vaccination campaigns (Martinez-Bravo and Stegmann, 2021). Disentangling crisis-induced preference formation from distrust in the ruling government requires a setting in which a government sponsored remedy can be compared to an externally provided remedy. As both Sputnik V and international vaccines compete in Russia, the setting provides a uniquely suited laboratory to study the effects of past crises on vaccination preferences.

5.1 The COVID-19 pandemic in Russia and the development of the Russian vaccine

COVID-19 was confirmed to have spread to Russia by the end of January 2020, when two individuals in Tyumen and Chita tested positive for the virus. Measures to contain the pandemic included border restrictions, the cancellation of events, school closures, and the declaration a non-working period (Chubarova et al., 2020). Despite these measures, external observers were rather critical of the Russian central government's handling of the crisis: The policy of devolving crucial public health decisions to regions and firms created the impression of a central government trying to shift blame for the toll of the pandemic (Lancet, 2020).

Although the governors' readiness to shield the government from blame for unpopular measures to counter the pandemic is part of the political equilibrium in Russia (Busygina and Filippov, 2021), it did not succeed in avoiding the quick erosion of trust in the central government's handling of the pandemic. The government tried to counter this problem by very quickly developing and approving its proper COVID-19 vaccine, Sputnik V. This feat was widely publicized on national television, among others with the president himself announcing the inoculation of one of his daughters. However, the lack of large scale testing or a publication of the results (Mahase, 2020) cast additional doubt about the vaccine's effectiveness in the minds of an already distrustful Russian population, which potentially contributed to Russia's very high degree of vaccination hesitancy (Arce et al., 2021).

5.2 Advantages of the Russian case for the empirical set-up

The Russian case provides a uniquely suited testing ground to examine the crisis-preferences nexus. First, Russia was the first country to announce the development of its own COVID-19 vaccine and launched its mass vaccination rollout in early December 2020, well before most industrialized countries. Despite this apparent success, vaccination rates remain as low as 43% one year later. These puzzlingly low vaccination rates raise questions about the reasons behind vaccination hesitancy amongst the Russians population. Second, Russia experienced a number of crises since World War II, and there is strong heterogeneity in exposure to crises across Russian sub-national regions that we can exploit for causal identification. Third, there are competing vaccines available in Russia. In August 2020, Russia was the first country to announce the development of a COVID-19 vaccine (Sputnik V). The Russian vaccine, however, struggles to achieve mass acceptance inside Russia and competes with widely-administered vaccines developed by Western and Chinese pharmaceutical firms. Our survey data shows that on top of a generally large degree of vaccine hesitancy, many respondents are skeptic about Sputnik V. A key requirement of our theoretical model on vaccination preferences and crisis experience is that individuals evaluate the vaccine as a remedy to a crisis. Individuals may not perceive the vaccine to provide a compelling remedy when they do not trust their developers or the government that promotes and organizes the administration of the vaccine. The unique setting of competing vaccines in Russia therefore allows us to investigate our theoretical prediction in cases where individuals may have learned from experience to put little trust in the effectiveness and reliability of remedies developed and advocated by their own government, as opposed to remedies developed in other countries that did not suffer from this history of less positive experiences.

In terms of statistical methodology, the Russian case study improves on our cross-country analysis in several regards: First, the gecoded data allows us to exploit variation in life-time discounted crisis experience across sub-national regions to test our theoretical prediction, while holding constant important confounding factors that characterise most cross-country studies, like differences in language, culture, legal environment, or access to information. Second, the data provides rich information on individuals' characteristics, which allows us to exploit regional variation in crisis experience. Compared to our international micro-level sample, we can relax the assumption that crises similarly influence all individuals of a birth-cohort within a country. Third, the survey is designed to specifically elicit preferences across individual vaccines, enabling us to disentangle effects of experience-based learning from disturbing effects of distrust.

5.3 Data on preferences for COVID-19 vaccination

To study Russian COVID-19 vaccination preferences, we use unique geocoded survey data of Russian individuals collected in November 2020. Consistent with the cross-national analysis, the survey is designed to elicit preferences before the first vaccine dose was administered. These vaccination preference questions were part of a comprehensive survey, that was specifically designed and conducted for studying the regional variation in Russia's attitudes towards COVID-19 and related policies. This survey is part of the project "Research on COVID-19 in Russia's Regions (RoCiRR)" funded and administered by the International Center for the Study of Institutions and Development (ICSID) at National Research University Higher School of Economics (Moscow, Russia) in collaboration with Ghent University (Belgium) and Columbia University (New York, USA). The survey was conducted between 5 November and 1 December 2020 with a sample recruited from the reputable online polling company Online Market Intelligence (OMI) that makes surveys through its panels in Russia, Ukraine, Kazakhstan, and Belarus, and is analogous to Amazon's MTurk in the United States. Data on vaccination preferences from the survey was published in Arce et al. (2021). The quality of our data is guaranteed by verified profiles of respondents in the OMI panel, and by removing of the respondents who filled 25 minute survey in less than 6 minutes or failed all three attention checks that were distributed across the questionnaire. The final clean sample includes vaccination preferences of 22,144 adult respondents from 61 Russian regions[11], where the majority of the population resides. In each region we

[11] Regions in Russia have varying status of autonomy and are normally referred to as federal subjects. For ease of understanding we use the term regions. Federal subjects have the status of oblasts, republics, krais, okrugs, and federal cities. A list of the 61 regions included in the analysis can be found in Table (A-4).

aimed to survey at least 150 respondents and imposed quotas on specific age groups, gender, and education levels to make the sample more representative for the Russian population. We surveyed mostly respondents in cities of more than 100,000 inhabitants that were hardest hit in Russia by that time. In the remaining 24 regions, criteria for the data quality and parameters of the survey were unfeasible, thus we excluded them as is standard in Russian regional studies literature.

The survey elicits respondents' preferences regarding COVID-19 vaccination via the question

(Q1) "If a COVID-19 vaccine becomes available in Russia, would you take it?"

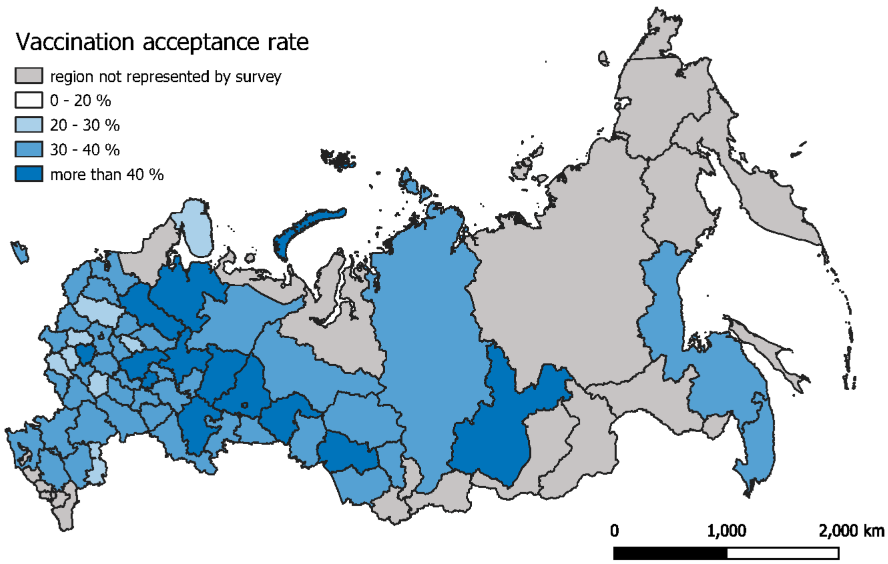
with the response options "Yes, if a Russian vaccine will be available", "Yes, if an imported vaccine will be available", "No", and "Don't know". Respondents were able to opt both for the Russian and an imported vaccine, if wanted. For our benchmark specification, we use a binary measure of vaccination preferences as our variable of interest, taking the value 1 if the individual would take either type of vaccine. We exclude respondents who opted for "Don't know" which leaves us with 16,077 respondents who opt for any type of vaccine.

At time of the survey, only 37% of survey participants stated they would get vaccinated if a vaccine became available. Figure (3) shows the geographic variation in vaccination preferences. Whilst over 45% of respondents were willing to get vaccinated in some regions, e.g. the oblasts Kirov (45.5%), Vologda (45.4%), and Novosibirsk (46.0%), vaccination preferences were only half as high in others, e.g. Tver oblast (24.9%), Kaluga oblast (26.1%), and Tambov oblast (26.5%). Vaccination preferences also substantially vary across gender, education, and income (see Figure (B-6)). Importantly, as Figure (B-7) shows, we observe heterogeneity in vaccination preferences not only in proximate factors but both across and birth cohort analogous to the cross-country stylized facts.

