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GDP Effects of Pandemics: A Historical Perspective

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Abstract

The paper estimates dynamic effects of pandemics on GDP per capita with local projections, controlling for the effects of wars and weather conditions, using a novel dataset that covers 33 countries and stretches back to the 13th century. Pandemics are found to have prolonged and highly statistically significant effects on GDP per capita - a pandemic killing 1% of the population tends to increase GDP per capita by approx. 0.3% after about 20 years. The results are qualitatively robust to various model specifications, geographical division of the sample and an exclusion of extreme events such as the Black Death and the New World epidemics. The effects of pandemics differ from those of wars and weather, which are negative and die out quicker, in line with the neoclassical growth model.

Keywords: pandemic, GDP, local projection, economic history, war, tree rings.

JEL: I15, N10, N30, N40, N50, O47.

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[1] The views expressed in this paper belong to the author only, and have not been endorsed by SGH or any other institutions. I am grateful to Adam Pigoń for useful suggestions. E-mail address: maciej.stefanski@doktorant.sgh.waw.pl

1. Introduction

The COVID-19 pandemic has reignited interest in the study of macroeconomic effects of epidemics. Will the effects of the pandemic be short-lasting, with the economy returning to its pre-crisis trend sooner or (just a bit) later, or will they last much longer, with GDP remaining depressed for many years or even decades to come? Perhaps history can help us answer this question to some degree – despite all the differences in the level of economic, organisational and healthcare development between the present and the past.

From a theoretical viewpoint, past pandemics may have had either a positive or negative impact on GDP per capita. On the one hand, they decreased the denominator, i.e. the population size, which could have led to an increase in the standard of living in Malthusian subsistence societies (Malthus 1798). In a more sophisticated economy, they also tended to increase the capital labour ratio, rising labour productivity and per capita income, in line with the neoclassical growth model (Solow 1956). A large catastrophic event like a pandemic may have also disturbed economic and power structures, perhaps leading to positive institutional changes and technological innovation, in the spirit of Schumpeterian creative destruction (Schumpeter 1942).

On the other hand, in the short run pandemics were likely to raise uncertainty and induce precautionary saving, lowering investment and consumption even without lockdowns and quarantines. The level of risk aversion may as well have increased in a more permanent manner as economic agents would fear the repetition of the catastrophe, in a mechanism similar to Bayesian updating (Kozlowski et al. 2020). At the same time, lower population density following a pandemic could have led to a decline in market economy activities (surplus production and trade) in a longer run due to lower effects of scale and higher transportation and transaction costs.

The identification of GDP per capita effects of pandemics is therefore very much an empirical question. To answer it, data on the size of pandemics (in terms of percentage of population killed by each pandemic) is assembled for a panel of 33 countries between 1252 and 2016. Since pandemics are not necessarily fully exogenous - the historical evidence suggests they might have been fostered by wars, droughts and poor living conditions – data on tree ring growth (to control for weather conditions) and incidence of wars is also gathered. Other than controlling for an endogenous element of pandemics, this allows me to compare the GDP effects of pandemics with those of wars and weather conditions.

After combining the gathered data with GDP per capita estimates from the Maddison Project Database, local projections in the spirit of Jorda (2005) with adjustments proposed by Teulings and Zubanov (2014) are run to estimate the impulse response functions of GDP per capita to pandemics, as well as wars and weather conditions. Pandemics are found to have a prolonged and highly statistically significant effect on GDP per capita, with a pandemic resulting in the death of 1% of population increasing GDP per capita by a maximum of 0.3%, this peak effect appearing after almost 20 years. To the contrary, the incidence of a war and one standard deviation increase in tree ring growth are estimated to depress GDP by about 1% and 0.5%, respectively, with the impacts dying out after 10-15 years.

The effects of pandemics are robust to various adjustments in the model specification and the use of GDP growth as a dependent variable. When a binary variable describing the incidence of pandemics is used as the main variable of interest, the sample is divided between Europe and the rest of the world, or the mostly deadly epidemics are excluded, the shape of impulse response functions remains similar, though quantitative estimates are larger and less precise.

Potential non-linearities with respect to pandemic size and its year of incidence are also investigated. It is found that small and largest pandemics have a positive effect on GDP per capita, while the impact of mid-size events is neutral or even negative. Similar conclusions are drawn from the specification that is non-linear with respect to time – early and recent pandemics (when losses in the population were largest and smallest, respectively) have a positive effect on GDP per capita, while epidemics in the 15th-17th centuries (which resulted in mid-size population losses) tend to decrease GDP.

Related Literature. This paper is related primarily to empirical studies on the economic consequences of pandemics. The most closely related paper is Jorda et al. (2020), in which authors use local projections to estimate the impact of pandemics (and wars) on interest rates and other macroeconomic variables, including GDP per capita, over a similar time frame. Their approach and data are much more limited, however – they do not use panel data, cover only the most (in)famous pandemics and wars, and neither control for weather conditions, include time trends, nor employ the Teulings-Zubanov adjustment. Finally, pandemics are represented by a binary variable. GDP per capita in the UK is found to be almost 10% higher 40 years after a pandemic, thus the effect is much larger than in this paper.

Focusing on more recent events and aiming at drawing conclusions relevant for the current COVID-19 crisis, Ma et al. (2020) use local projections and panel regressions to investigate the macroeconomic effects of the much smaller, but more recent post-World War 2 pandemics. They find that epidemics depress GDP by almost 3% at the outbreak and the effect does not fully die out within 5 years.

A couple of other papers study the short-run effects of the Spanish flu pandemic in given countries, investigating the relationship between regional pandemic incidence and economic outcomes (Brainerd and Siegler 2003, Karlsson et al. 2014, Barro et al. 2020). The results of these studies range from highly negative to positive impacts on GDP per capita.

Thus, the above-mentioned papers seem to suggest that the pre-20th century pandemics had a largely positive impact on GDP per capita, while the impact of more recent events (post-WW2 and to some extent the Spanish flu) was negative. This paper does not corroborate this conclusion, finding positive GDP per capita effects both in the medieval times and the 20th century.

The paper is also related to the literature on the pre-industrial economic growth in Europe, which debates whether per capita growth took place before 1750 (Jones 2000, Goldstone 2002, Broadberry and Wallis 2017, Goldstone 2019), in particular in England and the Netherlands (Broadberry 2013, de Pleijt and van Zanden 2019), pointing to the Black Death, overseas expansion and wars as potential sources of structural changes and growth (Pamuk 2007, Voigtlander and Voth 2013, de Pleijt and van Zanden 2016, O'Brien 2018, Jedwab et al. 2019, Prados de la Escosura and Rodriguez-Caballero 2020). Since the effects of pandemics are found to be prolonged and positive, the results of this paper support the view that pandemics played a role in spurring pre-industrial growth. The opposite is the case for wars, for which no long-run effects are identified.

The main contribution of this paper is thus a thorough study of both short-run and longer-run effects of pandemics on per capita income on a large sample of countries, controlling for wars and weather and using robust econometric techniques.

