NBER WORKING PAPER SERIES

SCARRED BUT WISER:
WORLD WAR 2'S COVID LEGACY

Michael Lokshin
Vladimir Kolchin
Martin Ravallion

Working Paper 28291
http://www.nber.org/papers/w28291

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2020

The authors thank Branko Milanovic for discussions and Toan Do, Ivan Torre and Dominique van de Walle for their comments. This paper's findings, interpretations, and conclusions are entirely those of the authors and do not necessarily represent the views of their employers including the World Bank, its Executive Directors, the countries they represent, or the National Bureau of Economic Research.

Scarred but Wiser: World War 2’s COVID Legacy
Michael Lokshin, Vladimir Kolchin, and Martin Ravallion
NBER Working Paper No. 28291
December 2020
JEL No. D02,D74,I12,N10

ABSTRACT

The paper formalizes and tests the hypothesis that greater exposure to big shocks induces stronger societal responses for adaptation and protection from future big shocks. We find support for this hypothesis in various strands of the literature and in new empirical tests using cross-country data on deaths due to COVID-19 and deaths during World War 2. Countries with higher death rates in the war saw lower death rates in the first wave of the COVID pandemic, though the effect faded in the pandemic’s second wave. Our tests are robust to a wide range of model specifications and alternative assumptions.

Michael Lokshin
World Bank
1818 H Street NW
Washington, D.C. 20037
mlokshin@worldbank.org

Vladimir Kolchin
World Bank
1818 H Street NW
Washington, D.C. 20037
vkolchin@worldbank.org

Martin Ravallion
Department of Economics
Georgetown University
ICC 580
Washington, DC 20057
and NBER
mr1185@georgetown.edu

"Let's be better prepared next time." Joseph Stiglitz, December 2020

1. Introduction

It is hard to be confident in our responses to rare events for which we have little direct experience. Big shocks are a case-in-point. By "big shocks" we mean unusual and highly covariate (negative) shocks, impacting virtually every member of society. Something can be learnt from observations of big shocks in other places, but direct experience of the shock is likely to be far more valuable.[2] The misfortune of directly observing one's own welfare, or that of friends and family, in the (negatively) shocked state carries important information. This "visceral" knowledge is not so easily transferable. Past experience with a big shock teaches people about the gains from investing in adaptation and protection, which brings benefits if a future big shock is realized. On the other hand, with little or no direct experience of a big shock, the perceived benefits from such investments will be lower.

Elements of this argument find support in research on how exposure to war and other forms of violent conflict affects behavior, collective actions, perceptions of fairness, and cooperation. Evidence from many countries indicates that people exposed to war violence increase their social participation and are more likely to take actions benefiting others; see the review of this literature in Bauer et al. (2016).

This paper formalizes and tests the hypothesis that countries with past experiences of a big shock tend to invest more in the institutions—including social capital as well as public health and social protection infrastructure—needed to cope with another big shock, and thus be less vulnerable to that shock. Our tests use data for the two biggest shocks of the last 100 years, namely World War 2 (WW2) and the pandemic of 2020 due to the novel coronavirus.
We assess whether countries with greater exposure to WW2—as reflected in death rates—experienced different COVID-19 outcomes in the pandemic. Our reasoning is that people in countries with larger prior human losses from WW2 will expect higher marginal benefits from social and political efforts that help facilitate greater willingness in the population to behave in ways that reduce the human toll of the pandemic. Voluntary compliance with various non-pharmaceutical interventions (NPIs) depends on people's trust in the government and each other,

[2] Educationalists have emphasized the importance of direct experience to knowledge, separately to formal education; see, for example, the discussions in Boud et al. (1993).

and the strength of the social fabric more generally. Social capital is not, however, costless to accumulate and maintain. Success in doing so can be expected to have deep roots in a country's history, including its past exposure to big shocks. The direct experience of such shocks provides important information in forming expectations about the gains from investing in adaptation and protection from future shocks.

In testing this theory, we focus on Europe—broadly defined to embrace the Nordic countries, Russia and Central Asia—though we also test robustness to using an extended set of countries with global coverage. WW2 impacted virtually every person in the European region, but in differing degrees. It was a combination of deaths, starvation, displacements, and hardship never before experienced at such a scale, and not since either. The emotional distress and fear for one's own life in WW2 came with fears about the lives of relatives and friends and the future of the countries people live in. On the physical level, civilians suffered from hunger, cold, and lack of basic amenities, while tens of millions faced a very real threat to their lives.

WW2 was not, of course, the only shock prior to the 2020 pandemic, but it is the obvious prior big shock for our test. This event was more severe than any other wars or pandemics in the twentieth century. The count of 50-75 million people who perished in WW2 was at least twice as high as the count in WW1, and much higher than the "Spanish Flu's" excess deaths in 1918-19 in Europe, estimated at 2.6 million (Ansart et al. 2009). Other pandemics, such as the Asian flu of 1957-1958 or the flu pandemic of 1968, had even smaller impacts. These later adverse shocks did not disrupt the normal functioning of the affected societies and were mainly perceived as episodes of a severe seasonal flu (Jackson 2009).

And the 2020 pandemic is the obvious recent shock. The pandemic represents a profound global health and economic crisis, affecting the lives of billions of people. There has clearly been considerable heterogeneity in the ability of governments and institutions to cope with the pandemic, and in often puzzling ways. For example, a number of developing countries in East Asia and Sub-Saharan Africa appear to have done a better job in dealing with the pandemic than have some of the rich countries of Europe and North America. It has been argued that prior experience with epidemics has influenced the differing country responses during the 2020 pandemic; see, for example, Mobarak and Mahbub (2020). Yet, despite the exploding research on COVID-19, there is still no consensus on the theory explaining the heterogeneity across countries in the impact of the pandemic on health and economic outcomes.

The efforts to fight the COVID-19 pandemic have been compared to WW2 by some world leaders. The response to this global emergency forced some countries to adopt the war-type contingency measures of increased governmental oversight, rationing, restrictions to personal freedoms, ramp up production, and redeployment of resources. The memories of the past wars are part of European shared identity that, in the current crisis, awaken the idea of duty, personal responsibilities, and call for national cohesion and personal sacrifices for the greater good.

We find support for the predictions of our theoretical model in the empirical relationship between casualties during WW2 and the deaths related to COVID-19. There is a strong negative correlation between the total human losses during WW2 and the first wave of deaths related to COVID. Consistently with expectations based on our model, this effect of WW2 deaths faded over time as the pandemic moved into its second wave.

The following section outlines our hypothesis on how investments in adaptation and protection against shocks are influenced by past experiences of big shocks. Section 3 summarizes some relevant insights from the literature. Section 4 describes the data we have assembled for testing the hypothesis. The results of our tests are presented in Section 5. Section 6 concludes.

2. Foundations of the hypothesis

Our hypothesis is that direct experience with big shocks influences the various actions taken by the people of a country in preparing for and responding to future shocks and thus the outcomes of those shocks. A country that experiences a big shock has a valuable insight into the benefits of investing in adaptation and protection against future shocks. The experience of the shock is a lesson to help assure future preparedness. A country that has not yet experienced a big shock forms an expectation of welfare in the shocked state that is also influenced past experience, which makes the country less inclined to invest in adaptation and protection. We provide a simple formalization of this hypothesis before we take it to the data.