5.4 Crisis experience at the subnational level

In this case study, we aim to exploit the variation in crisis experience and vaccination preferences across 61 Russian regions. We replicate our methodology for measuring crisis experience outlined in Section (4.2) at the level of Russian regions instead of countries. We take the exact same steps in *conceptualizing* and *aggregating* crises in the Russian context. The sole difference lies in *operationalizing* crises, where we require

Figure 3 HETEROGENEITY IN VACCINATION PREFERENCES IN RUSSIA ACROSS REGIONS



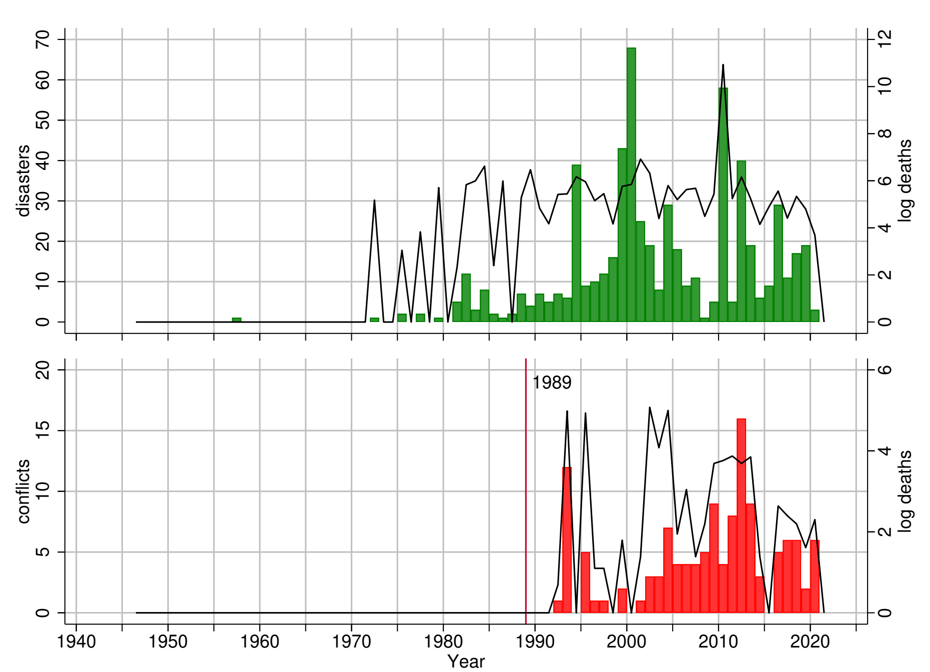
Notes: The map shows the share of surveyed individuals willing take (any) vaccine across our sample of 61 Russian regions. The preference to get vaccinated is taken from answering the questions "If a COVID-19 vaccine becomes available in Russia, would you take it?" either with "Yes, if a Russian vaccine will be available" and/or with "Yes, if an imported vaccine will be available". The survey includes 16,077 individuals and was conducted between 5 November and 1 December 2020.

our main input data on disasters and conflict to be geocoded at the subnational level to exploit regional variation.[12]

For the data on natural and technical disasters taken from EM-DAT, geolocating individual disasters across Russian regions was easily achieved with some manual coding. Parallel to the approach taken in the cross-national analysis, we take the number of disasters and the number of deaths per region-year as input variables for our index. For conflict data, we leverage the UCDP Georeferenced Event Dataset (GED, Version 21.1) compiled by Sundberg and Melander (2013), as the UCDP/PRIO Armed Conflict Dataset used in the cross-country analysis only provides country-level data without further disaggregation. The Georeferenced Event Dataset spans the years 1989 to 2020 and covers all observations of conflict where armed force between organized actors or by organized actors against civilians results in at least one death. The data is geocoded

[12]We use Russian regional codes as per GOST 7.67-2003.

Figure 4 CRISES IN RUSSIA ACROSS TIME (REGIONAL INDEX)



Notes: The figure shows how our measures of crises develop over time in our sample of 61 regions of Russia. Crises are measured as natural and technical disasters including previous epidemics (upper panel) or conflict (lower panel) both as the number of events per region-year and by a logged death count. Data on crises spans the years 1946 to 2020 and is taken from EM-DAT (Centre for Research on the Epidemiology of Disasters, 2021) and the UCDP Georeferenced Event Dataset (Sundberg and Melander, 2013). Displayed are aggregated values for all 61 regions, namely the number of events across all regions for a given year, as well as the log of the sum of deaths across all regions for a given year.

and allows us to collect both the number of conflicts and the aggregate number of conflict deaths for a given region-year. To achieve maximum comparability to the conflict definition of the Armed Conflict Dataset used for the cross-country analysis, we restrict the data to conflict observations with ≥ 25 deaths in a given year and use the count of conflicts for a given region-year. This provides a comparable measure to the definition employed in the cross-country analysis; empirically, the geocoded death counts improve on accuracy.

Figure (4) shows how the measures of crises in the 61 Russian regions in our sample are distributed over time. Natural and technical disasters are increasingly reported since the 1970s. Whilst many region-events occur around the years 2000 and 2010 (upper panel), the number of deaths from disasters peaks in 2010.[13] Conflict observations notably increased between 2000 and 2015 with spikes in the number of region-events in 1993 and 2013. As coverage for the GED starts only in 1989, one might suspect our estimates to suffer from coverage bias. However, we omit only one relevant conflict event due to shorter time coverage. We separately account for this one observation - this does not change our results. For a detailed account see Appendix C.

Figure (5) shows the geographic distribution of disaster and conflict occurrence across the 61 regions in our survey sample. Natural and technical disasters particularly affected the Ural regions as well as central and eastern parts of Russia (Figure (5a)). Over the years, disasters clustered in Moscow City (49 disasters in 27 years), Moskva oblast (47 disasters in 26 years), and Khabarovsk krai (29 disasters in 20 years). In terms of disaster-related deaths, the Moskva oblast (12,763 deaths during our sample period), Moscow City (12,673), and Voronezh oblast (11,228) were most heavily affected. Conflicts are less prevalent and took place only in the western parts of Russia (Figure (5b)). The Stavropol krai had the longest exposure to conflicts (60 conflicts in 20 years), followed by Moscow City (28 conflicts in 10 years), and Moskva oblast (5 conflicts in 5 years). The highest casualties in the sample arose in Moscow City (548 deaths), Stavropol krai (281), and Volgograd (48 deaths).

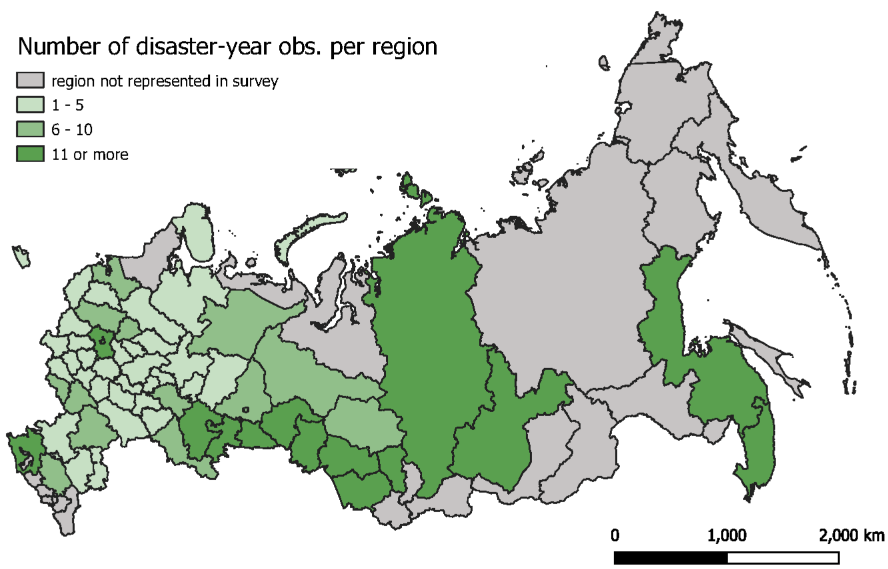
We aggregate this data on disasters and conflict via PCA, yielding a crisis index for a given region r in year t. Using this index, we construct the lifetime discounted crisis experience for all Russian individuals in our survey, again replicating our approach outlined in Section (4.2). We map the individual lifetime discounted crisis experience to the answers provided in the survey.

5.5 Empirical strategy

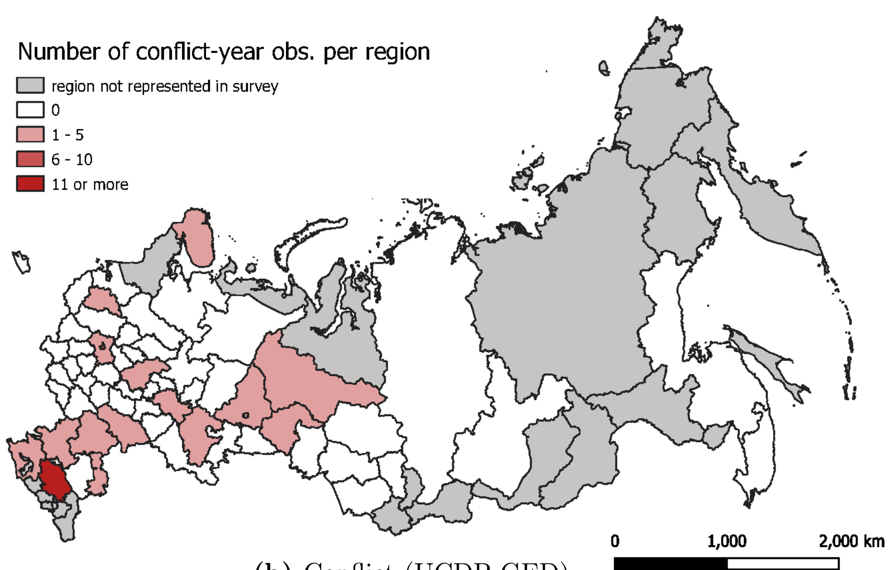
We estimate the effect of lifetime discounted crisis experience on vaccine preferences across sub-national regions in Russia, replicating our cross-national micro-level model of Equation (9) as closely as possible via

[13] A high count of region-disasters can stem from a high number of events, a high number of affected regions, or from both. A cold wave in May 2000, for example, affected 35 regions alone, accounting for half of the disaster-count in 2000 in Figure (4). In terms of recorded deaths, the most severe disasters are the 2010 heat wave (claiming more than 55,000 lives), the 1995 Neftegorsk earthquake (around 2,000 casualties), as well as the 1989 Ufa railway-pipeline disaster with more than 600 deaths recorded in EM-DAT.