Regarding the current COVID-19 pandemic, the results of this paper do not point to declining positive effects of pandemics over time – if anything, the opposite is the case. Thus, while the results of this study should not be accepted at face value when relating to COVID-19 due to the obvious differences in the economic, organisational and healthcare structure with the pre-20th century world, they could be regarded as a reason of optimism that the long-run effects of the pandemic might not be as disastrous as often anticipated, and certainly not as disastrous as in the case of financial crises (Jorda et al. 2013, Reinhart and Rogoff 2014).

The paper is structured as follows: Section 2 describes the data, while Section 3 discusses the empirical framework. In Section 4, the baseline results and the results accounting for non-linearities with respect to pandemic size and time are presented, while Section 5 provides robustness checks. Finally, Section 6 discusses the limitations of the study and concludes.

2. Data

The dataset covers 33 countries[2] over the period of 1252 to 2016[3]. Only countries with continuous estimates of GDP per capita starting before World War I are included, so that the Spanish flu pandemic is covered[4].

[2] Argentina, Australia, Austria, Belgium, Canada, Switzerland, Chile, Cuba, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Indonesia, India, Italy, Japan, Mexico, Malaysia, Netherlands, Norway, New Zealand, Peru, Philippines, Poland, Portugal, Romania, Russia, Sweden, United States, and South Africa.

[3] Data on pandemics and wars is available over the whole 1252-2016 period, while the coverage of tree ring and GDP per capita data is limited. See the Appendix for details.

Pandemics are expressed in terms of the percentage of population that died due to a given event in a given year. Death toll estimates are more prevalent than infection estimates and are more likely to reflect the relative social and economic costs of an event. While these estimates might be imprecise and often vary across sources, they are preferable to a binary variable describing pandemic incidence that effectively gives equal weights to very different events. Nevertheless, the robustness of baseline results to the use of a binary dependent variable is discussed in subsection 5.3.

Data on incidence of pandemics and their death tolls is gathered from a large variety of sources – see Appendix A for more details. Death estimates are divided by population estimates from the Maddison Project Database (interpolated when necessary). Only pandemics that killed at least 0.1% of population per year are included. Endemic diseases are included only in the years of notable spikes in deaths. When pandemics are reported to have lasted for several years, the death toll is spread evenly over time, unless data suggests otherwise. The binary variable describing pandemic incidence, used in one of the robustness checks, additionally includes events that seem to be significant, but for which no death toll estimates are available.

Data on the size of pandemics is presented in **Figure *1***.

GDP per capita data comes primarily from the 2018 version of the Maddison Project Database (Bolt et al. 2018)[5]. As I am interested in GDP growth over time, rather than the comparison of relative GDP per capita levels across countries, the 2011 PPP benchmark series is used. Data for the Netherlands and the UK is projected backwards with estimates for Holland and England, respectively, assuming a constant relation of income levels between these regions and entire countries. Data for Italy is extended with estimates for North and Central Italy from Malanima (2011) in the same fashion. For Spain, recent estimates by Prados de la Escosura et al. (2020) are used. There are 9966 non-empty observations (out of 25245 possible ones for 33 countries over the whole time frame).

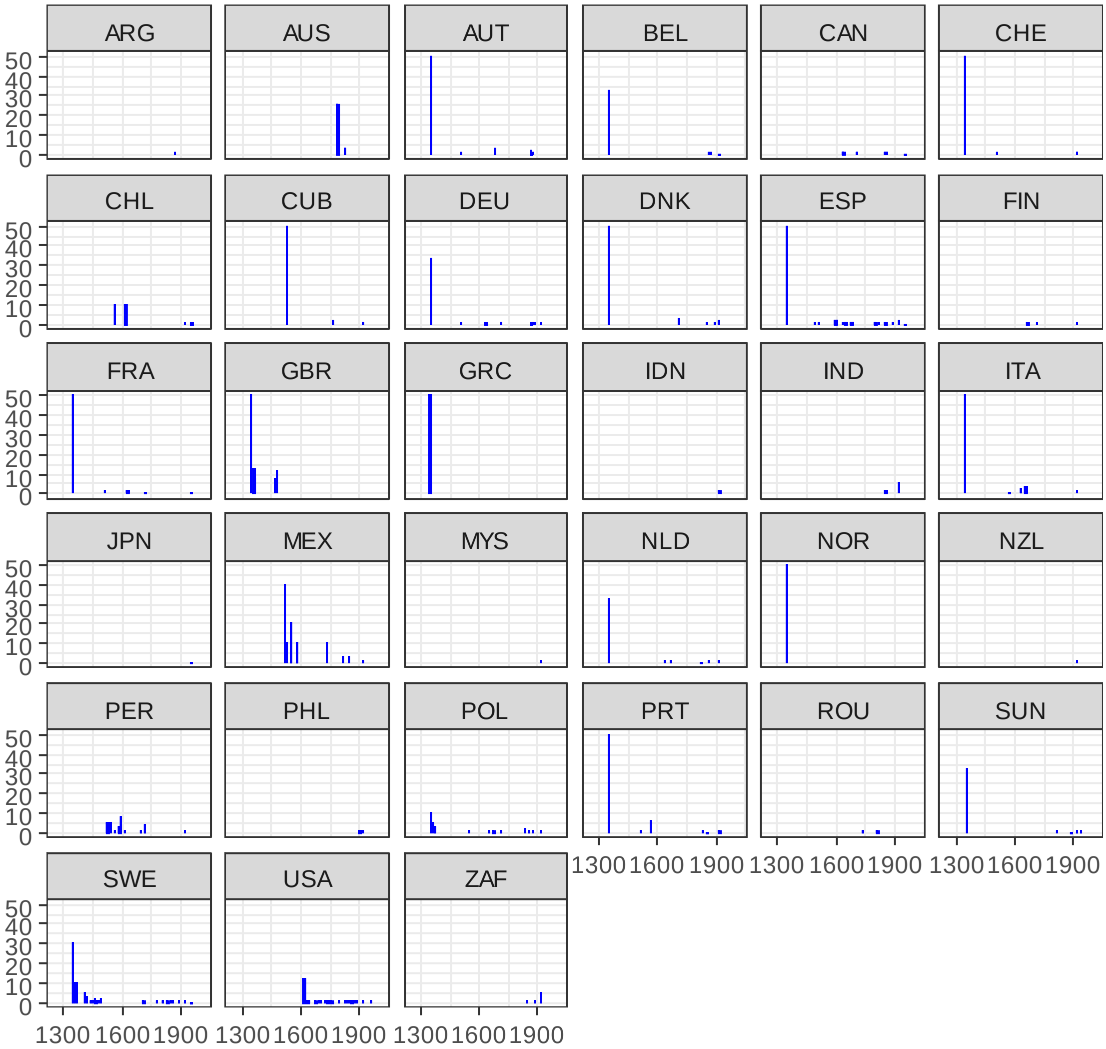
Since the incidence of pandemics is not necessarily fully exogenous, the inclusion of control variables might be warranted. In particular, historical evidence suggests that pandemics are often associated with **wars**. Looting, devastation, sieges, the resulting poor nutrition, as well as large concentrations and movements of troops are conducive to disease outbreaks and support their spread. For example, diseases are considered to be the main cause for the huge decline of population in Germany during the Thirty Years War (Outram 2001), plagues swept through Central and Eastern Europe during the Great Northern War (Kroll and Kruger 2006), typhus killed a large chunk of Napoleon's Grande Armée during the invasion

[4] Not all such countries are included, however – Bolivia, Brazil, Colombia, Ecuador, Korea, Sri Lanka, Panama, Singapore, Taiwan, Uruguay and Venezuela all have continuous GDP per capita estimates starting before 1914 (though, with the exception of Venezuela, no earlier than 1870), but are not covered.