There is a big covariate shock, s_t, that can occur in a country at any date $t = 1, 2$, with the shocked and unshocked values denoted $s_t = 1$ and $s_t = 0$, respectively. Knowing the realization of the state of the world at the initial date $t = 1$, there is a continuous costly action, denoted τ, that can be taken by the people and government of a country at $t = 1$ to reduce the welfare impact of a future shock should it occur at $t = 2$. The action can be interpreted as investment in a set of actions to adapt and protect from shocks. There are multiple political, economic and social dimensions to this set of actions, but for analytic convenience we collapse them into a single dimension. The cost of investing in τ is, of course, incurred whether or not there is a shock in $t = 2$, and a benefit from τ is only realized if a big shock happens.

Social welfare is denoted $u(\tau, s_t)$. Welfare in the unshocked state, $u(\tau, 0)$, is known and is decreasing and concave in τ, $u_\tau(\tau, 0) < 0$ and $u_{\tau\tau}(\tau, 0) < 0$ (where the τ subscripts denote first and second partial derivatives)[3]. By interpretation, if the unshocked state is realized in period 2 then the country would have been better off *ex post* not investing in higher τ.

Welfare in the shocked state is a random variable with some known distribution. We take this uncertainty to be a multiplicative (rather than additive) factor, such that the marginal gain from extra τ in the shocked state, $u_\tau(\tau, 1)$, is also a random variable, as is the second derivative $u_{\tau\tau}(\tau, 1)$. A country's past experience, s_1, influences the expected marginal gain, $E[u_\tau(\tau, 1)|s_1]$, from investing in a higher τ.

Social welfare, if the shocked state is realized, is strictly increasing in τ at any given realization of the uncertainty, implying that $E(u_\tau(\tau, 1)|s_1) > 0$. We allow the possibility that expected welfare in the shocked state is convex in τ ($E(u_{\tau\tau}(\tau, 1)|s_1) > 0$), which is interpretable as increasing returns to higher τ in the midst of a big shock. However, we assume that expected welfare across the potential future states is concave in τ, i.e., $p.E(u_{\tau\tau}(\tau(i),1)|s_1) + (1 - p).u_{\tau\tau}(\tau(i), 0) < 0$ for $i = 0,1$ where p is the probability of a big shock in period 2, with $0 < p < 1$. As long as the probability of a big shock is low enough, this overall concavity property will hold even when there are increasing returns to investing in adaptation and protection in the shocked state.

We can now formalize our hypothesis. We make two key assumptions. The first is that the level of τ is chosen to maximize the country's expected welfare in period 2, conditional on whether or not a big shock was experienced in period 1. The fact that the expectation is conditional on the past experience of shocks entails that the chosen action is also conditional on that history, which we write as $\tau = \tau(s_1)$. Thus, our first main assumption is that:

$$\tau(s_1) = \arg\max_{(\tau)} p.E(u(\tau, 1)|s_1) + (1 - p).u(\tau, 0) \text{ for } s_1 = 0, 1 \tag{1}$$

[3] The latter assumptions can be rationalized by imagining the special case in which u(τ,0) = ũ(0)-c(τ) where c(τ) is an increasing convex cost function, although we do not need this separable structure.

This formalizes the intuition that the expectation about the welfare gains plays an important role in how much a country invests in adaptation and protection given the threat of a future big shock. Experiencing the shock in the first period clearly reveals a lot about $u(\tau, 1)$. To the extent that the knowledge gained is a global public good, it will not matter which countries are shocked initially. However, it is unlikely that such knowledge only spills over borders in a perfect way. Seeing others experiencing a big shock may be a partial substitute for the direct experience, but the latter conveys important extra information about the gains from adaptation and protection. Residents of the unshocked country can be taken to form their expectation about the efficacy of action to address future big shocks based on a probability distribution that combines the external signals about $u_\tau(\tau, 1)$ with its own observed value of $u_\tau(\tau, 0)$. The difference in the information sets available to people in countries that have observed a big shock versus those that have not, yields a systematic difference in expectations about the efficacy of actions to adapt to, or protect from future big shocks. Thus, the direct experience of a big shock has a special salience when laying the foundations for responding to possible future shocks.

This reasoning motivates our second assumption. On the one hand, we allow that a country that did not experience the initial shock will come to know something about the likely effectiveness of investing in τ held by countries that did experience a shock. On the other hand, its lack of direct experience entails that the previously unshocked country still attaches some positive weight ($r > 0$) on its own past experience. Note that we rule out the (seemingly unlikely) case in which the country's own history of direct experience with shocks has no bearing on the matter ($r = 0$). We can write this second assumption as:

$$E(u_\tau(\tau, 1)|s_1 = 0\,) = r.\,u_\tau(\tau(0),0) + (1\,-\,r).\,E(u_\tau(\tau, 1)|s_1 = 1\,) \qquad (2)$$

Given that $u_\tau(\tau(0),0) < u_\tau(\tau(1),1)$, it follows that $Eu_\tau(\tau(1),1) > Eu_\tau(\tau(0),0)$.

We can now derive the key implications for our empirical investigation. The first-order conditions for optimal $\tau(s_1)$ are that:[4]

$$p.\,E(u_\tau(\tau(i),1)|s_1 = i) + (1-p).\,u_\tau(\tau(i), 0) = 0 \text{ for } i = 0,1 \qquad (3)$$

[4] The second-order conditions are satisfied given that expected welfare across shock prospects is concave in τ.

Given that $r > 0$, two solutions for $\tau(i)$, one for each of $i = 0,1$, emerge. Taking the difference between the realizations of (3) for each of $i = 0$ and $i = 1$ we have:

$$p.E[u_\tau(\tau(1),1) - u_\tau(\tau(0),1)] + (1-p).[u_\tau(\tau(1),0) - u_\tau(\tau(0),0)] = 0 \quad (4)$$

Under our second assumption, the first term is positive, so the second term must be negative, $u_\tau(\tau(1),0) < u_\tau(\tau(0),0)$, implying that $\tau(1) > \tau(0)$ given that welfare in the unshocked state is concave in τ.

Thus, we predict that countries that experience a big shock will allocate more resources to adaptation and protection in response to the possibility of a future big shock.

Three further implications can be noted. First, the investment in adaptation and protection will also depend on the probability of shocks occurring. (Note that $\tau(s_1)$ is also, in general, an implicit function of p.) More precisely, on differentiating (3):

$$\frac{\partial\tau(i)}{\partial p} = \frac{u_\tau(\tau(i),0) - Eu_\tau(\tau(i),1)}{pEu_{\tau\tau}(\tau(i),1) + (1-p))u_{\tau\tau}(\tau(i),0)} > 0 \text{ for } i = 0,1 \quad (5)$$

The more likely the future shock, the more the country invests in protection from that shock.

Second, among countries that experience the shock in the second period, those that were shocked in the first period will be better off *ex post*, in the sense that $u(\tau(1),1) > u(\tau(0),1)$. (This follows from the fact that $u(\tau, 1)$ is increasing in τ.)

Third, imagine a series of big shocks. The policy response to the threat of a future shock characterized by the above model can be interpreted as generating a negative serial dependence in the impacts of a series of big shocks. Assuming that this times-series process is stationary, one would expect the effect of experiencing the shock in the first period to fade over time.[5] Countries that did not adapt and protect in anticipation of the period 2 shock—because they did not have a direct experience of a big shock in period 1—learn from experiencing a big shock in period 2 and adjust accordingly, in anticipation of a shock in period 3 (or an extended exposure to the period 2 shock, as in our empirical application later). In terms of our model, one can think of this as a reduction in the weight r attached to the initial (unshocked) marginal benefit of higher τ (equation 3). By the same token, success in avoiding the worst impacts of the shock in period 2 will lower the expected marginal gains from continuing to protect and adapt given the prospect

[5] Our other assumptions so far cannot rule out a non-stationary process, implying that successive big shocks have larger and larger welfare effects, alternating positively and negatively. That can be considered an empirical question.

of a shock in period 3. Intuitively, the country will become complacent, leading to greater impacts of a period 3 shock.