Figure 5 HETEROGENEITY IN CRISIS EXPERIENCE IN RUSSIA ACROSS REGIONS



(a) Natural disasters (EM-DAT)



(b) Conflict (UCDP GED)

Notes: The maps show number of crisis-year observations across regions. Crises are measured as natural and technical disasters including previous epidemics (5a) or conflict (5b). Data on crises spans the years 1946 to 2020 and is taken from EM-DAT (Centre for Research on the Epidemiology of Disasters, 2021) and the UCDP Georeferenced Event Dataset (Sundberg and Melander, 2013).

$$\text{Vacc}_{rjh} = \psi C^o_{rh} + \mathbf{A}_j \boldsymbol{\alpha} + \mathbf{B}_r \boldsymbol{\rho} + \mathbf{X}_j \boldsymbol{\gamma} + \eta_k + \zeta_h + \varepsilon_{rjh}, \tag{12}$$

where Vacc_{rjh} reflects vaccination preferences of individual j of birth-cohort h that lives in Russian region r. Our key variable of interest, C^o_{rh}, measures life-time discounted crisis experience of birth-cohort h of region r. We account for indirect COVID-19 exposure via the number of infections (total and per capita) and deaths (total and per capita) in respondents' region at the time the survey was conducted via the matrix $\mathbf{B}_r$ and also include measures for direct COVID-19 exposure by asking about respondents' knowledge of COVID-19 cases in their social peer group ($\mathbf{A}_j$). Replicating our empirical setting used for the cross-national analysis, we also include socio-economic characteristics (gender, education, and income) of respondents ($\mathbf{X}_j$). Finally, in extended versions of Equation (12), we also address heterogeneity in time-invariant factors across the eight federal districts of Russia (η_k) and birth-cohorts (ζ_h).

5.6 Baseline results

Table (2) reports the benchmark results for Russia. To maximize comparability, the model specifications closely replicate the specifications reported for our cross-national sample in Table (1). For comparison we report all specifications including models that account for cross-regional heterogeneity in time-invariant factors. These should be interpreted with caution given that the fixed effects for regions capture large parts of the variation in our data. The results are reported for vaccination preferences on any vaccine, combining preferences for Sputnik V and the competing imported vaccines.

The main finding of Table (2) is that contrary to the cross-national sample, crisis experience across Russian respondents decreases their willingness to get vaccinated against COVID-19. The effect is statistically significant at the 1% level in most cases. Taken together, greater crisis experience in Russia seems to reduce the willingness for COVID-19 vaccination, contradicting the results from the cross-national sample.

Robustness: The results for Russia are robust across a number of additional analyses. Our benchmark measure of crisis experience considers the number of conflict events rather than the number of casualties to maximize comparability with the cross-national results. For Russia, however, we can use fine-grained geocoded data on the number of conflict deaths. Using this data for the construction of lifetime discounted

Table 2 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — RESULTS FOR RUSSIA

Dependent variable: Covid 19-Vaccination Preference, Russian survey, Vacc_{rjh}

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^{o}_{rh}	-0.204***	-0.513***	-0.273***	-0.0738	-0.154**	-0.389***	-0.271***
	(0.0653)	(0.0927)	(0.0638)	(0.0714)	(0.0698)	(0.107)	(0.0916)
Obs. (# of Ind.)	16077	16077	16077	16077	16077	16077	16077
R-Squared (adj.)	0.001	0.009	0.056	0.003	0.058	0.068	0.075
Pers. C19 Cont.	-	X	-	-	-	X	X
Reg. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (12). Lifetime discounted crisis experience is measured via our measure described in Section (5.4) to account for the recency bias. Geocoded individual-level data on vaccination preferences for individuals in Russia are elicited in a unique survey described in Section (5.3). Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if individuals in the peer group of respondents had fallen sick with COVID 19. Regional COVID-19 controls ("Reg. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' region at the time the survey was conducted (November 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed effects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

crisis experience does not alter the inferences (see Table A-13 in the appendix). Our findings are also robust when we additionally account for nation-wide crises in Russia, estimate probit models or include a larger set of socioeconomic controls. A further threat to identification would be confounding effects from regional in- or outmigration. We control for these effects by re-estimating our model for the subset of individuals who lived in the same region they were born in at the time the survey was conducted. Doing so does not change the inferences. All tables for robustness tests are available upon request.

5.7 Competing vaccine types

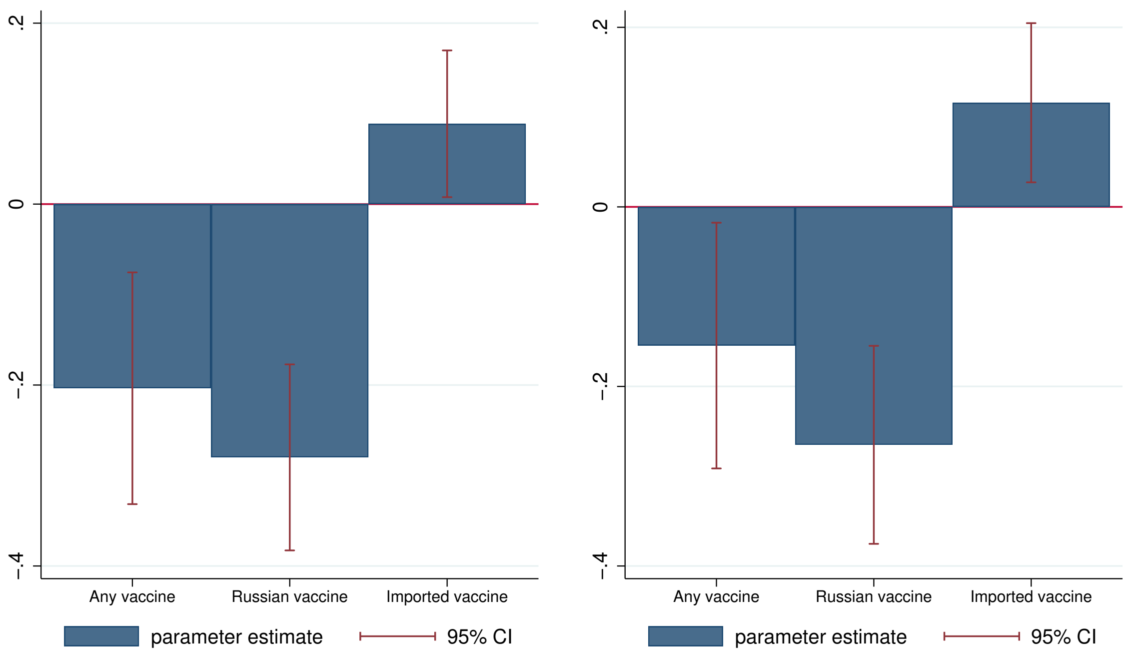
The unique setting of "competing vaccines" provided by the Russian case study allows us to disentangle experience effects initiated by crises experienced over the life-time and potentially disturbing effects from distrust in the authorities that supported the development of the vaccine and that manage and organize the administration of vaccine doses. We exploit this setting by separately accounting for vaccination preferences towards the Sputnik V vaccine and vaccines developed by international pharmaceutical firms. Figure (6) shows treatment effects of life-time discounted crisis experience on three types of vaccine preferences, including (i) preferences for *any* vaccine, (ii) preferences for the *Russian* vaccine, and (iii) preferences for *international* vaccines. The underlying results are reported in Tables (A-14)–(A-15) in the appendix.

The figures shows that the effect of life-time discounted crisis experience on vaccination preferences heavily depends on the type of vaccine. Illustrating the overall effect of Table (2) as a benchmark, the results show that the effect of crisis experience is particularly negative regarding respondents' preferences towards the Russian vaccine. In contrast and consistent with the findings of our cross-national analysis, however, the effect of crisis experience is *positive* regarding preferences for imported vaccines.

The control group underlying the results for the imported vaccine in Figure (6) is composed of individuals who do not prefer to get vaccinated or who prefer getting vaccinated only with the Russian vaccine. As a complementary analysis to examine differences in crisis-induced preference formation across types of vaccines, we investigate the sub-sample of individuals in the survey that report that they are willing to take the vaccine. This analysis allows us to study the effect of crisis experience on preferences based on a more comparable control group. The sub-sample consists of 4,786 individuals, amounting to 30% of the total number of 16,077 individuals included in the survey. For this sub-sample of respondents, we construct a dummy variable that equals 1 if the respondent would only take the imported vaccine, and zero otherwise. We replicate all model specifications reported in the benchmark estimates for Russia (Table 2) for the sub-sample of individuals willing to take a vaccine, and report the results in Table (3). This analysis uncovers a fundamental change in the effects of crisis experience on preferences. Consistent with the findings of our cross-national sample, lifetime discounted crisis experience positively impacts individuals' preferences to get vaccinated with the imported vaccine.