[5] The 2020 edition of the database has been published recently, but it does not include important new time series. The main modification is the change back to the 1990 PPP benchmark, which does not have any effect on pre-1950 growth estimates and thus should not substantially influence the results of this paper.

of Russia (Conlon 2014), while one of the most deadly pandemics in history - the Spanish flu - broke out at the end of World War I.

Figure 1. Data on the size of the pandemics (% of population killed in a given year)



Source: Own compilation based on various sources – see Appendix A for details.

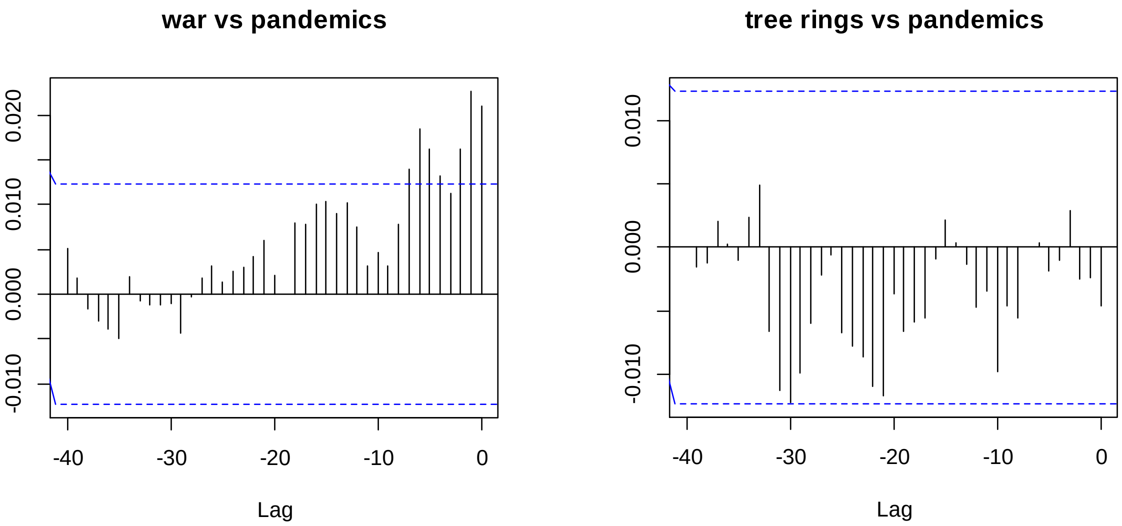
Thus, to control for a potential causal impact of wars on pandemics, data on war incidence, expressed in terms of a binary variable, is gathered from a very large number of sources – see Appendix B for details. Included are conflicts that either caused major destruction of physical capital and/or disruption of social and economic activity, or required a substantial military effort from a given country, i.e. a substantial part of its military force was used and actively engaged in warfare. For countries that did not exist as independent entities at the time of conflicts, they are reported to have taken part in a war if warfare had taken place on their territory or the population of the country had taken part in the conflict by being drafted into the military in significant numbers.

Weather is another factor that can potentially affect outbreaks and spread of pandemics. Long periods of drought may facilitate spread of diseases by causing poor nutrition and thus weaker immunity of both humans and disease transmitters. On the other hand, transmitters of some diseases (e.g. mosquitoes) benefit from wet weather conditions. Thus, long periods of drought followed by wet conditions might be particularly dangerous as they combine abundant populations of transmitters with weaker human immunity – some historical evidence suggests this could have been the reason why the 1545-48 cocoliztli epidemic in Mexico was so deadly (Acuna-Soto et al. 2002).

To proxy for the effects of weather, data on tree ring growth is used. Tree growth is clearly associated with weather conditions – in fact, temperature, precipitation and drought indices are reconstructed from tree ring data when more direct measures are not available (e.g. Briffa et al. 2004, Cook et al. 2004, Yang et al. 2014). At the same time, tree ring data is available for a larger number of countries over longer time periods than the reconstructed data on temperature, weather and droughts.

Tree ring data is gathered from the NOAA Paleoclimatology database and expressed in terms of the standardised growth index, computed according to the standard chronology method. When several locations are available for a given country, one of them is picked, taking into account time coverage and proximity in distance and altitude to most densely populated areas. For details on the data sources, see Appendix C. Tree ring data is not available for Cuba and Malaysia, shrinking the sample to 31 countries and 8218 observations.

Figure 2. Cross correlation plots



Cross-correlation plots (**Figure 2**) suggest that pandemics are indeed weakly, but statistically significantly and positively correlated with contemporaneous and past wars (up to 8 years back). The correlation between tree rings and pandemics is negative and strongest at 20-30 year lag, thus bad weather conditions seem to increase the likelihood of a pandemic outbreak. The relationship is not statistically significant, however.

3. Empirical framework

3.1 Local projections and non-stationarity of GDP per capita

Local projections in the spirit of Jorda (2005) are used to estimate the impulse response function (IRF) of GDP per capita to pandemics (as well as wars and weather conditions) over the 40-year horizon. This method entails estimating a set of conditional forecast regressions for the IRF horizon h, which in the simplest case can be written as follows:

$$y_{t+h} = \alpha^h + \beta^h d_t + \varepsilon_t$$

where y_t is the dependent variable, and d_t is an exogenous shock for which the impulse response is computed. The impulse response function is made of the coefficients β^h:

$$IRF(h) = \beta^h$$

In the context of this paper, local projections have several advantages over IRFs computed from VAR models and analytical IRFs obtained from single equation ARDL models:

- Local projections are more robust to model misspecification, especially at longer horizons (Jorda 2005, Teulings and Zubanov 2014, Plagborg-Moller and Wolf 2020);
- Local projections are more flexible – lags and non-linearities can be added in a straightforward manner[6];
- Comparing to VAR models, local projections are much easier to estimate in a panel data setup.

However, Jorda (2005) local projections are biased if the shock reappears over the forecasting horizon (Teulings and Zubanov 2014). This can be corrected for by including shocks that take place between time $t+1$ and $t+h$ in the regressions.