The following sections point to evidence consistent with these predictions, drawing first on the literature and then by studying new empirical evidence across countries.

3. Insights from the literature

Here we review evidence from two different literatures that can be interpreted as offering partial support for the hypothesis formalized above, though they are not conclusive. The first is literature indicating that residents of a place exposed to war violence tend to be more cooperative and altruistic after the war. The effect also persists over time, regardless of whether the war was experienced by a person herself or by family members or friends; the impact of exposure seems even to increase over time. Societies exposed to wars often were able to return to pre-war levels of institutional qualities and to a high level of trust in a relatively short time. Grosjean (2014) uses survey data from 35 countries in Europe and Central Asia to investigate the effects of exposure to WW2 and more recent conflicts among respondents' parents and grandparents. Her results show a positive correlation between past war experiences and contemporary participation in collective actions and community groups. At the same time, war seems to diminish trust in politics. A study based on a representative sample of adults from 14 European countries demonstrates that early-life exposure to WW2 increases individual resilience and optimism about life, leading to a higher probability of survival (Arpino et al. 2019). Bellucci et al. (2020) use the European Survey on Health, Ageing, and Retirement to show that war-exposed individuals have higher resilience to shocks and increased perception of uncertainty and uncontrollability of the environment. Cassar et al. (2013) explore the effects of war-related violence on trust and cooperation in Tajikistan and found that exposure to war enhanced prosocial behavior. A study of the effect of violence during Nepal's civil war found that violence-affected communities had higher levels of prosocial motivation and public good cooperation (Gilligan et al. 2013). Similarly, civic participation increases in the districts of Uganda, where battle events took place (De Luca and Verpoorten 2015). Bellows and Miguel (2009) show that households in Sierra Leone that experience war violence are more likely to join political and community groups and more likely to vote. Bauer et al. (2020) review multiple studies pointing in the same direction: that social cooperation is enhanced by past exposure to war violence.

The second set of studies pertains to the role of social capital and trust for compliance with the recommendations for NPIs during the 2020 pandemic.[6] Data on real-time mobile phone locations in Italy demonstrate a higher decline in personal mobility in areas with higher social capital (Durante et al., 2020). Similar results are found by Barrios et al. (2020) for a sample of counties in the US and European countries. In a sample of 84 countries, Elgar et al. (2020) find that trust in government fosters lower COVID-19 mortality, though they also find that (controlling for trust in government) stronger social bonds in a country may facilitate the spread of infection. Based on survey data from China, Wu (2020) finds evidence that, in determining responses to the pandemic, trust in government is a more important aspect of social capital than trust in other individuals. Bargain and Aminjonov (2020) found that regions with higher trust experienced larger reductions in non-essential mobility following the implementation of containment policies in March 2020. Bartscher et al. (2020) provide evidence from seven European countries that culture and social capital have a considerable impact on the containment of COVID-19 and the number of deaths. Similarly, the study by Olsen and Hjorth (2020) of individual willingness to engage in social distancing in Denmark shows that individuals with high social and political trust are more likely to comply with social distancing measures. The overarching message from these studies is that voluntary compliance with NPIs depends on the local and individual levels of social and political capital. However, we do not know to what extent the identified behavioral and institutional covariates of NPI can be linked to past experience with big shocks.

Both these links are evident in the (widely reported) success of Vietnam in containing the spread of COVID-19, with fewer deaths per capita than most other countries, despite being a relatively poor country. The proximate causes of Vietnam's success against COVID-19 are well known, namely the mass public health response, led by the government, but embracing an extensive community-based effort of testing, tracing, and quarantining. What is less widely appreciated is that there are deeper causative factors at work, embedded in the county's history of resistance and war, which helped create the foundation of social solidarity and collective action that underpinned the COVID response (Nguyen 2020). And the government regularly reminded its citizens of the war experience in mustering the COVID effort.

[6] Wu (2020) provides a more complete review of the sociological literature on the role of social capital in success in dealing with the COVID-19 pandemic.

Yet, a further observation of relevance is found in the calls heard during the 2020 pandemic for investing more in the institutions of social organization and scientifically-grounded policy making that can help protect from future shocks, recognizing that this is not the last pandemic or other crisis to be faced. The quote from Stiglitz (2020) at the outset of this paper—explicitly in the context of his observations on the economic and health impacts of the pandemic in America in 2020—is an example. It can hardly be surprising that these calls have been heard more in countries such as the U.S. that were hit so hard by COVID-19, clearly reflecting institutional and governmental failures. Of course, we do not know yet if the lessons will be carried to practice, and political and social frictions in the learning process can be expected. But the pressure for anticipatory action is clearly motivated in no small measure by the direct experience of very high COVID mortality in the U.S. in 2020.

4. Evidence on World War 2 and the COVID-19 pandemic in Europe

We test for an effect of exposure to WW2, as measured by the country's death rate, on outcomes under the COVID-19 pandemic. In addition to the potential impact of WW2 experience, we take it that mortality from COVID-19 depends on a country's demographic composition, total population, population density, the average level of education in the country, and the measures of government effectiveness or democracy (Bosancianu et al., 2020). In terms of our model in Section 2, these variables can be thought of as determinants of the probability of a big shock occurring.

We use multiple data sources. Data on COVID-19 come from the European Center for Disease Prevention and Control (2020). We use COVID-19 related-deaths-per-million of the population as our main dependent variable. Data on war military casualties is derived from UCDP/PRIO Battle Death Data (Bethany et al. 2006) and Wikipedia; civilian casualties are based on multiple sources of mostly country-specific data (Wikipedia 2020). Civilian casualties in the post-Soviet countries come from Erlikman (2004). We use death as a proportion of the population as our control variable. The total deaths as a proportion of the population come directly from the Wikipedia dataset. Military deaths as a proportion of the population are calculated as a ratio of military (battle) deaths and the population of that country in 1939. Both total and military deaths for several countries that did not exist during WW2 are imputed based on the corresponding losses of the "parent" countries.[7] The list of countries with WW2 casualties and COVID-19 statistics are shown in Table 1.

Recall from Section 2 that our hypothesis about the response to past big shocks is conditional on the probability of such shocks occurring (p), which one would expect to differ systematically across countries. There may also be differences in the welfare function $u(\tau, s_t)$ at given values of τ and s_t. For example, richer countries will presumably be better positioned to protect their citizens through the health care system. We will test the predictions of our model controlling for GDP per capita (in constant 2011 PPP $) drawing on the World Development Indicators (World Bank 2020). We will also allow for differences in voice and accountability, using data from the World Governance Indicators (WGI) database produced by the World Bank (Kaufmann et al. 2010). The indicator ranges from -2.5 (i.e., the lowest level of voice and accountability) to 2.5 (the highest level of voice and accountability). Data on population density and the median age of the population come from the DELVE COVID-19 database (Bhoopchand et al., 2020). We also control whether a country belonged to the axis of powers during WW2,[8] and if the country was a member of the communist bloc.[9] The descriptive statistics for our main variables and a summary of data sources are shown in Table 2.

Figure 1 provides a scatterplot of COVID deaths per million people on the total losses in WW2 as a proportion of the pre-war population. Consistent with our hypothesis, we see that countries with higher death rates during WW2 tended to have lower COVID-19 mortality rates. Next, we see if this is robust to adding controls relevant to the probability of experiencing a big shock, and whether the finding is robust to various changes in the specifications for our test.