We interpret the change in the effect of crisis experience on vaccination preferences

Figure 6 EFFECT OF CRISIS EXPERIENCE ON VACCINATION PREFERENCES ACROSS TYPES OF VACCINES



(a) Parsimonious specification **(b)** Extended specification

Notes: The figure shows the estimated parameter on lifetime discounted crisis experience on vaccination preferences separately for the Russian vaccine and an imported vaccine. The parameter estimates refer to the most parsimonious specification and an extended specification that accounts for individual-level controls and differences across Russian regions. Vertical lines represent 95% confidence intervals. The full results are reported in Tables (A-14)–(A-15) in the appendix.

across vaccine types as a strong sign that trust in authorities matters a great deal for crisis-induced preference formation. Individuals that experienced crises in sub-national Russian regions tend to be less willing to take a vaccine that is supported and administered by the government. This behavior may largely reflect experienced-based learning when individuals observed ineffective crisis management in the past. In contrast, individuals are more willing to take a vaccine that was developed outside the influence of the Russian government. We argue that both findings are in line with our theoretical prediction. When individuals have learned from past crises not to trust the effectiveness of the Russian remedy (θ is low) or have learned to fear the negative side effects of government prescribed remedies (ρ is high), the expected value

Table 3 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — RESULTS FOR RUSSIA, SUB-SAMPLE OF VACCINE-TAKERS

Dependent variable: Covid 19-Vaccination Preference (Imp. Vaccine), Russian survey, Vacc_{ijh}

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^o_{rh}	0.520***	0.593***	0.508***	0.585***	0.581***	0.610***	-0.0385
	(0.123)	(0.175)	(0.123)	(0.136)	(0.135)	(0.206)	(0.173)
Obs. (# of Ind.)	4786	4786	4786	4786	4786	4786	4786
R-Squared (adj.)	0.004	0.006	0.033	0.006	0.035	0.035	0.112
Pers. C19 Cont.	-	X	-	-	-	X	X
Reg. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (12). The table only considers those respondents that report that they would be willing to take the vaccine. Lifetime discounted crisis experience is measured via our measure described in Section (5.4) to account for the recency bias. Geocoded individual-level data on vaccination preferences for individuals in Russia are elicited in a unique survey described in Section (5.3). Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if individuals in the peer group of respondents had fallen sick with COVID 19. Regional COVID-19 controls ("Reg. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (November 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed efects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

of the net pay-off of the Russian vaccine $d_{t-1} = \theta_{t-1} - \rho_{t-1}$ is small and could even turn negative, implying the reversal of the relation between vaccination preferences and crisis experience. This reversal, however, does not apply for the preferences to be inoculated with foreign vaccines, which remain unaffected by past negative experiences with the remedies of the Russian government and therefore still exhibit a positive relation with crisis experience.

6 Conclusion

Individuals' willingness to get vaccinated is a necessary condition to the success of global vaccination campaigns. Studies for many countries have uncovered a considerable degree of heterogeneity in preferences towards vaccination against COVID-19. A recurring empirical regularity is that vaccination preferences not only vary across socio-economic characteristics, but also across birth-cohorts within countries. Our theoretical framework building on experienced-based learning shows how experiencing a common shock translates into such cohort-specific preferences. Using individual-level data for 19 countries and a unique geocoded survey for Russia, we provide evidence that is in line with our theoretical prediction.

Our paper shows how experience-based preference formation contributes to explaining the observed heterogeneity in vaccination preferences, going beyond directly observable correlations regarding socio-economic characteristics or local exposure to the pandemic. Understanding these deep roots of preference formation may be helpful when the policy goal is to design measures that increase individuals' willingness to take the vaccine. Finally, viewing global immunization as a collective action problem, our results suggest that experience effects have tangible implications beyond individual preference formation. Examining the role of experience effects in driving collective action failure is a promising avenue for future research.

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Appendix A: Supplementary Tables

Table A-1 SUMMARY STATISTICS: MICRO LEVEL-EVIDENCE ACROSS COUNTRIES

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Vacc_{ijh}	0.650	0.240	0	1	13197
Vaccination Preferences (Q1)	3.956	1.260	1	5	13197
Vaccination Preferences (Q2)	3.272	1.162	1	5	13197
C^o_{ih} ($\lambda = 0$)	0.190	0.167	0.005	0.748	13197
C^o_{ih} ($\lambda = 1$)	0.194	0.168	0.006	0.710	13197
C^o_{ih} ($\lambda = 3$)	0.190	0.162	0.007	0.686	13197
Personal C19	0.852	0.355	0	1	12380
Country C19 Cases	309563.162	506013.934	12257	2234475	13197
Country C19 Cases p.c.	0.003	0.002	0	0.007	13197
Country C19 Deaths	20547.365	28500.672	26	119941	13197
Country C19 Deaths p.c.	0	0	0	0.001	13197
Gender (Female=1)	0.537	0.499	0	1	13076
Educational Level	2.000	0.941	1	4	13167
Income Level	3.527	0.769	1	4	12574
Birthyear	1979.914	15.190	1946	2002	13197
Birth Cohort	1975.599	15.601	1940	2000	13197
Region Dummy	6.100	3.030	1	11	13197

Table A-2 SUMMARY STATISTICS: MICRO LEVEL-EVIDENCE IN RUSSIA

Variable	Mean	Std. Dev.	Min.	Max.	N
Vacc_{ijh}	0.366	0.482	0	1	16077
C^o_{rh} $(\lambda = 0)$	0.053	0.058	0	0.331	16077
C^o_{rh} $(\lambda = 1)$	0.056	0.059	0	0.283	16077
C^o_{rh} $(\lambda = 3)$	0.052	0.055	0	0.26	16077
Personal C19	0.909	0.287	0	1	16077
Region C19 Cases	99176.504	207087.874	14127	1323757	16077
Region C19 Cases p.c.	0.031	0.019	0.006	0.105	16077
Region C19 Deaths	2582.895	3924.346	183	21876	16077
Region C19 Deaths p.c.	0.001	0	0	0.003	16077
Gender (Female=1)	0.637	0.481	0	1	16077
Education Level	4.202	1.082	1	5	16077
Income Level	3.370	0.861	1	6	16077
Birthyear	1984.512	9.339	1946	2003	16077
Birth Cohort	1980.034	9.971	1940	2000	16077
Russian Federal Districts	3.857	2.258	1	8	16077

Table A-3 SUMMARY STATISTICS: INDEX CONSTRUCTION

Panel A: Variables used in PCA					
Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Disasters (Count)	6.001	11.296	0	102	1,425
Disasters (Deaths)	3.435	2.878	0	13.413	1,425
Conflict (Dummy)	0.293	0.886	0	7	1,425
Index (rescaled)	0.138	0.156	0	1	1,425

Panel B: Eigenvectors from PCA			
Variable	**1st Comp.**	**2nd Comp.**	**3rd Comp.**
Disasters (Count)	0.614	-0.266	-0.744
Disasters (Deaths)	0.594	-0.466	0.656
Conflict (Dummy)	0.521	0.844	0.128

Table A-4 LIST OF RUSSIAN FEDERAL SUBJECTS REPRESENTED IN SURVEY

English Name	Numeric GOST 7.67 code	English 3-letter GOST 7.67 code
Altai krai	643-301	RU-ALT
Arkhangelsk oblast	643-314	RU-ARK
Astrakhan oblast	643-320	RU-AST
Bashkortostan	643-109	RU-BAS
Belgorod oblast	643-326	RU-BEL
Bryansk oblast	643-332	RU-BRY
Chelyabinsk oblast	643-618	RU-CHE
Chuvashia	643-177	RU-CHV
Irkutsk oblast	643-368	RU-IRK
Ivanovo oblast	643-362	RU-IVA
Kaliningrad oblast	643-374	RU-KAG
Kaluga oblast	643-380	RU-KAL
Karelia	643-137	RU-KAR
Kemerovo oblast	643-392	RU-KEM
Khabarovsk krai	643-612	RU-KHA
Khanty-Mansijsk a.o.	643-748	RU-KHM
Kirov oblast	643-398	RU-KIR
Komi Republic	643-141	RU-KOM
Kostroma oblast	643-404	RU-KOS
Krasnodar krai	643-410	RU-KRA
Kurgan oblast	643-422	RU-KUG
Kursk oblast	643-428	RU-KUR
Leningrad oblast	643-434	RU-LEN
Lipetsk oblast	643-440	RU-LIP
Marij El	643-145	RU-MAR
Mordovia	643-149	RU-MOR
Moscow oblast	643-452	RU-MOS
Moscow (city)	643-001	RU-MOW
Murmansk oblast	643-458	RU-MUR
Novgorod oblast	643-470	RU-NGR
Nizhni Novgorod oblast	643-464	RU-NIZ
Novosibirsk oblast	643-476	RU-NVS
Omsk oblast	643-484	RU-OMS
Orenburg oblast	643-490	RU-ORE
Oryol oblast	643-496	RU-ORL
Perm krai	643-510	RU-PER
Penza oblast	643-504	RU-PNZ
Primorsky krai	643-516	RU-PRI
Pskov oblast	643-522	RU-PSK
Rostov oblast	643-528	RU-ROS
Ryazan oblast	643-534	RU-RYA
Samara oblast	643-540	RU-SAM
Saratov oblast	643-546	RU-SAR
Smolensk oblast	643-564	RU-SMO
Saint-Petersburg	643-002	RU-SPB
Stavropol krai	643-570	RU-STA
Sverdlovsk oblast	643-558	RU-SVE
Tambov oblast	643-576	RU-TAM
Tatarstan	643-157	RU-TAT
Tomsk oblast	643-588	RU-TOM
Tula oblast	643-594	RU-TUL
Tver oblast	643-582	RU-TVE
Tyumen oblast	643-600	RU-TYU
Udmurtia	643-165	RU-UDM
Ulyanovsk oblast	643-606	RU-ULY
Volgograd oblast	643-344	RU-VGG
Vladimir oblast	643-338	RU-VLA
Vologda oblast	643-350	RU-VLG
Voronezh oblast	643-356	RU-VOR
Yaroslavl oblast	643-630	RU-YAR
Krasnoyarsk krai	643-416	RU-KYA

Table A-5 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — RESULTS FOR $\lambda = 0$

Dependent variable: Covid 19-Vaccination Preference, continuous indicator, Vacc_{ijh}

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^o_{ih}	0.158***	0.330***	0.193***	0.115***	0.107***	0.233***	0.400***
	(0.0128)	(0.0227)	(0.0131)	(0.0216)	(0.0217)	(0.0308)	(0.0237)
Obs. (# of Ind.)	13197	13197	13197	13197	13197	13197	13197
R-Squared (adj.)	0.012	0.033	0.036	0.068	0.082	0.088	0.069
Pers. C19 Cont.	-	X	-	-	-	X	X
Count. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (9). lifetime discounted crisis experience is measured via our composite measure described in Section (4.2), using a regulating parameter of $\lambda = 0$ (equal weights assigned to all observed crises episodes) to account for the recency bias. Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if the respondent or a family member had fallen sick with COVID 19. Country COVID-19 controls ("Count. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (June 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed efects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table A-6 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — RESULTS FOR $\lambda = 3$