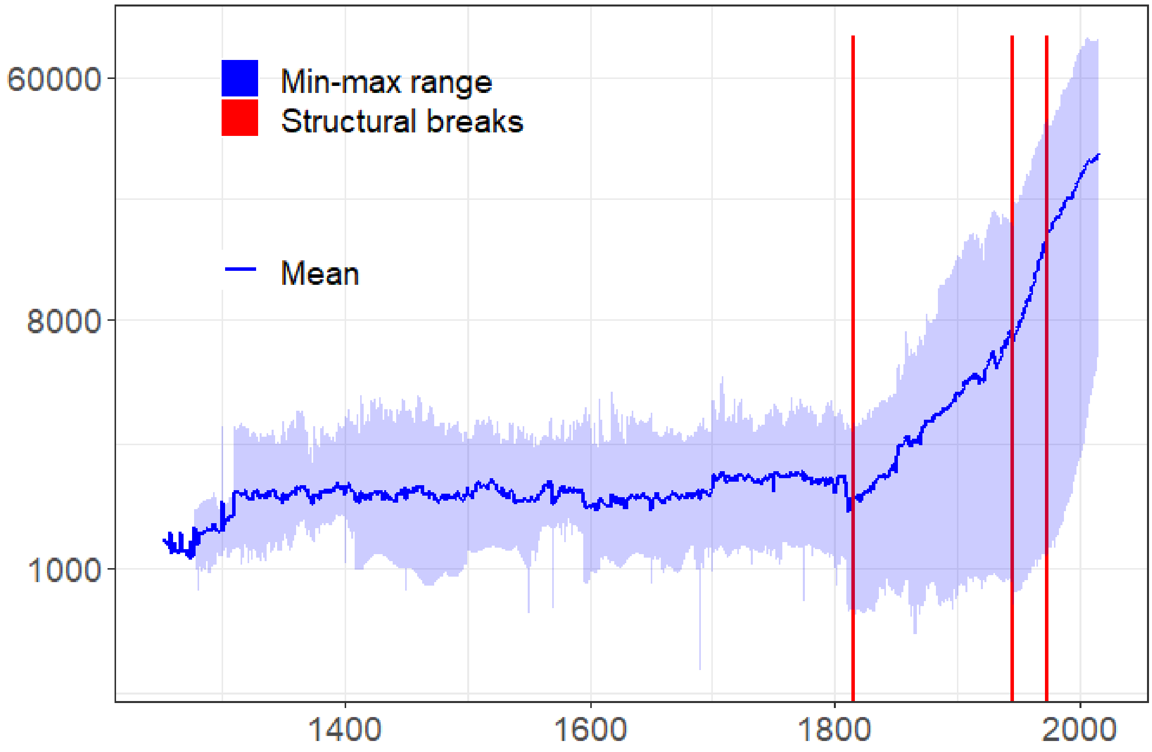
Moreover, if the variable of interest is not (fully) exogenous, control variables that are correlated with it (and the dependent variable) should be added to the regression in order to single out the exogenous component of the variation. However, even if the variable of interest is exogenous, the inclusion of control variables that are correlated with the dependent variable improves the efficiency of the model and IRF estimates (Jorda et al. 2020).

Non-stationarity of GDP per capita series is another issue relevant for the design of the empirical framework (**Figure 3**). Differencing would be the easiest solution, but it would make the study of the effects of pandemics on GDP per capita level more difficult (in particular, testing for statistical significance would be cumbersome). Given the aim of this paper to study longer-run impact of pandemics and the debatable quality of data on annual GDP growth rates in the earlier history, the effects on levels seem of more relevance than effects on growth rates.

[6] Increasing the number of lags is limiting degrees of freedom much faster in VAR models than in local projections, while making the computation of IRFs much more cumbersome in ARDL models.

An alternative is to account for the structural shifts in trend GDP growth. With this aim, a common piecewise time trend is included in the regressions, with structural breaks in 1815 (the Congress of Vienna, i.e. the end of Napoleonic wars), 1945 (the end of World War II) and 1973 (the first oil shock). These dates reflect both important historical events and changes in the slope of log mean GDP per capita trend, as visible in **Figure 3**. Other specifications, including the regression using first differences, are considered in the robustness checks Section 5.

Figure 3. GDP per capita in the sample of 33 countries (2011 USD, log scale)



Source: Own calculations based on Maddison Project Database, extended with Malanima (2011) for Italy and Prados de la Escosura et al. (2020) for Spain.

3.2 Baseline and non-linear specifications

All the above considered, the following set of regressions is estimated for $h = 0, 1, \dots, 40$:

$$\ln y_{i,t+h} = \mu_i^h + \sum_{j=0}^{30} \beta_j^h P_{i,t-j} + \sum_{k=1}^{30} \gamma_k^h y_{i,t-k} + \sum_{l=0}^{30} \theta_l^h war_{i,t-l} + \sum_{m=0}^{30} \vartheta_m^h tr_{i,t-m} + \delta_1^h t + \alpha_1^h vienna_t$$
$$+ \delta_2^h vienna_t * t + \alpha_2^h ww2_t + \delta_3^h ww2_t * t + \alpha_3^h oil_t + \delta_4^h oil_t * t + \sum_{n=0}^{h-1} \pi_n^h P_{i,t+h-n}$$
$$+ \sum_{o=0}^{h-1} \varphi_o^h war_{i,t+h-o} + \sum_{p=0}^{h-1} \omega_p^h tr_{i,t+h-p} + \varepsilon_{i,t+h}$$

where $y_{i,t}$ is ln GDP per capita for country i at time t, μ_i is a country fixed effect, $P_{i,t}$ is the percentage of people killed by a pandemic in country i at time t, $war_{i,t}$ is a dummy variable equal to 1 if a conflict takes place in country i at time t, $tr_{i,t}$ is the tree ring standardised growth index in country i at time t; $vienna_t$, $ww2_t$ and oil_t are dummies equal to 1 since 1815, 1945 and 1973, respectively, and 0 before; while $\varepsilon_{i,t}$ is an idiosyncratic error term. The last 3 terms before the error term reflect the Teeulings-Zubanov adjustment, i.e. these are the shocks that take place between time $t+1$ and $t+h$.

The impulse response of ln GDP per capita to a pandemic that killed 1% of the population is defined as follows:

$$IRF(h) = \beta_0^h$$

Impulse responses to wars and tree ring changes are constructed analogically, i.e. $IRF\_war(h) = \theta_0^h$ and $IRF\_tr(h) = \vartheta_0^h$.

30 lags of GDP per capita as well as the pandemic, war and tree ring variables are included in the specification in order to control for the potential endogeneity of pandemics, and improve the model fit and thus estimate efficiency. Alternative numbers of lags are considered in the subsection 5.1 of the robustness checks.

The set of regressions is estimated with the fixed effects estimator. Even though this estimator is biased in a dynamic panel setting (Nickell 1981), the downward bias on the lagged dependent variable coefficient is diminishing with increasing time dimension of the panel, and thus can be safely ignored in the sample which covers 765 years.

Standard errors are corrected for heteroskedasticity and autocorrelation using Driscoll and Kraay (1998) approach. This is important since conditional forecasts of the type considered here suffer from serial correlation (Teulings and Zubanov 2014).

The baseline specification assumes that the effects of pandemics are linear in size. This might be a strong assumption, however – while small events are likely to have limited effects, especially in the longer run, large events might cause structural and institutional shifts, leading to pronounced effects in the long run.