5. Controls and tests for robustness

Adding controls for other variables likely to influence COVID-19 mortality, we still find that it is negatively correlated with total losses during WW2.[10] Our most parsimonious

[7] For example, losses for Balkan countries are imputed based on the losses of Yugoslavia.
[8] The "Axis powers" formally took the name after the Tripartite Pact was signed by Germany, Italy, and Japan on 27 September 1940, in Berlin. The pact was subsequently joined by Hungary, Romania, and Bulgaria (Hill 2003).
[9] The Council for Mutual Economic Assistance (COMECON) was an economic organization from 1949 to 1991 under the leadership of the Soviet Union that comprised, among other countries, Albania, Bulgaria, Czechoslovakia, Hungary, Poland, Romania and the Soviet Union (Kaser 1967).
[10] While a nonlinear relationship is suggested by Figure 1, we chose a more parsimonious linear regression. We did two tests on functional form. First, we included the squared value of WW2 mortality, but its coefficient was not

specification is in Table 3, which includes five controls. The specification in column (1) uses total WW2 deaths per capita. At mean points, the elasticity of COVID deaths to WW2 deaths is about -0.4. We also see that countries with higher GDP per capita have lower death rates from COVID-19. On the other hand, countries with older and larger populations, and countries with a higher share of educated people have significantly higher deaths per million from COVID-19.

Our variable for WW2 deaths includes both civilian and military losses. Some countries in our sample that suffered military losses (e.g., UK or Italy) had limited military activities on their territories. Thus, the population of these countries was, to a degree, isolated from the direct and most severe impact of the war. Mechanically, we can infer non-military deaths by subtracting recorded military deaths from the total. However, it should be noted that these two series come from different sources, and measurement errors may increase as a result of this calculation. While acknowledging this concern, the results in column (2) of Table 3 separate military deaths from non-military. This suggests that it is non-military losses that account for the correlation with COVID-19 deaths. Nonetheless, given the measurement concerns, we will focus on total deaths in our robustness tests.

Table 4 provides the coefficients on WW2 deaths for various changes in specifications. Column (1) in Table 4 shows the extended specification of the regression in column (1) of Table 3. Column (2) in Table 4 shows the same specification as column (1) but with controls for communist regimes and the axis of power. The specification in row (1) adds dummy variables of whether the communist party was dominant in a country before 1991 and whether a country belonged to the axis powers. None of these extra variables had a significant effect on COVID-19 death rates, and the coefficient on WW2 deaths changes little.[11] A systematic COVID-19 death underreporting could alter our results. Such underreporting might be especially pronounced in several countries of the former Soviet Union, such as Belarus, Tajikistan, and Uzbekistan. (Turkmenistan reports no deaths from COVID-19 and thus is not included in our sample.) To test the sensitivity of our results to such underreporting, we triple the officially reported rates for

significantly different from zero. Second, we tested a specification with the inverse hyperbolic sine transformation of deaths per million as a dependent variable, with the same transformation applied to WW2 deaths. This gave qualitatively similar results.

[11] Estimations of the cumulative COVID-19 infection rates on the same set of covariates produce no significant results. We also estimated specifications with other governance indicators from WGI dataset: Political Stability and Absence of Violence, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption. None of these variables show significant coefficients in estimations. These results are available from the authors.

these countries. The results of that simulation are shown in Table 4 and are consistent with our main specification.

Another concern could be related to the endogeneity of losses during WW2 to the death toll of COVID-19. One could argue that the most altruistic and socially and politically active people would be more likely to die during the war. A society with high levels of social capital might suffer disproportional losses. Then the argument that the exposure to war violence increases social capital, which, in turn, helps to reduce COVID-19 mortality is reversed. The fact that WW2 ended 75 years before the 2020 pandemic clearly reduces the concerns for such non-random selection. Nevertheless, to partially address this potential bias, we estimate our model on a sample of countries that were attacked by removing countries representing the axis powers.[12] The results of this estimation are shown in row (3) of Table 4. The coefficient on the losses during WW2 is still significant and inversely related to the deaths from COVID-19, although the power of its significance declines.

We use the DFBETA influence statistics (Bollen and Jackman 1990) to identify the influential outliers in our regression. The method measures the difference, scaled by the estimated standard error of the coefficient, between the regression coefficient when the i^{th} observation (country) is included and excluded.[13] Figure 2 provides the scatter plot of the values of DFBETA statistics. Based on these results, Belarus (BRL) and Armenia (ARM) have a strong influence on the result of our estimations. The estimates of our main specification, excluding these countries from the sample, are shown in row (4) of Table 4.

We also conducted a falsification test to see if our results might be driven by unobservable confounding factors. The idea behind the falsification test is to demonstrate that the effect does not exist in the context where we expect no effect (see, for example, Rothstein 2010). We use the deaths from cardiovascular diseases, which predominantly affect the elderly population, as a placebo outcome. We assume that cardiovascular deaths are not affected by the levels of social capital and trust in society. Another measure of placebo outcome is deaths from influenza and pneumonia during the season of 2017/2018. These diseases are similar to COVID-

[12] An emerging literature that studies heroic actions and altruism during the war finds that the majority of heroic acts happened when the combatants defended their land (vs. being on the attack), e.g., Franco et al (2011). A possible explanation of this phenomenon could be that it is based on the evolutionary mechanism of protecting of close kin (Rusch and Stormer 2015).

[13] Our criterion for selecting observations is that: $|DFBETA_i| > 2/\sqrt{N}$, where N is the sample size.

19 in terms of contagion risks, but no social distancing and NPI were implemented to stop the infection despite the fact it killed more than 650,000 people worldwide in 2018 (Paget et al. 2019). We assume that influenza and pneumonia deaths are not associated with social capital and levels of trust in society that are required to internalize the negative externalities of the lockdowns. Thus, at least through these channels, the losses during WW2 should have no influence on contemporary deaths from cardiovascular or influenza and pneumonia diseases. This is confirmed in Table 4, which gives the coefficients on WW2 losses in rows (5) and (6); the coefficients are smaller in magnitude and not significantly different from zero.

Our regressions in Table 3 are based on total deaths per million registered on August 31, 2020. Rows (7) and (8) in Table 4 show that our main results are qualitatively stable when we use mortality rates on June 30 and July 31, 2020 as dependent variables.

While the main theater of WW2 was in Europe, many non-European countries participated in the battles in Europe and in the Asia-Pacific region. In the last row of Table 4, we give the results when we extend our sample to include 28 more countries that participated in WW2.[14] The results of the estimations on this larger sample of 76 countries are consistent with the results based on our sample of European countries. The total war losses are negatively and significantly correlated with the cumulative deaths from COVID-19, although the magnitudes of these correlations are lower compared to those found for the European sample. This could probably be explained by attenuation bias due to noisier data on war casualties in countries that participated in WW2 through other countries.[15]

6. The second wave of COVID-19

As noted in Section 2, a further implication of our theoretical argument is that a third shock should see greater effort at addressing the shock, similarly to our argument about the effect of a first shock. The second wave of COVID-19 provides a test of this prediction.

Table 5 gives the regressions corresponding to Table 3 but this time for cumulative COVID deaths in the second wave, defined as the number of new COVID-19 related deaths that

[14] The added countries comprises are Australia, Burundi, Brazil, Canada, China, Egypt, Ethiopia, Indonesia, India, Iran, Japan, Cambodia South Korea, Laos, Mexico, Myanmar, Mongolia, Malaysia, Nepal, New Zealand, Philippines, Papua New Guinea, Rwanda, Singapore, Thailand, United States of America, Vietnam, South Africa.