Dependent variable: Covid 19-Vaccination Preference, continuous indicator, Vacc_{ijh}

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^{o}_{ih}	0.160***	0.375***	0.197***	0.135***	0.120***	0.338***	0.414***
	(0.0130)	(0.0253)	(0.0133)	(0.0213)	(0.0213)	(0.0342)	(0.0254)
Obs. (# of Ind.)	13197	13197	13197	13197	13197	13197	13197
R-Squared (adj.)	0.012	0.033	0.036	0.069	0.082	0.089	0.067
Pers. C19 Cont.	-	X	-	-	-	X	X
Count. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (9). lifetime discounted crisis experience is measured via our composite measure described in Section (4.2), using a regulating parameter of $\lambda = 3$ (progressively declining weights assigned to recently observed crises episodes) to account for the recency bias. Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if the respondent or a family member had fallen sick with COVID 19. Country COVID-19 controls ("Count. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (June 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed efects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table A-7 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — VACCINATION PREFERENCES (Q1) ($\lambda = 1$)

Dependent variable: Covid 19-Vaccination Preferences, continuous indicator, Vacc_{ijh}

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^o_{ih}	0.300***	1.735***	0.360***	0.587***	0.513***	1.642***	1.874***
	(0.0557)	(0.115)	(0.0584)	(0.107)	(0.107)	(0.168)	(0.119)
Obs. (# of Ind.)	13197	13197	13197	13197	13197	13197	13197
Pers. C19 Cont.	-	X	-	-	-	X	X
Count. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (9). lifetime discounted crisis experience is measured via Q1 of the Lazarus et al. (2021) survey on vaccination preferences described in Section (4.2), using a regulating parameter of $\lambda = 1$ (linearly declining weights assigned to recently observed crises episodes) to account for the recency bias. Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if the respondent or a family member had fallen sick with COVID 19. Country COVID-19 controls ("Count. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (June 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed efects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table A-8 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — VACCINATION PREFERENCES (Q1) ($\lambda = 0$)

Dependent variable: Covid 19-Vaccination Preferences, continuous indicator, Vacc_{ijh}

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^o_{ih}	0.282***	1.479***	0.344***	0.484***	0.441***	1.186***	1.761***
	(0.0560)	(0.108)	(0.0588)	(0.109)	(0.110)	(0.159)	(0.115)
Obs. (# of Ind.)	13197	13197	13197	13197	13197	13197	13197
Pers. C19 Cont.	-	X	-	-	-	X	X
Count. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (9). lifetime discounted crisis experience is measured via Q1 of the Lazarus et al. (2021) survey on vaccination preferences described in Section (4.2), using a regulating parameter of $\lambda = 0$ (equal weights assigned to all observed crises episodes) to account for the recency bias. Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if the respondent or a family member had fallen sick with COVID 19. Country COVID-19 controls ("Count. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (June 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed efects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table A-9 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — VACCINATION PREFERENCES (Q1) ($\lambda = 3$)

Dependent variable: Covid 19-Vaccination Preference, continuous indicator, Vacc_{ijh}

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^o_{ih}	0.303***	1.830***	0.371***	0.590***	0.509***	1.826***	1.909***
	(0.0577)	(0.122)	(0.0605)	(0.108)	(0.109)	(0.178)	(0.125)
Obs. (# of Ind.)	13197	13197	13197	13197	13197	13197	13197
Pers. C19 Cont.	-	X	-	-	-	X	X
Count. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (9). lifetime discounted crisis experience is measured via Q1 of the Lazarus et al. (2021) survey on vaccination preferences described in Section (4.2), using a regulating parameter of $\lambda = 3$ (progressively declining weights assigned to recently observed crises episodes) to account for the recency bias. Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if the respondent or a family member had fallen sick with COVID 19. Country COVID-19 controls ("Count. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (June 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed efects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table A-10 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — VACCINATION PREFERENCES (Q2) ($\lambda = 1$)

Dependent variable: Covid 19-Vaccination Preference, continuous indicator, Vacc_{ijh}							
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^o_{ih}	0.836***	1.175***	1.022***	0.562***	0.531***	1.174***	1.398***
	(0.0585)	(0.112)	(0.0614)	(0.106)	(0.106)	(0.169)	(0.115)
Obs. (# of Ind.)	13197	13197	13197	13197	13197	13197	13197
Pers. C19 Cont.	-	X	-	-	-	X	X
Count. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (9). lifetime discounted crisis experience is measured via Q2 of the Lazarus et al. (2021) survey on vaccination preferences described in Section (4.2), using a regulating parameter of $\lambda = 1$ (linearly declining weights assigned to recently observed crises episodes) to account for the recency bias. Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if the respondent or a family member had fallen sick with COVID 19. Country COVID-19 controls ("Count. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (June 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed efects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table A-11 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — VACCINATION PREFERENCES (Q2) ($\lambda = 0$)

Dependent variable: Covid 19-Vaccination Preference, continuous indicator, Vacc_{ijh}							
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^o_{ih}	0.830***	1.065***	1.020***	0.524***	0.503***	0.971***	1.344***
	(0.0592)	(0.106)	(0.0621)	(0.109)	(0.109)	(0.161)	(0.112)
Obs. (# of Ind.)	13197	13197	13197	13197	13197	13197	13197
Pers. C19 Cont.	-	X	-	-	-	X	X
Count. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (9). lifetime discounted crisis experience is measured via Q2 of the Lazarus et al. (2021) survey on vaccination preferences described in Section (4.2), using a regulating parameter of $\lambda = 0$ (equal weights assigned to all observed crises episodes) to account for the recency bias. Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if the respondent or a family member had fallen sick with COVID 19. Country COVID-19 controls ("Count. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (June 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed efects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table A-12 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — VACCINATION PREFERENCES (Q2) ($\lambda = 3$)

Dependent variable: Covid 19-Vaccination Preference, continuous indicator, Vacc_{ijh}							
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^{o}_{ih}	0.826***	1.094***	1.021***	0.535***	0.502***	1.186***	1.343***
	(0.0600)	(0.118)	(0.0631)	(0.106)	(0.107)	(0.179)	(0.121)
Obs. (# of Ind.)	13197	13197	13197	13197	13197	13197	13197
Pers. C19 Cont.	-	X	-	-	-	X	X
Count. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (9). lifetime discounted crisis experience is measured via Q2 of the Lazarus et al. (2021) survey on vaccination preferences described in Section (4.2), using a regulating parameter of $\lambda = 3$ (progressively declining weights assigned to recently observed crises episodes) to account for the recency bias. Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if the respondent or a family member had fallen sick with COVID 19. Country COVID-19 controls ("Count. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (June 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed efects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table A-13 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — RESULTS FOR RUSSIA, ALTERNATIVE SPECIFICATION OF CRISIS EXPERIENCE

Dependent variable: Covid 19-Vaccination Preference, Russian survey, Vacc_{rjh}

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^o_{rh}	-0.214***	-0.585***	-0.291***	-0.0703	-0.160**	-0.444***	-0.308***
	(0.0706)	(0.104)	(0.0689)	(0.0767)	(0.0751)	(0.121)	(0.103)
Obs. (# of Ind.)	16077	16077	16077	16077	16077	16077	16077
R-Squared (adj.)	0.001	0.009	0.056	0.003	0.058	0.068	0.075
Pers. C19 Cont.	-	X	-	-	-	X	X
Reg. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (12). Lifetime discounted crisis experience is measured via our measure described in Section (5.4) to account for the recency bias. The employed measures considers the number of casualties rather then counting events as in our benchmark specification. geocoded individual-level data on vaccination preferences for individuals in Russia are elicited in a unique survey described in Section (5.3). Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if individuals in the peer group of respondents had fallen sick with COVID 19. Regional COVID-19 controls ("Reg. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' region at the time the survey was conducted (November 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed effects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table A-14 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — RESULTS FOR RUSSIA, RUSSIAN VACCINE

Dependent variable: Covid 19-Vaccination Preference, Russian survey, Vacc_{rjh}

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^o_{rh}	-0.303***	-0.485***	-0.346***	-0.242***	-0.289***	-0.395***	-0.135*
	(0.0558)	(0.0810)	(0.0546)	(0.0608)	(0.0597)	(0.0942)	(0.0794)
Obs. (# of Ind.)	14975	14975	14975	14975	14975	14975	14975
R-Squared (adj.)	0.002	0.004	0.049	0.003	0.049	0.054	0.077
Pers. C19 Cont.	-	X	-	-	-	X	X
Reg. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (12). The table considers preferences towards the Russian vaccine. Lifetime discounted crisis experience is measured via our measure described in Section (5.4) to account for the recency bias. Geocoded individual-level data on vaccination preferences for individuals in Russia are elicited in a unique survey described in Section (5.3). Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if individuals in the peer group of respondents had fallen sick with COVID 19. Regional COVID-19 controls ("Reg. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (November 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed effects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table A-15 PREFERENCES TOWARDS COVID-19 VACCINATION AND CRISIS EXPERIENCE — RESULTS FOR RUSSIA, IMPORTED VACCINE

Dependent variable: Covid 19-Vaccination Preference, Russian survey, Vacc_{rjh}							
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
C^o_{rh}	0.0940**	0.0393	0.0737*	0.146***	0.123**	0.0731	-0.0732
	(0.0442)	(0.0607)	(0.0443)	(0.0482)	(0.0483)	(0.0709)	(0.0616)
Obs. (# of Ind.)	14975	14975	14975	14975	14975	14975	14975
R-Squared (adj.)	0.000	0.003	0.007	0.001	0.007	0.010	0.025
Pers. C19 Cont.	-	X	-	-	-	X	X
Reg. C19 Cont.	-	X	-	-	-	X	X
Soc-Econ. Cont.	-	-	X	-	X	X	X
Regional FE	-	-	-	X	X	X	-
Birth Coh. FE	-	-	-	-	-	-	X