Therefore, an alternative specification investigates whether the effects of pandemics on GDP per capita depend on the size of a pandemic. For this purpose, up to the 4th order polynomial terms of the pandemic variable at time t are added to the regressions (new terms in red):

$$\ln y_{i,t+h} = \mu_i^h + \sum_{j=0}^{30} \beta_j^h P_{i,t-j} + \rho_1^h P_{i,t}^2 + \rho_2^h P_{i,t}^3 + \rho_3^h P_{i,t}^4 + \sum_{k=1}^{30} \gamma_k^h y_{i,t-k} + \sum_{l=0}^{30} \theta_l^h war_{i,t-l}$$
$$+ \sum_{m=0}^{30} \vartheta_m^h tr_{i,t-m} + \delta_1^h t + \alpha_1^h vienna_t + \delta_2^h vienna_t * t + \alpha_2^h ww2_t + \delta_3^h ww2_t * t$$
$$+ \alpha_3^h oil_t + \delta_4^h oil_t * t + \sum_{n=0}^{h-1} \pi_n^h P_{i,t+h-n} + \sum_{o=0}^{h-1} \varphi_o^h war_{i,t+h-o} + \sum_{p=0}^{h-1} \omega_p^h tr_{i,t+h-p}$$
$$+ \varepsilon_{i,t+h}$$

which results in the following expression for the impulse response function:

$$IRF(h) = \beta_0^h + 2\rho_1^h P_{i,t} + 3\rho_2^h P_{i,t}^2 + 4\rho_3^h P_{i,t}^3$$

Cubic form of the impulse response function gives enough flexibility to cover various forms of non-linearity.

The effects of pandemic might also differ over time with i.a. changing economic structures and healthcare practices. To test this hypothesis, the pandemic variable at time t is interacted with up to 2nd order polynomial terms of time (new terms in red):

$$\ln y_{i,t+h} = \mu_i^h + \sum_{j=0}^{30} \beta_j^h P_{i,t-j} + \tau_1^h P_{i,t} t + \tau_2^h P_{i,t} t^2 + \sum_{k=1}^{30} \gamma_k^h y_{i,t-k} + \sum_{l=0}^{30} \theta_l^h war_{i,t-l} + \sum_{m=0}^{30} \vartheta_m^h tr_{i,t-m}$$
$$+ \delta_1^h t + \alpha_1^h vienna_t + \delta_2^h vienna_t t + \alpha_2^h ww2_t + \delta_3^h ww2_t t + \alpha_3^h oil_t + \delta_4^h oil_t t$$
$$+ \sum_{n=0}^{h-1} \pi_n^h P_{i,t+h-n} + \sum_{o=0}^{h-1} \varphi_o^h war_{i,t+h-o} + \sum_{p=0}^{h-1} \omega_p^h tr_{i,t+h-p} + \varepsilon_{i,t+h}$$

which gives the following expression for the impulse response function:

$$IRF(h) = \beta_0^h + \tau_1^h t + \tau_2^h t^2$$

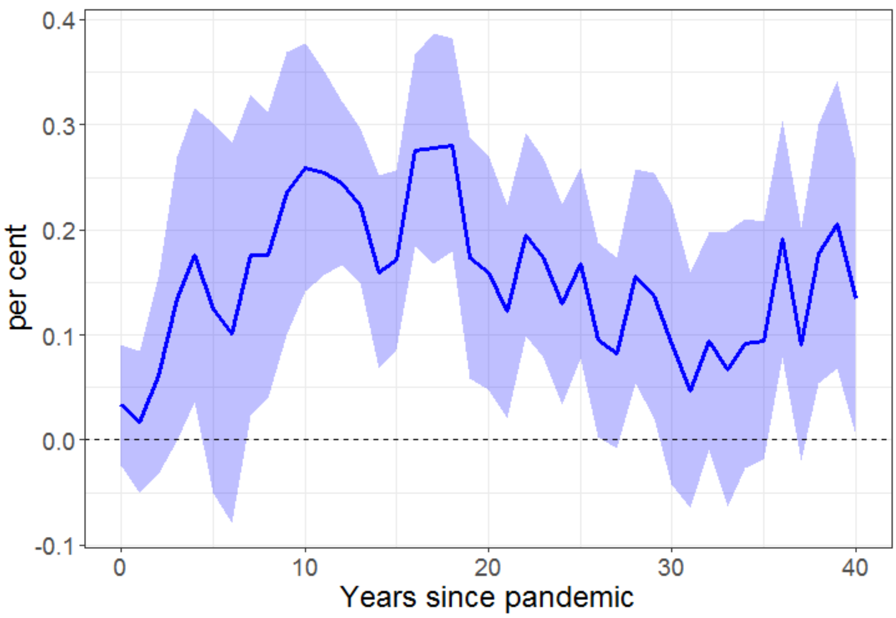
4. Results

4.1 Baseline estimates

The response of GDP per capita to a pandemic that kills 1% of the population in a given year, obtained from the baseline specification, is presented in **Figure 4**.

In the short run, positive and negative effects of pandemics on per capita income seem to roughly cancel each other out. After several years, positive effects associated with higher per capita land and capital begin to dominate. In the second decade following the pandemic, GDP per capita is about 0.25% higher, with the peak effect of 0.28% after 18 years. Afterwards, the effects of pandemics partially dissipate, but remain positive and statistically significant even after 40 years. Thus, pandemics seem to have a positive impact on GDP per capita in the long run, perhaps because they induce positive institutional changes[7].

Figure 4. Response of GDP per capita to a pandemic resulting in the death of 1% of the population in a given year



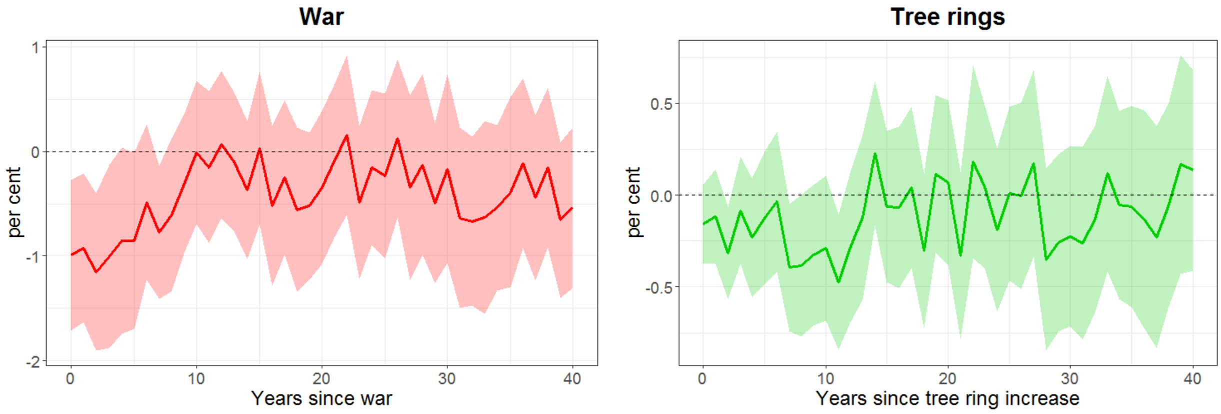
Shaded area is a 90% confidence band around response estimates.