[15] For example, during WW2, Royal Nepalese Army fought on the Burmese front, and, at the same time, Nepalese soldiers fought as a part of British army (Cross and Gurung 2002).

occurred between August 1 and December 1, 2020. We see an attenuated effect (compared to Table 3) that is no longer significantly different from zero. Note that some deaths in the second wave arise from infections in the first wave. This is likely to bias upwards (in absolute value) our estimate of the effects of WW2 deaths on COVID deaths in the second period. Correcting for this bias would thus further reinforce our conclusion that the effect of WW2 deaths has faded over time, as the pandemic continued.

In Figure 3 we provide more detail. The lower solid line plots coefficients on the total losses during WW2 for cumulative COVID deaths at each month from February to September. The upper solid line shows the coefficients for the cumulative death counts starting August 1. The cumulative deaths for the upper line are calculated as cumulative deaths in month *t* less cumulative deaths on August 1. The dashed lower line shows the coefficients if we continue the first time series to December 1. So, we see clearly how the effect of WW2 deaths fades as the second wave proceeds.

To help verify this argument, it is of interest to see the effect of WW2 deaths on wave 2 COVID mortality when we control for wave 1 mortality, as given in Table 6. This picks up the underlying positive serial dependence in COVID mortality arising from the epidemiology. Of course, wave 1 mortality is likely to be endogenous in the regressions in Table 6, as there are undoubtedly latent factors influencing COVID deaths in both waves. Nonetheless, we can at least confirm that the partial correlation between WW2 deaths and wave 2 COVID deaths is attenuated when this control is added (comparing Tables 2,5, and 6).

This pattern in the data is consistent with our overall argument, but there is another insight. Figure 4 provides the transitions in COVID death rates between waves 1 and 2, plotted against WW2 death rates (similarly to Figure 1). We see the expected decline in COVID death rates in wave 2 among countries that had low WW2 death rates. At the same time, we see a rise in death rates among the countries hit harder by WW2. In terms of our model in Section 2, this is consistent with the idea that countries that were well prepared for the onset of the period 2 shock (having experienced the period 1 shock) have a tendency to become complacent and not be as well protected as the period 2 shock continues.

7. Conclusions

We have proposed and tested the hypothesis that past experiences of big shocks influence the success of a society in coping with future big shocks. The mechanism we suggest is that direct experiences of a shock have a strong influence on societal expectations about the gains from investing in adaptation and protection, recognizing that this requires social and political efforts in creating and maintaining social capital.

We have found support for the hypothesis in various strands of the literatures related to both wars and pandemics, including that of 2020. We have also found support in new empirical findings indicating that COVID-19-related mortality is inversely correlated with the losses countries experienced during World War 2. Consistently with our argument, this effect fades over time as people learn. Our results are robust to adding controls for other factors influencing COVID mortality and to different model specifications and assumptions.

References

Ansart S, Pelat C, Boelle PY, Carrat F, Flahault A, and A. Valleron (2009). "Mortality burden of the 1918-1919 influenza pandemic in Europe." *Influenza Other Respir Viruses 3*(3): 99-106.

Arpino, B., Conzo, P., and F. Salustri, (2019). "I'm a Survivor, Keep on Surviving: Early-life Exposure to Conflict and Subjective Survival Probabilities in Adult Life" Working Paper Series No. 201904. University of Turin.

Bartscher, A., Seitz, S., Siegloch, S., Slotwinski, M., and N. Wehrhöfer (2020). "Social Capital and the Spread of COVID-19: Insights from European Countries," IZA Discussion Paper 13310

Bargain, O., and U. Aminjonov (2020). "Trust and Compliance to Public Health Policies in Times of COVID-19," IZA Discussion Paper 13205.

Barrios, J., Benmelech, E., Hochberg, Y., Sapienza, P., and L. Zingales, (2021). "Civic capital and social distancing during the Covid-19 pandemic☆," *Journal of Public Economics*, vol 193.

Bauer, M., Blattman, C., Chytilová, J., Henrich, J., Miguel, E., and T. Mitts (2016). "Can War Foster Cooperation?" Journal of Economic Perspectives 30(3): 249-274

Bellucci D., Fuochi, G., and P. Conzo (2020). "Childhood Exposure to the Second World War and Financial Risk taking in Adult Life," Journal of Economic Psychology 79: 102-126

Bellows J., and E. Miguel (2009). "War and Local Collective Action in Sierra Leone." Journal of Public Economics 93: 1144-1157.

Bethany, L., Gleditsch, N., and B. Russett. (2006). "The Declining Risk of Death in Battle." International Studies Quarterly 50(3): 673-680.

Bhoopchand, A., Paleyes, A., Donkers, K., Tomasev, N. and P. Ulrich (2020). DELVE Global COVID-19 Dataset. Published June 2, 2020. Available from http://rs-delve.github.io/data_software/global-dataset.html.

Bollen, K. and R. Jackman. (1990). "Regression Diagnostics: An Expository Treatment of Outliers and Influential Cases." In Modern Methods of Data Analysis, ed. J. Fox and J. S. Long, 257–291. Newbury Park, CA: SAGE.

Bosancianu, C. M., Dionne, K. Y., Hilbig, H., Humphreys, M., KC, S., Lieber, N., & Scacco, A. (2020). “Political and Social Correlates of COVID-19 Mortality.” SocArXiv Working Paper.

Boud, A., Ruth C., and D. Walker (eds) (1993). *Using Experience for Learning*. Buckingham: Open University Press.

Cassar, A., Grosjean, P., and S. Whitt (2013). “Legacies of Violence: Trust and Market Development.” Journal of Economic Growth 18(3): 285-318.

Cross, J., and B. Gurung (2002). Gurkhas at War: Eyewitness Accounts from World War II to Iraq. Greenhill Books

De Luca, G., and M. Verpoorten (2015a). “Civil war and political participation: evidence from Uganda,” Economic Development and Cultural Change 64: 113–141.

Demirguc-Kunt, A., Lokshin, M., and I. Torre (2020). “The Sooner, the Better: The Economic Impact of Non-Pharmaceutical Interventions during the Early Stage of the COVID-19 Pandemic,” Policy Working Paper Series No. 9257, World Bank

Durante, R., Guiso, L., and G. Gulino (2020). “Civic capital and social distancing: evidence from Italians’ response to COVID-19”, VoxEU.org, April 16.

Elgar, F., Stefaniak, A. and M. Wohl (2020). “The Trouble with Trust: Time-series Analysis of Social Capital, Income Inequality, and COVID-19 Deaths in 84 countries,” Social Science and Medicine 263.

Erlikman, V. (2004). Poteri narodonaseleniia v XX veke: spravochnik. Moscow 1993

European Center for Disease Prevention and Control (2020). “The daily number of new reported cases of COVID-19 by country worldwide”, Available at: https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-COVID-19-cases-worldwide (Accessed September 20, 2020)

Franco, Z., Blau, K., and P. Zimbardo, (2011). “Heroism: A Conceptual Analysis and Differentiation between Heroic Action and Altruism,” Review of General Psychology 15 (2): 99-113

Grosjean, P. (2014). “Conflict and Social and Political Preferences: Evidence from World War II and Civil Conflict in 35 European Countries,” Comparative Economic Studies, 56(3): 424–451

Gilligan, M., Pasquale, B., and C. Samii (2014). "Civil War and Social Cohesion: Lab-in-the-field Evidence from Nepal." American Journal of Political Science, 58(3): 604–19.

Hill, R. (2003). Hitler Attacks Pearl Harbor: Why the United States Declared War on Germany. Boulder, CO: Lynne Rienner.