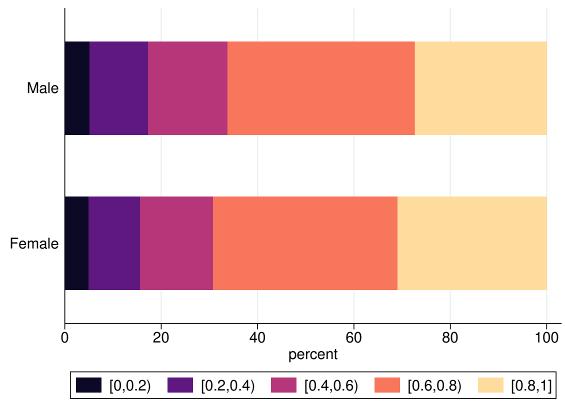
Notes: The table shows the results of the estimations on the effect of individuals' lifetime discounted crisis experience on vaccination preferences, empirically estimating variants of Equation (12). The table considers preferences towards the imported vaccine. Lifetime discounted crisis experience is measured via our measure described in Section (5.4) to account for the recency bias. Geocoded individual-level data on vaccination preferences for individuals in Russia are elicited in a unique survey described in Section (5.3). Personal COVID-19 controls ("Pers. C19 Cont") are dummy variables that are equal to one if individuals in the peer group of respondents had fallen sick with COVID 19. Regional COVID-19 controls ("Reg. C19 Cont.") include variables that capture the number of COVID-cases and COVID-deaths in the respondents' country at the time the survey was conducted (November 2020). Socioeconomic controls ("Soc-Econ. Cont.") include variables for gender, income level, and educational background. "Regional FE" and "Birth Coh. FE" denote fixed effects for regions and for birth cohorts. The standard errors reported in parentheses are adjusted to arbitrary heteroskedasticity.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

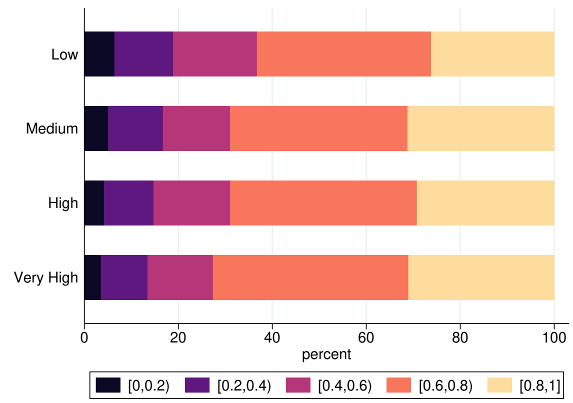
Appendix B: Supplementary Figures

Figure B-1 HETEROGENEITY IN VACCINATION PREFERENCES: SOCIOECONOMIC CHARACTERISTICS, CROSS-NATIONAL SAMPLE

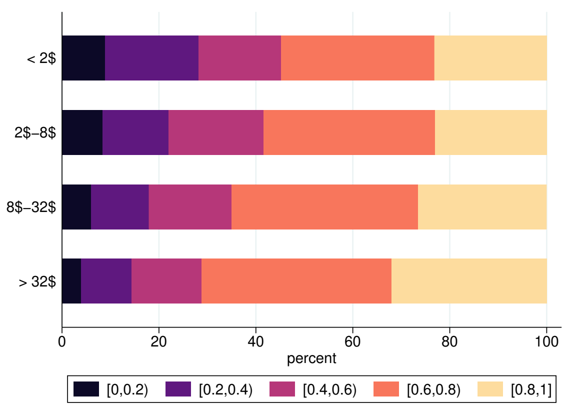
(a) Gender



(b) Education

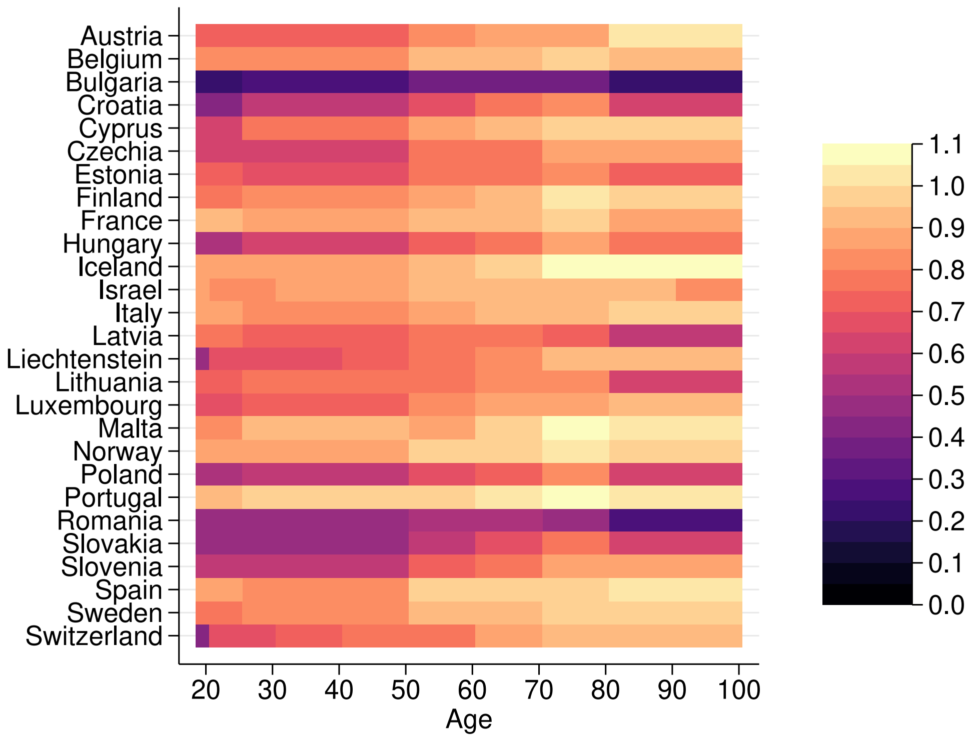


(c) Income



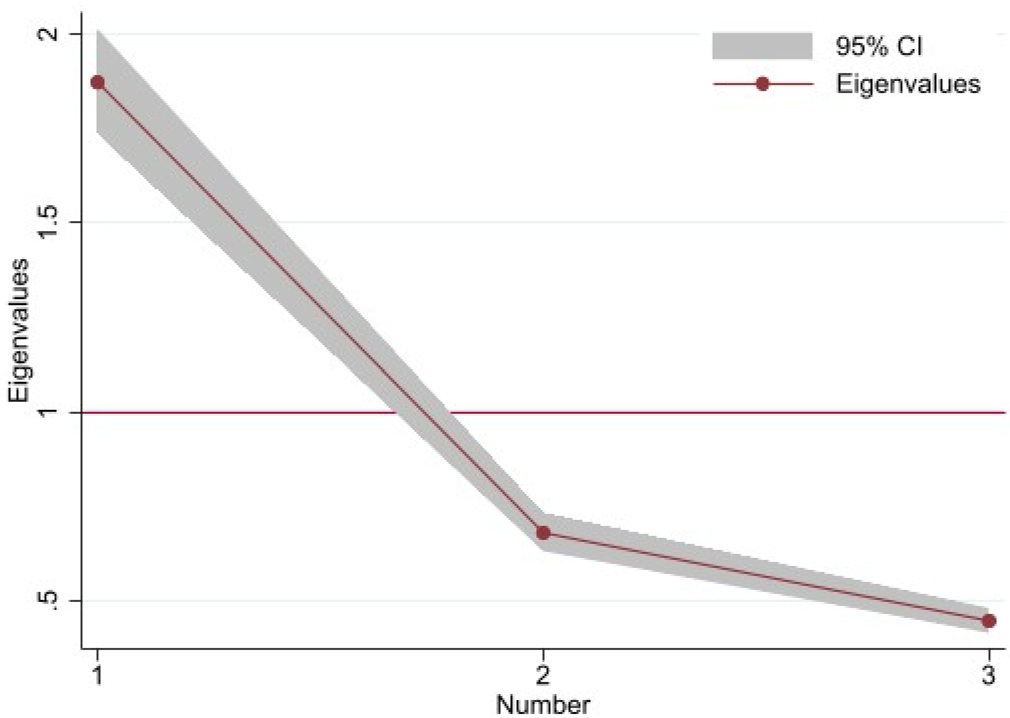
Notes: The figure shows the percentage of respondents with a standardized vaccination index in a given range. Higher scores indicate higher vaccination preferences. Vaccination preferences are based on own calculations using raw data on vaccination preferences taken from Lazarus et al. (2021). Following their notation on educational levels, "Low" corresponds to "Less than high school". "Medium" to "High School or some college", "High" to "Bachelor" and "Very High" to "Postgraduate". Income levels refer to Gapminder income levels, the US Dollar equivalent individuals' daily income.