The effects of pandemics are very different than those of war and weather (**Figure 5**). A war depresses GDP per capita by about 1% on impact and the effect gradually fades away over the next 10 years. Wars destroy capital while killing a smaller part of the population than pandemics. In line with the neoclassical growth model, this negative impact on capital labour ratio, together with other disruptive effects of wars, generates a negative response of GDP per capita. At the same time, wars – unlike pandemics - have no statistically significant effect on GDP per capita in the long run, contradicting the claims that they were one of the drivers of growth in pre-industrial Europe (Voigtlander and Voth 2013, O'Brien 2018).

In turn, one standard deviation increase in tree ring growth has a borderline significant, negative impact on GDP per capita that persists over the first decade, peaks at 0.5% after 11 years and fades away soon afterwards. These results are somewhat counterintuitive as weather conditions that are conducive to tree growth have a negative and quite persistent impact on per capita income. Perhaps weather conditions that support tree growth are not necessarily conducive to crop growth, especially in the case of excessively wet conditions.

[7] For example, the Black Death is often mentioned as one of the driving factors behind the process of enclosure in England, which led to a more effective use of land and eventually the creation of a landless working class that found employment during the industrial revolution.

Figure 5. Response of GDP per capita to a war (left panel) and one standard deviation increase in tree ring index (right panel)

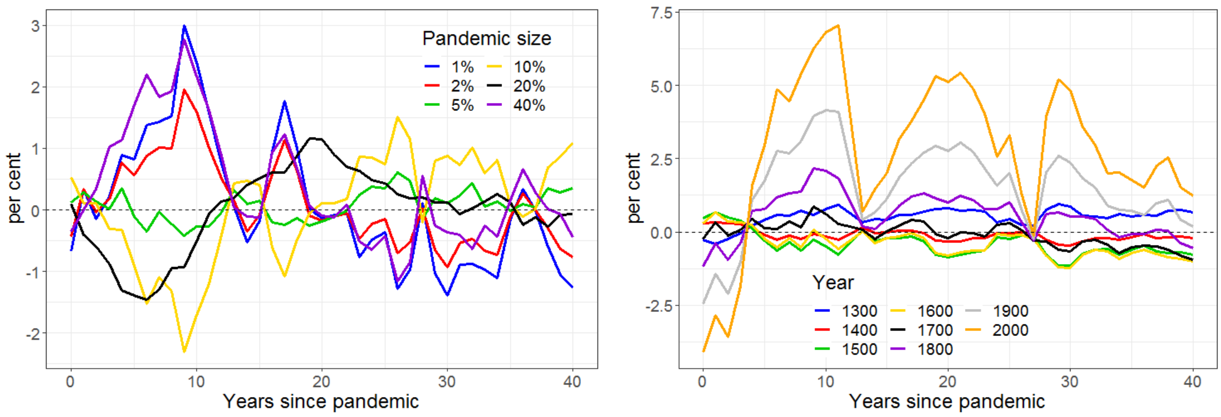


Shaded areas are 90% confidence bands around response estimates.

4.2 Non-linearities and time dependence

The impulse responses obtained from specifications which allow for non-linearity with respect to the pandemic size and time are presented in **Figure 6**.

Figure 6. Response of GDP per capita to a pandemic: non-linear specifications with respect to the pandemic size (left panel) and time (right panel)



Impulse responses are scaled per 1% annual pandemic death toll.

Impulse responses vary wildly both with respect to the pandemic death toll and over time, and these differences are often counterintuitive and difficult to interpret. The smallest (<=2% of population killed) and largest (40% death toll) pandemics have a highly positive impact on GDP per capita in the first decade, slightly positive in the second decade and slightly negative afterwards. The effects of mid-sized pandemics are largely a mirror image – negative in the first decade and positive after more than 20 years. Especially a highly positive short-run impact of small pandemics is puzzling – those are unlikely to lead to large institutional changes, do not have large impact on capital labour ratios, and tend to happen more recently, when more advanced containment measures are likely to negatively affect economic activity in the short run.

Time-varying impulse responses are consistent with the pandemic-size-varying ones. Even though the initial impact is – as intuition would suggest – negative, most recent pandemics tend to have a puzzlingly large positive effect on GDP per capita. Pandemics from the beginning of the sample (which coincides with the Black Death) also have a positive (though much smaller) effect on per capita income, while Renaissance time (1400-1600) pandemics tend to depress GDP per capita.

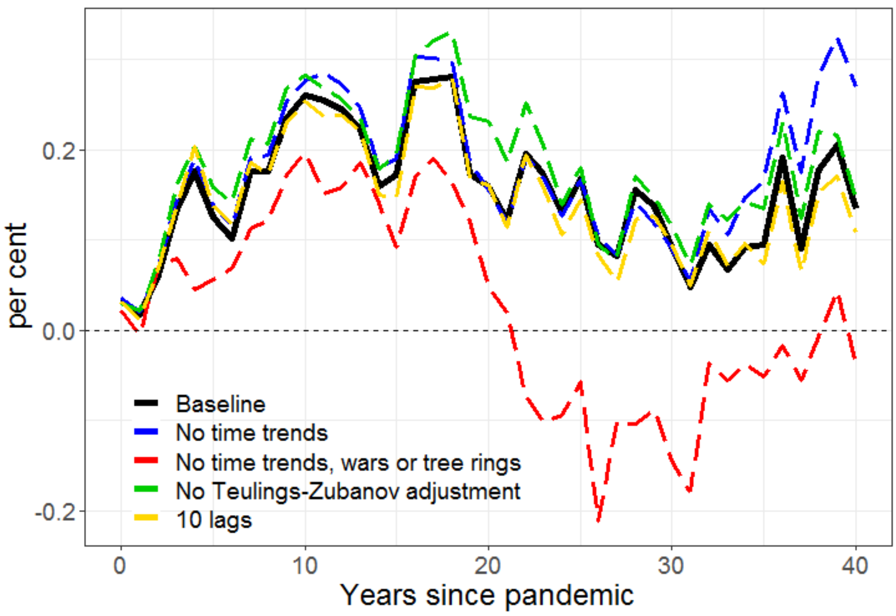
Due to the lack of a clear-cut pattern, the non-linear IRFs should be interpreted with extra caution. Having said that, one important conclusion may be drawn – there is no evidence that more recent and smaller pandemics have a less positive effect on GDP per capita than the baseline results would suggest. If anything, the opposite is true.

5. Robustness checks

5.1 Specification adjustments

As the first robustness check, the baseline specification is simplified by removing the piecewise time trend, the control variables and the Teulings-Zubanov adjustment (shocks that take place between time *t+1* and *t+h*) as well as decreasing the number of lags of all the explanatory variables. The impulse response functions resulting from these robustness checks are presented in **Figure 7**.

Figure 7. Response of GDP per capita to a pandemic resulting in the death of 1% of the population in a given year: alternative model specifications



Estimates prove to be highly robust to the above-mentioned modifications. Dropping the time trends, the Teulings-Zubanov adjustments and decreasing the number of lags has very little effect on impulse responses. Only removing the control variables has a larger impact on the estimates, particularly in the longer run, when positive effects of pandemics no longer persist. Therefore, the inclusion of wars and tree rings is an important addition to the model, while other specification choices have virtually no impact on the conclusions of this study.