Jackson C. (2009). "History lessons: the Asian flu pandemic." The British Journal of General Practice: the journal of the Royal College of General Practitioners 59(565): 622–623.

Kaser, M. (1967). Comecon: Integration problems of the planned economies, Oxford University Press.

Kaufmann, D., Kraay, A., and M. Mastruzzi (2006). "Measuring governance using cross-country perceptions data." In International Handbook on the Economics of Corruption, ed. S Rose-Ackerman. Cheltenham, UK: Edward Elgar.

Mobarak, A., and R. Mahbub (2020). "What the US can Learn from how African Countries Handled Covid," Opinion CNN.

Nguyen, M. (2020). "Vietnam's War Against COVID-19. Vietnam's Campaign Against COVID-19 is Infused with Military Imagery, Playing Into Existing Strands Of National Identity." The Diplomat, October 19.

Olsen, A., and F. Hjorth (2020). "Willingness to distance in the COVID-19 pandemic," University of Copenhagen, mimeo, https://osf.io/xpwg2/

Paget, J., Speeuwenberg, P., Charu, V., Taylor, R., Luliano, D., Bresee, J., Simonsen, L., and C. Viboud, (2019). "Global mortality associated with seasonal influenza epidemics: New burden estimates and predictors from the GLaMOR Project." Journal of Global Health 9(2): 020421

Rusch H. and C. Stormer (2015). "An Evolutionary Perspective on War Heroism," Militarire Spectator 3: 140-150.

Rothstein, J. (2010). "Teacher Quality in Educational Production: Tracking, Decay, and Student Achievement." Quarterly Journal of Economics 125(1):175–214.

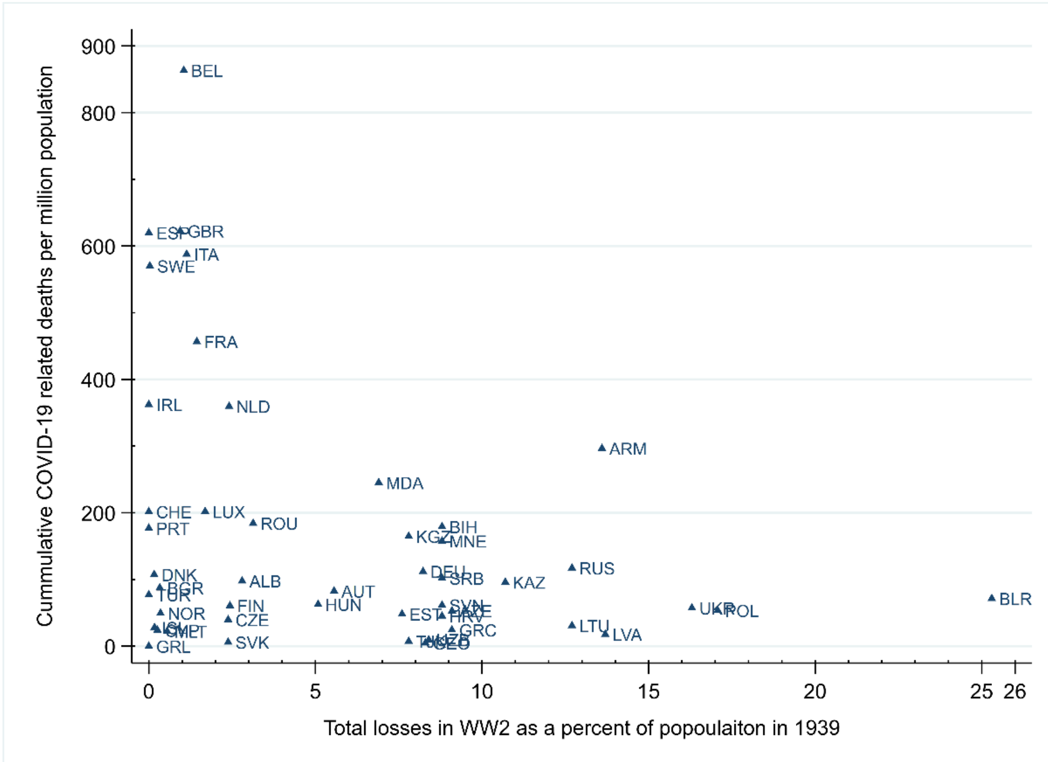
Stiglitz, J. (2020). "COVID-19 Policy Responses and Implications for Our Economic Future," Webinar, Global Economic Challenges Network, Georgetown University.

Wikipedia (2020). "World War II casualties," Available at (Accessed: September 13, 2020).

World Bank (2020). World Development Indicators. Washington DC: World Bank.

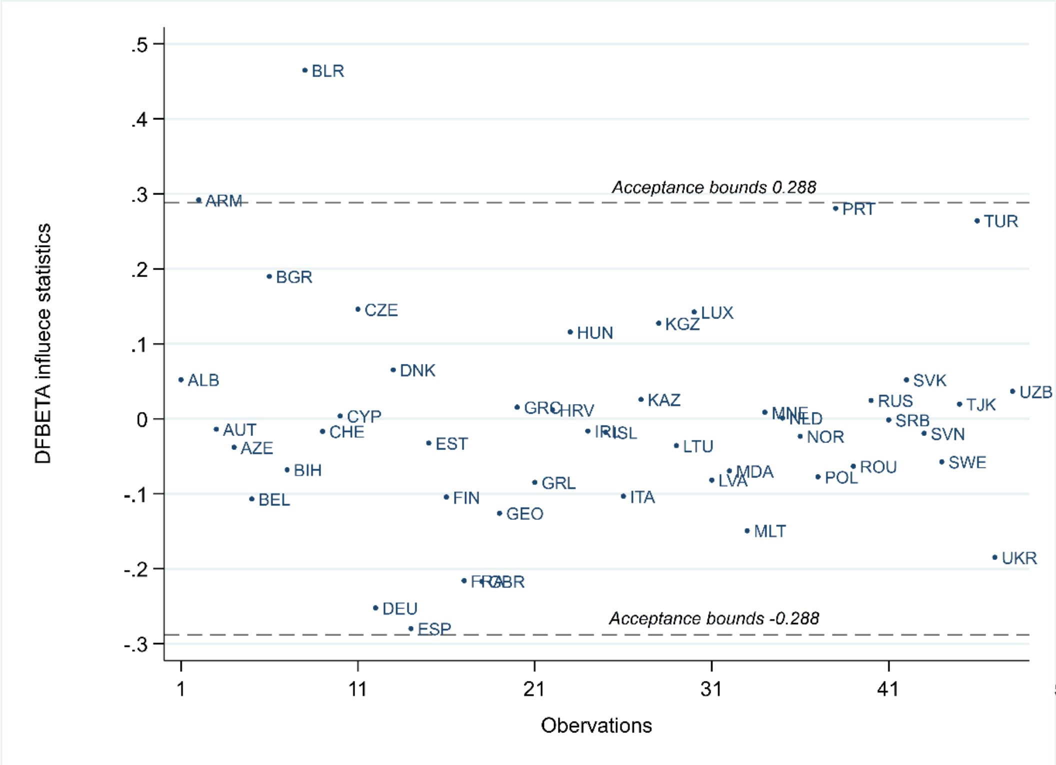
Wu, C. (2020). “Social capital and COVID-19: A Multidimensional and Multilevel Approach,” *Chinese Sociological Review*, published on line 8 October.

Figure 1: Cumulative deaths related to COVID-19 as of August 31, 2020 by total losses in WW2 as percentage of population in 1939



Note: ISO country codes.