Figure B-2 HETEROGENEITY IN VACCINATION RATES: COUNTRIES AND AGE COHORTS



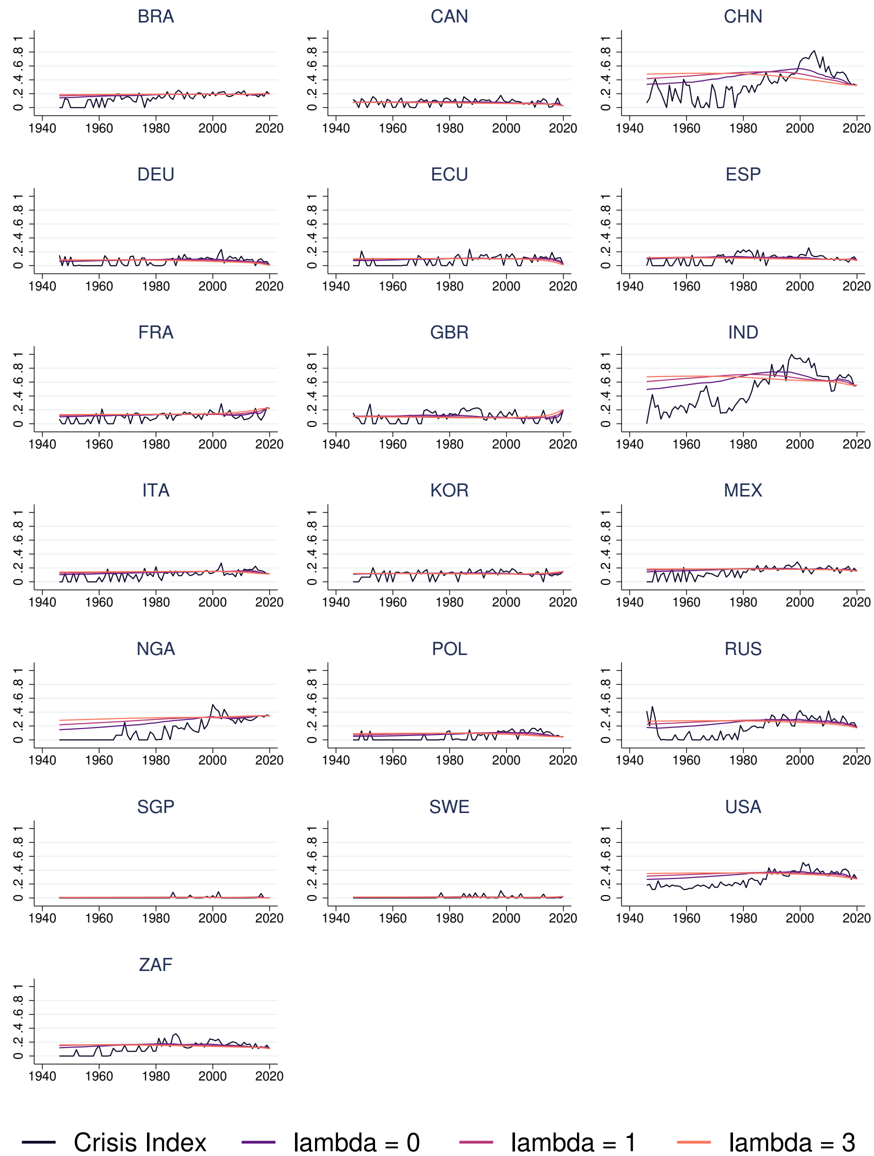
Notes: The figure shows the mean vaccination rate by country and age cohort. The vaccination rate is measured as the share of people in an age cohort who have received at least one dose of a COVID-19 vaccine on 19 November 2021 (for Switzerland on 21 November 2021). The definition of age cohorts differ across countries. The sample consists of 27 predominantly European countries, for which age-specific data on vaccination rates was available. Data is taken from Ritchie et al. (2020).

Figure B-3 SCREEPLOT OF EIGENVALUES, PRINCIPAL COMPONENT ANALYSIS ON CRISIS INDEX COMPONENTS



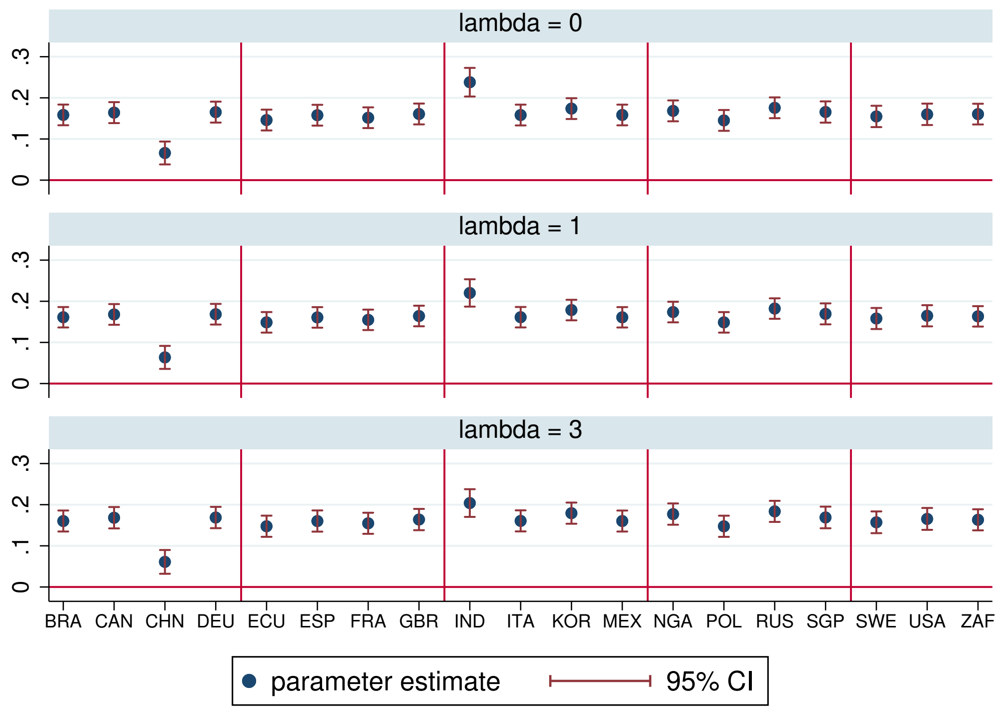
Notes: The figure shows the screeplot of eigenvalues that we obtain after running our principal component analysis on the components we use to model the crisis history of countries (see Section 4.2). The red dots illustrate the eigenvalue for each of the principal components, the surrounding gray areas report 95% confidence intervals for the eigenvalues of each component.

Figure B-4 LIFETIME DISCOUNTED CRISIS EXPERIENCE ACROSS COUNTRIES FOR DIFFERENT CHOICES OF λ



Notes: The figure shows how the country-specific crisis indices has developed over time and presents cohort-specific lifetime discounted crisis experience for different choices of λ. The sample consists of the 19 countries in the survey on vaccination preferences (see Section 2.1). The index accounts for natural and technical disasters as well as conflict in a given country-year (see Section 4.2 for details on the construction). It covers the years 1946–2020 and is standardized to take values between 0 and 1. Cohort-specific lifetime discounted crisis experience for different choices of λ are calculated from the index (see Section 4.2.6).

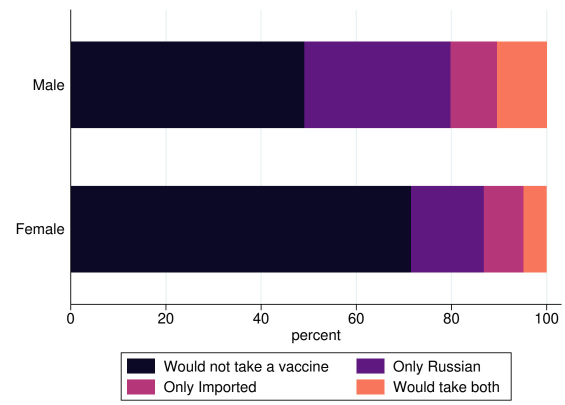
Figure B-5 JACK-KNIFE ANALYSIS OF BENCHMARK RESULTS



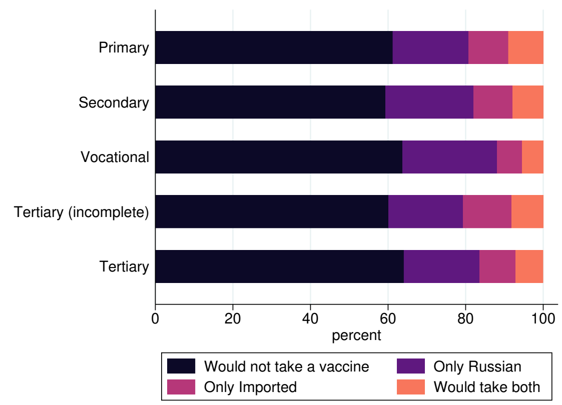
Notes: The figure shows the results of a jack-knife analysis of the benchmark results on crisis experience and vaccination preferences reported in Table (1). The figures replicates the benchmark regressions I times, using samples that neglect observations from $i \in I$ countries.