5.2 GDP growth a dependent variable

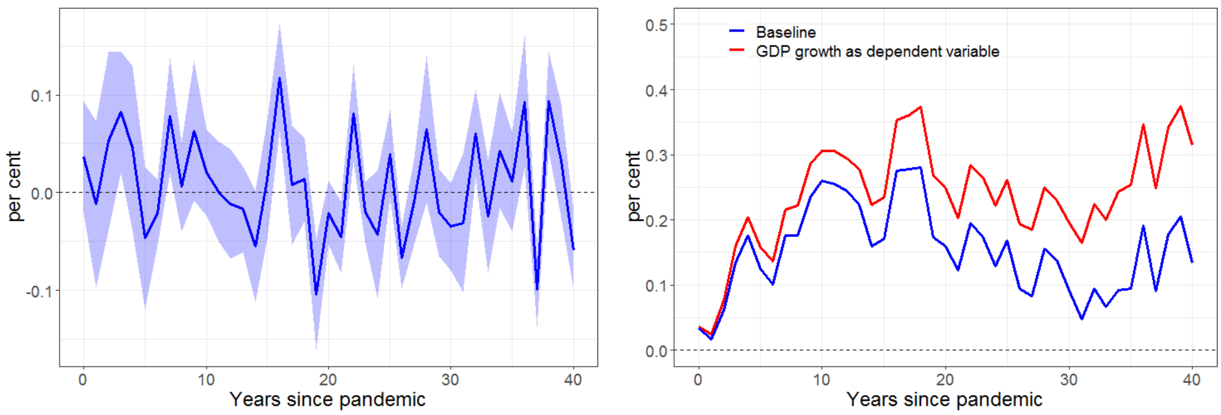
Differencing is the alternative solution to the problem of non-stationarity of ln GDP per capita series. Growth of GDP per capita then becomes the dependent variable in the specification and the time trend variables are dropped. The dummy variables that account for time-varying equilibrium GDP growth rates are retained:

$$\begin{aligned}\hat{y}_{i,t+h} = \mu_i^h &+ \sum_{j=0}^{30} \beta_j^h P_{i,t-j} + \sum_{k=1}^{30} \gamma_k^h \hat{y}_{i,t-k} + \sum_{l=0}^{30} \theta_l^h war_{i,t-l} + \sum_{m=0}^{30} \vartheta_m^h tr_{i,t-m} + \alpha_1^h vienna_t \\ &+ \alpha_2^h ww2_t + \alpha_3^h oil_t + \sum_{n=0}^{h-1} \pi_n^h P_{i,t+h-n} + \sum_{o=0}^{h-1} \varphi_o^h war_{i,t+h-o} + \sum_{p=0}^{h-1} \omega_p^h tr_{i,t+h-p} \\ &+ \varepsilon_{i,t+h}\end{aligned}$$

where $\hat{y}_{i,t}$ is GDP per capita growth in country i at time t.

The impulse responses of GDP per capita growth and GDP per capita level to a pandemic are presented in **Figure** *8*.

Figure 8. GDP per capita growth as a dependent variable: the response of GDP per capita growth to a pandemic (left panel) and the cumulated response of GDP per capita level (right panel)



Response to a pandemic resulting in the death of 1% of the population in a given year. Shaded area is a 90% confidence band around response estimates.

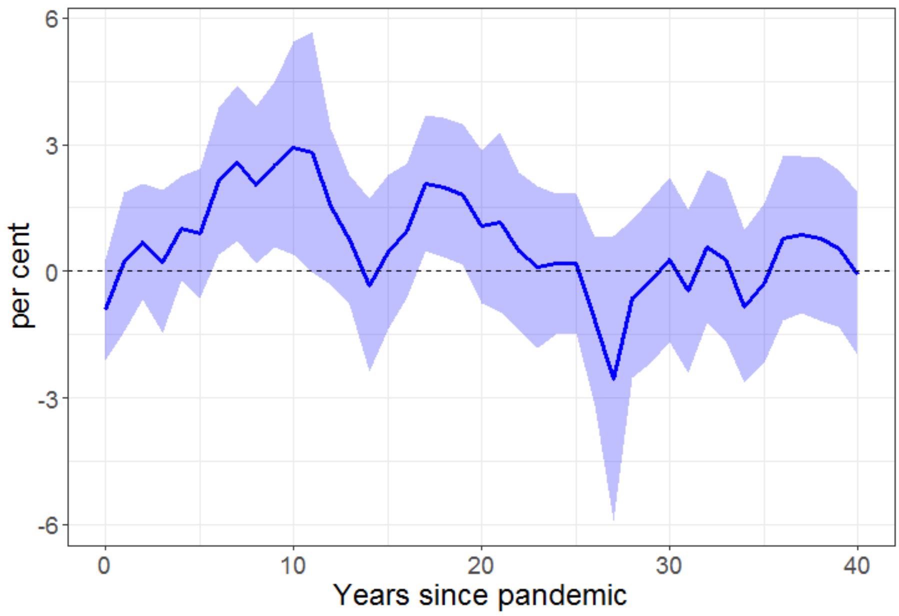
The response of GDP per capita growth is volatile and difficult to interpret, but mostly positive in the first 18 years. The cumulated response is similar to the baseline estimate, but points to a larger positive effect of pandemics in the longer run. Nevertheless, the conclusions remain the same. Thus, the results are robust to differencing GDP per capita.

5.3 Binary pandemic variable

Like in Jorda et al. (2020), a binary variable can be used as the main variable of interest. In this way, one limits problems associated with the measurement error of an explanatory variable. It is also possible to cover pandemics for which death toll estimates are not available. The binary variable equals 1 only in the first year of an epidemic in a given country (in the pandemic size variable the death toll is spread evenly over the years of the pandemic).

The impulse response obtained from the binary pandemic variable specification is presented in **Figure 9**.

Figure 9. Response of GDP per capita to a pandemic event (binary pandemic variable specification)



Shaded area is a 90% confidence band around response estimates.

The main qualitative conclusion remains the same – pandemics have a positive impact on GDP per capita. However, the effect peaks after 10 years instead of almost 20 and disappears after about 20 years, with no statistically significant impact in the longer run. Quantitatively, the effect is larger than in the baseline specification – GDP per capita is higher by as much as 3% 10 years after the pandemic[8].