Figure 2: DFBETA influence statistics and acceptance bounds



<u>Note</u>: ISO country codes.

Figure 3: Effect of total losses during WW2 on death rate from COVID-19, Feb 1-Dec 1, 2020, and August 1-Dec 1, 2020

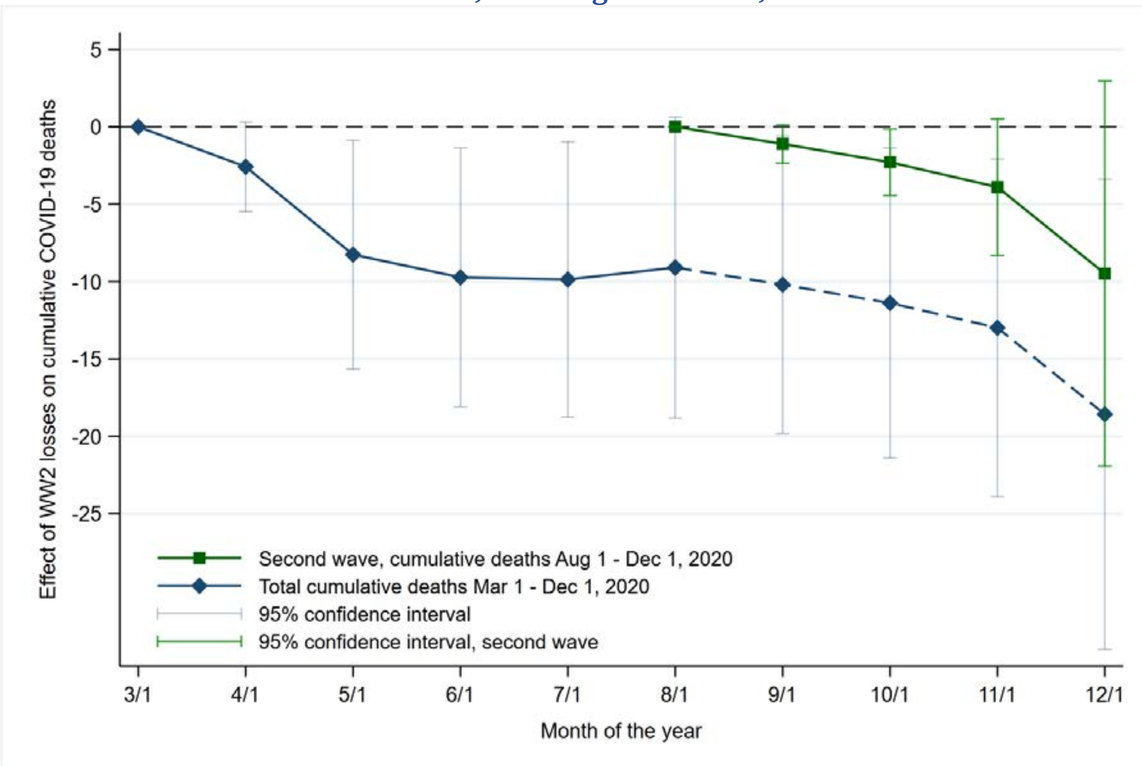
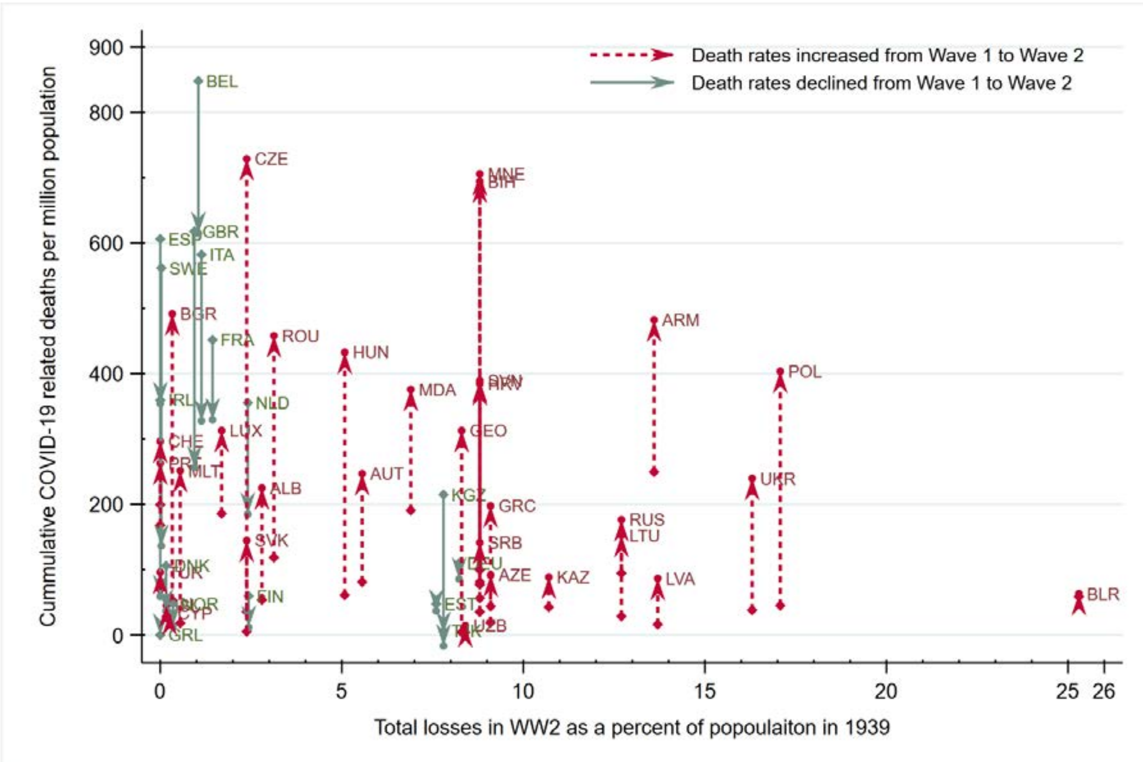


Figure 4: Transitions in COVID death rates from Wave 1 to Wave 2 plotted against WW2 death rate



Note: ISO country codes.

Table 1: Losses in WW2 by country and other historic information

Country	Losses in WW2 as % of 1939 population Total	Military	Axis powers	Post-communist countries
Albania	2.80	2.80		YES
Armenia	13.60	11.36		YES
Austria	5.56	0.00		
Azerbaijan	9.10	6.42		YES
Belgium	1.05	0.11		
Bulgaria	0.33	0.29	YES	YES
Bosnia and Herzegovina	8.80	5.11		YES
Belarus	25.30	6.85		YES
Switzerland	0.00	0.00		
Cyprus	0.26	0.88		
Czechia	2.38	0.28		YES
Germany	8.23	5.05	YES	
Denmark	0.16	0.00		
Spain	0.00	0.00		
Estonia	7.60	2.86		YES
Finland	2.44	1.76	YES	
France	1.44	0.50		
United Kingdom	0.94	0.88		
Georgia	8.30	5.26		
Greece	9.10	0.25		
Greenland	0.00	0.00		
Croatia	8.80	5.11		YES
Hungary	5.08	1.49		YES
Ireland	0.00	0.17		
Iceland	0.17	0.00		
Italy	1.14	0.74	YES	
Kazakhstan	10.70	5.04		YES
Kyrgyzstan	7.80	4.58		YES
Lithuania	12.70	0.85		YES
Luxembourg	1.69	0.00		
Latvia	13.70	1.59		YES
Moldova	6.90	2.02		YES
Malta	0.55	0.87		
Montenegro	8.80	5.11		YES
Netherlands	2.41	0.14		
Norway	0.35	0.10		
Poland	17.08	0.92		YES
Portugal	0.00	0.00		
Romania	3.13	1.88	YES	YES
Russia	12.70	6.13		YES
Serbia	8.80	5.11		YES
Slovakia	2.38	0.28		YES
Slovenia	8.80	5.11		YES
Sweden	0.03	0.00		
Tajikistan	7.80	3.27		YES
Turkey	0.00	0.00		
Ukraine	16.30	3.99		YES
Uzbekistan	8.40	5.04		YES