Figure B-6 HETEROGENEITY IN VACCINATION PREFERENCES: SOCIOECONOMIC CHARACTERISTICS, RUSSIAN SAMPLE

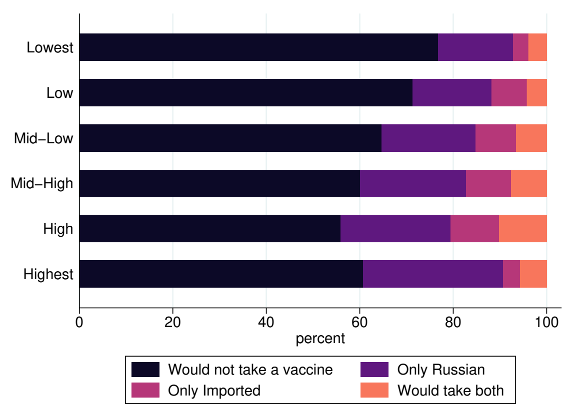
(a) Gender



(b) Education

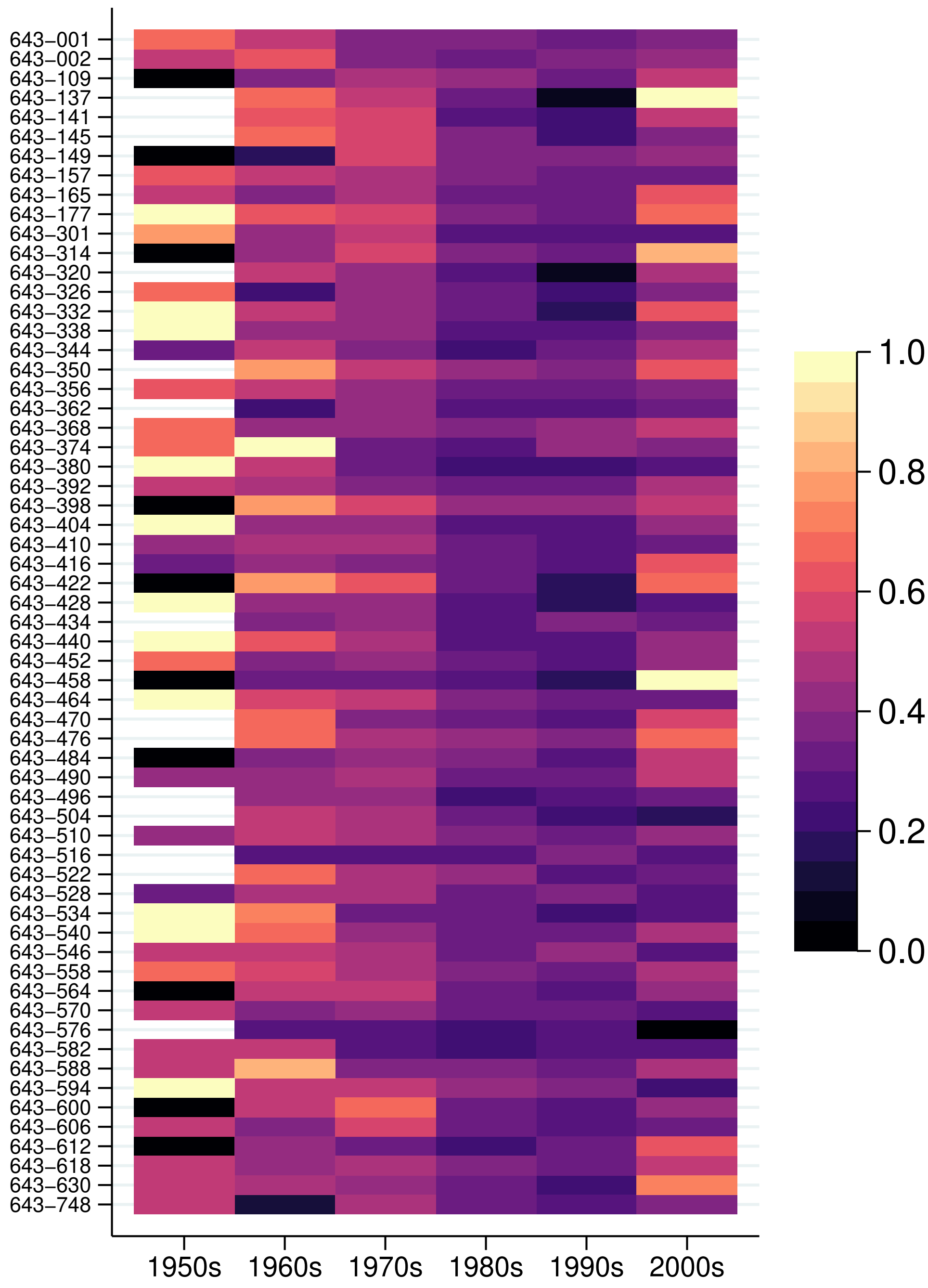


(c) Income



Notes: The figure shows the share of surveyed individuals willing take (any) vaccine across different socioeconomic characteristics. The preference to get vaccinated is taken from answering the questions "If a COVID-19 vaccine becomes available in Russia, would you take it?" either with "Yes, if a Russian vaccine will be available" and/or with "Yes, if an imported vaccine will be available". Regarding income levels (Panel b), "Lowest" refers to "We don't even have enough money for food", "Low" to "We have enough money for food, but not enough money for clothes", "Mid-Low" to "We have enough money for food and clothes, but buying more expensive things, such as a TV or refrigerator, causes us problems", while "Mid-High" corresponds to "We can buy some expensive things like refrigerator or TV, but we can't buy a car", "We can buy a car, but we cannot say that we are not constrained in funds" and "Highest" to "We can afford anything we need". The survey includes 16,077 individuals from 61 regions and was conducted between 5 November and 1 December 2020.

Figure B-7 HETEROGENEITY IN VACCINATION PREFERENCES: REGIONS AND BIRTH COHORTS



Notes: The figure shows the share of surveyed individuals willing take (any) vaccine across birth cohorts and Russian regions. The preference to get vaccinated is taken from answering the questions "If a COVID-19 vaccine becomes available in Russia, would you take it?" either with "Yes, if a Russian vaccine will be available" and/or with "Yes, if an imported vaccine will be available". The survey includes 16,077 individuals from 61 regions and was conducted between 5 November and 1 December 2020.

Appendix C: Notes on the construction of the regional crisis index

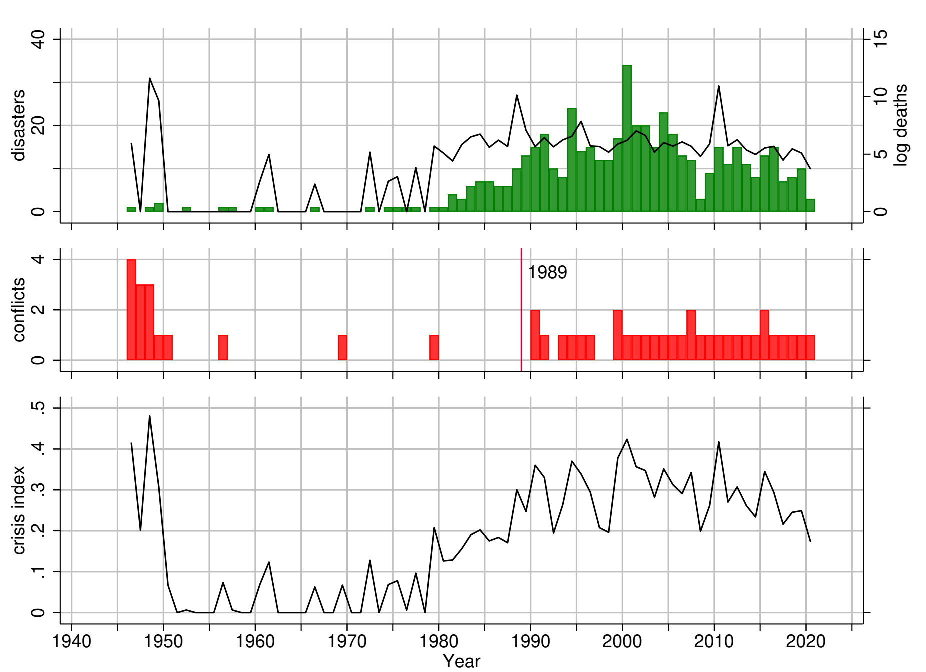
For the construction of the Russian regional crisis index, we face the challenge of obtaining regional-level data for our two measures of crises. For natural and technical disasters, we use the EM-DAT dataset (Centre for Research on the Epidemiology of Disasters, 2021). EM-DAT provides information on the exact location of a disaster – we manually coded the respective Russian region.

For conflict, we leverage the UCDP Georeferenced Event Dataset (GED, Version 21.1) compiled by Sundberg and Melander (2013). The GED locates conflict events on sub-national administrative levels which allows for the attribution of events to specific Russian regions. The GED differs from the UCDP/PRIO Armed Conflict Dataset (ACD, Pettersson et al. (2021)) in two regards. First, the definition of a conflict and the data entries vary. The ACD contains conflicts, where at least one actor is a state and the use of armed force results in at least 25 deaths. Conflicts are specified over a time period – from this we can calculate a count variable of conflict observations in a given country-year. The GED includes observations on conflicts between organized actors (at least one) with a threshold of at least one death. Observations are coded for a given region and year and include estimates on the number of deaths – from this we can calculate both event and death counts for conflict observations in a given region-year. To account for the difference in definitions and the lack of information on the number of deaths in the ACD, we use the number of conflicts with more than 25 deaths in a given region-year in the case study to replicate the measure used in the cross-country analysis. To use the most detailed information available, we also construct an index using GED death numbers instead of conflict counts in separate regressions – this does not change our results.

The second difference between the GED and ACD dataset is their coverage: Whilst the ACD covers the years 1946–2020, the GED only includes data in the period 1989–2020. As we need lifetime coverage also for older individuals in the case study, we must compute the index starting in 1946. To investigate a possible issue with coverage bias, we look at the conflict events in Russia reported in the ACD. Figure (C-1) plots those events in the second panel. For Russia (formerly the Soviet Union), there are a few events registered before 1989. These are

1. the Soviet occupation of the Baltic states in the 1940s,

Figure C-1 CRISES IN RUSSIA ACROSS TIME (COUNTRY INDEX)



Notes: The figure shows how our measures of crises (upper two panels) and the country-level for Russia (lower panel) develop over time. The country crisis index is computed from natural and technical disasters including previous epidemics (first panel) or conflict (second panel) as the number of events per country-year and by a logged death count. Data on crises spans the years 1946 to 2020 and is taken from EM-DAT (Centre for Research on the Epidemiology of Disasters, 2021) and the UCDP Armed Conflict Dataset (Pettersson et al., 2021). The crisis index covers the years 1946–2020 and is standardized to take values between 0 and 1 (see Section 4.2 for details on the construction).

2. the Soviet intervention in Hungary in 1956,

3. the Sino-Soviet border conflict in 1969, and

4. the Soviet invasion of Afghanistan in 1979.

Of those events, only the Sino-Soviet border conflict took place in a region in which the respondents of our survey currently reside, all other conflicts occurred outside today's Russia and hence could not have directly affected the survey respondents. Hence, coverage bias should be minimal. We still address the possible issue by manually including the Sino-Soviet conflict for Russian individuals in Primorsky Krai as a robustness check. The results are qualitatively similar to our baseline estimates.