Table 2: Descriptive statistics for the main variables

	Mean	Std Dev	Min	Max	Data Source
Dependent variables (as of August 31, 2020)					
Cumulative COVID death rate (per mln)	164.77	198.84	0.00	863.43	ECDC
Cumulative COVID infection rate (per 100,000)	417.35	313.95	0.00	1,479.18	ECDC
Controls					
Total losses in WW2 as % of 1939 population	5.70	5.73	0.00	25.30	Wiki, COV
Military losses in WW2 as % of 1939 population	2.30	2.61	0.00	11.36	Wiki
GDP per capita	30,813	18,417	2,924	95,666	WDI
Population median age	40.12	5.27	23.30	47.90	DELVE
Population density	133.17	208.74	0.14	1,394.00	DELVE
Population in 2019, millions	18.98	28.93	0.06	145.87	ECDC
Secondary school enrollment (gross)	108.53	17.42	83.15	158.54	WDI
Voice and accountability index	0.55	0.98	-1.80	1.69	WGI
Axis of powers countries	0.10	0.31	0.00	1.00	COW
Post-communist countries	0.52	0.50	0.00	1.00	Wiki
Falsification analysis variables					
Influenza-pneumonia mortality (per 100,000)	12.71	6.65	2.05	39.28	WHO
Cardiovascular disease mortality (per 100,000)	267.26	154.94	86.06	724.42	IHME

Note: ECDC is the European Centre for Disease Prevention and Control; COV is the Correlates of War Project dataset; DELVE is Global COVID-19 Dataset (Bhoopchand et al. 2020); Wiki is Wikipedia: The Free Encyclopedia; WGI is the World Governance Indicator database; WDI is the World Development Indicators database; WHO is the World Health Organization; IHME is the Institute for Health Metrics and Evaluation.

Table 3: Regressions for COVID-19 deaths per million people

	(1)		(2)	
	Coef.	*SE*	Coef.	*SE*
Total losses in WW2 as share of 1939 population	-11.24**	*5.07*		
Civilian losses in WW2 as share of 1939 population			-14.50***	*4.81*
Military losses in WW2 as share of 1939 population			2.72	*15.54*
Log GDP per capita	-89.02*	*51.24*	-83.56	*52.02*
Population median age	11.34	*7.61*	11.02	*7.53*
Population density	0.10	*0.16*	0.09	*0.16*
Population in 2017, millions	1.95*	*1.04*	1.99*	*1.10*
Secondary school enrollment (gross)	5.59*	*2.91*	5.82*	*3.02*
Voice and accountability	-12.38	*45.58*	4.16	*51.61*
Constant	24.92	*474.99*	-72.42	*480.74*
R^2	0.379		0.399	

Note: N=48. Robust (Huber-White-Hinkley) standard errors; ***: significant at a 1% level; **: 5% level; * : 10% level.

Table 4: Coefficients on total losses in WW2 for alternative model specifications

Model Specification	(1) Coef.	(1) *SE*	(2) Coef.	(2) *SE*
(1) Including controls for Axis powers and post-Communist			-11.70	*5.39*
(2) Misreporting simulation (COVID-19 deaths x 3)	-9.60*	*5.61*	-9.57	*6.01*
(3) Sub-sample of non-Axis powers	-10.13*	*5.45*	-9.18	*5.63*
(4) DFBETA influential observation analysis	-16.17***	*5.07*	-18.46***	*5.64*
(5) Falsification test: Influenza-pneumonia mortality	-0.13	0.25	-0.24	0.24
(6) Falsification test: Cardiovascular disease mortality	3.42	3.06	3.42	3.06
(7) Cumulative COVID-19 deaths as of July 31, 2020	-10.16*	5.12	-10.47*	5.30
(8) Cumulative COVID-19 deaths as of June 30, 2020	-10.66**	*4.83*	-10.86**	*4.83*
(9) Extended set of countries engaged in WW2 (n=76)	-9.47**	*4.57*	-7.26*	*4.21*

Note: Specification in row (1) shows the coefficient on total losses for the regression in Table 2 with added controls for communist countries and axis of power. Specification in row (2) triples the COVID-19 death rates in Belarus, Tajikistan, and Uzbekistan. Specification in row (3) excluded from estimations countries that belonged to axis powers: Germany, Italy, Romania, Finland, and Bulgaria. Specification (4) excludes from the sample Belarus and Armenia. Specification (5) and (6) uses mortality rates from cardiovascular diseases and from pneumonia and influenza in 2018 as the dependent variable. Specifications (6) and (7) use as dependent variable the total cumulative COVID-19 related deaths per million as of June 30 and July 31, 2020. Specification in row (9) extends the sample by including counties that participated in the Asia-Pacific region. Robust standard errors; ***: significant at a 1% level; **: 5% level; * : 10% level.

Table 5: Regressions for the second wave COVID-19 deaths per million

	(1)		(2)	
	Coef.	*SE*	Coef.	*SE*
Total losses in WW2 as share of 1939 population	-9.49	*6.35*		
Civilian losses in WW2 as share of 1939 population			-11.79	*8.28*
Military losses in WW2 as share of 1939 population			0.19	*13.51*
Log GDP per capita	-1.78	*2.22*	-1.66	*2.26*
Population median age	26.98***	*6.24*	26.95***	*6.44*
Population density	0.04	*0.13*	0.04	*0.13*
Population in 2019, millions	-0.97	*0.76*	-0.95	*0.82*
Secondary school enrollment (gross)	-1.83	*2.73*	-1.65	*2.76*
Voice and accountability	-78.96	*60.44*	-67.85	*63.36*
Constant	-480.56	*399.22*	-523.28	*405.54*
R^2	0.327		0.337	

Note: N=48. Robust standard errors; *** indicates that the coefficient is significant at a 1% level, ** - at a 5% level, * - at a 10% level.

Table 6: Regressions for the second wave of COVID-19 deaths controlling for first wave

	(1)		(2)	
	Coef.	*SE*	Coef.	*SE*
Total losses in WW2 as share of 1939 population	-5.57	*7.03*		
Civilian losses in WW2 as share of 1939 population			-6.62	*8.80*
Military losses in WW2 as share of 1939 population			-1.55	*11.20*
1st waive COVID-19 death per million	0.43**	*0.16*	0.42**	*0.16*
Log GDP per capita	-1.39	*1.96*	-1.35	*1.99*
Population median age	24.47***	*7.25*	24.51***	*7.39*
Population density	0.00	*0.07*	0.00	*0.07*
Population in 2019, millions	-1.76**	*0.86*	-1.73*	*0.87*
Secondary school enrollment (gross)	-4.01**	*1.68*	-3.89**	*1.65*
Voice and accountability	-72.59	*63.11*	-68.02	*64.08*
Constant	-225.94	*337.44*	-249.32	*338.35*
R^2	0.442		0.444	

Note: N=48. Robust standard errors; *** indicates that the coefficient is significant at a 1% level, ** - at a 5% level, * - at a 10% level. First wave COVID-19 death per million is a cumulative death measure till July 31, 2020. Second wave is from August 1 until December 1.