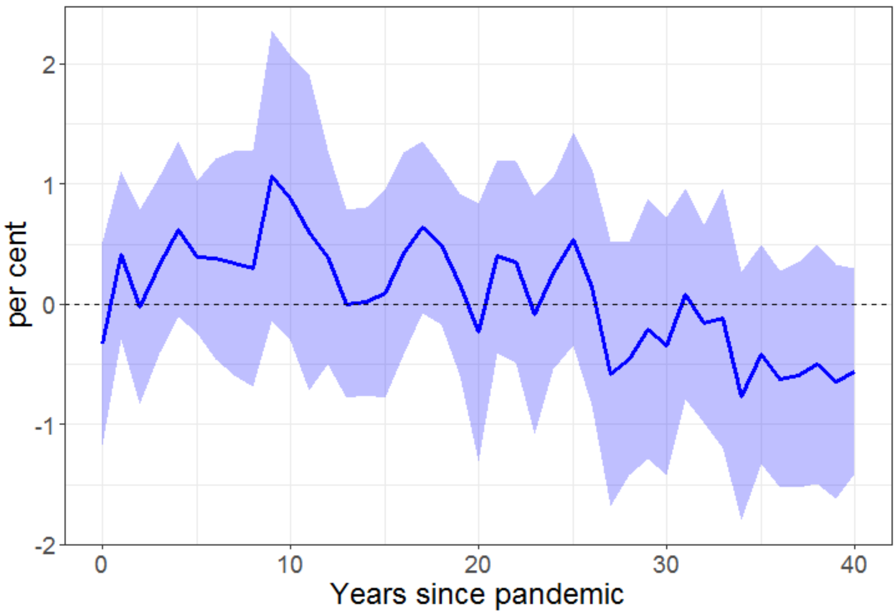
[8] The numbers from the baseline and the binary variable specifications are not directly comparable, but taking into account that an average pandemic killed about 1.2% of population per year, and there are almost twice as few (169 to 308) pandemic events as observations with positive pandemic size (since only the first year of the pandemic is denoted in the binary variable case), it is clear that the binary variable specification points to significantly larger effects of pandemics than the baseline specification.

Relative to the baseline, the binary variable specification attributes higher weight to smaller events. It is not therefore surprising that the impulse response function is similar to those obtained from the non-linear specification for small pandemics (Figure 6, left panel). It also makes sense that no significant longer-run effect is found, as small events are unlikely to generate structural shifts.

5.4 Excluding large pandemics

Figure *1* clearly shows that while most of the pandemics are relatively small, killing at most a few per cent of the population, there have been several extremely large events such as the Black Death and the pandemics in the New World that dominate the sample and might heavily influence the results. Thus, these large events are eliminated from the sample to investigate whether the effects of pandemics differ across large and relatively small events[9]. The impulse response function without large pandemics is presented in **Figure *10***.

Figure 10. Specification without large pandemics: response of GDP per capita to a pandemic resulting in the death of 1% of the population in a given year



Shaded areas is a 90% confidence band around response estimates.

Qualitatively the results are similar to the baseline – in the first 20 years pandemics tend to have a positive impact on GDP per capita, though the response is not statistically significant at a 10% level. Peak effect comes much earlier (after 9 years), though, and clearly there is no positive impact in the longer run. The latter result is quite intuitive – only large events are

[9] In particular, observations before 1500 are eliminated for European countries that experienced the Black Death and the recurring plague epidemics (Austria, Belgium, Switzerland, Germany, Denmark, Spain, France, the UK, Greece, Italy, Norway, the Netherlands, Poland, Portugal, Russia, and Sweden), observations before 1600 for countries that were colonised first (Cuba, Mexico, and Peru) and observations before 1650 for Chile and the US that were colonised later.

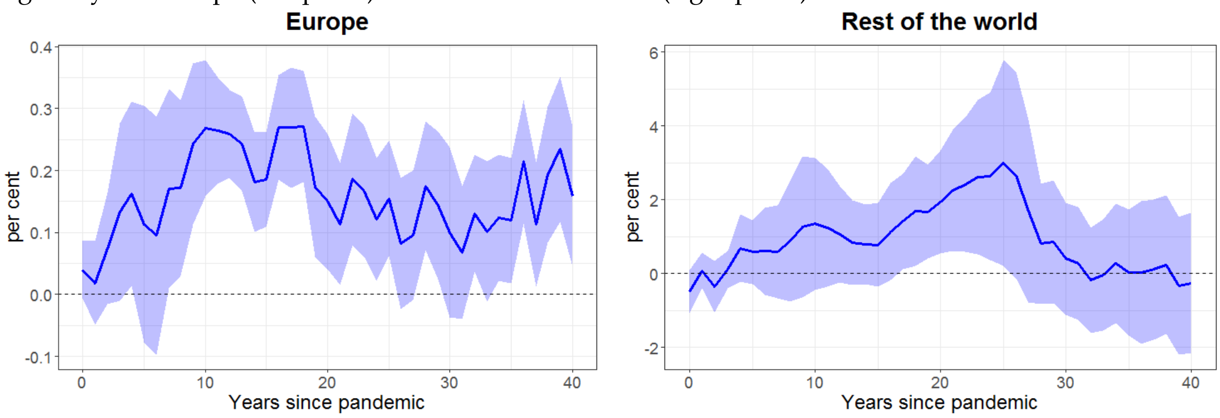
capable of generating structural shifts in the longer run. Quantitatively the effect is larger (1% at peak vs 0.3% in the baseline).

5.5 Europe vs rest of the world

Do the effects of pandemics differ geographically? In particular, is there any difference between the Old and New Worlds? Acemoglu et al. (2001) claim that in the New World, diseases discouraged settlement and led to the creation of highly persistent, extractive institutions that limited future economic growth. Hence, the New World pandemics could as well have had negative impact on GDP per capita.

To test this hypothesis, the sample is divided between Europe (including Central and Eastern Europe; 18 countries) and the rest of the world (15 countries; all of them but Japan used to be colonies). The impulse responses to pandemics in these subsamples are shown in Figure 11.

Figure 11. Response of GDP per capita to a pandemic resulting in the death of 1% of the population in a given year: Europe (left panel) vs the rest of the world (right panel)



Shaded area are 90% confidence bands around response estimates.

The impulse response for Europe is virtually identical to the baseline, which is not very surprising given that almost 80% of the observations come from the Old Continent. In the rest of the world, the IRF is qualitatively similar – pandemics have a persistent, positive impact on GDP per capita. Thus, there is no evidence of the negative feedback loop between diseases and institutions as claimed by Acemoglu et al. (2001). The peak effect comes somewhat later (after 25 years) and is significantly larger (about 3%), though, and pandemics seem to have no impact in the longer run as the impulse response drops to virtually zero after 30 years.

6. Conclusions, discussion and caveats

The paper finds that pandemics have a positive impact on GDP per capita. The peak effect appears after 10 to 20 years, but positive impact persists for a few years more. In the short run (the first few years) there is no statistically significant effect, however. These findings are robust to various specifications and subsamples.

In the baseline specification, the impulse response remains significant even after 40 years, thus pandemics have a positive impact on GDP per capita in the long run. However, this result disappears outside of Europe and when the binary pandemic variable is used, the control variables are dropped, or the largest pandemics are excluded. Judging from that, it seems to be the case that only large pandemics have a long-run effect on per capita income. This seems reasonable, but is not confirmed by the specification that explicitly accounts for non-linearities.

Quantitatively, in the baseline specification the effects are rather limited – at peak, GDP per capita increases by less than 0.3% following a pandemic that kills 1% of the population. However, quantitative results are not very robust - they tend to increase manifold when the binary pandemic variable is used and large pandemics are excluded, outside of Europe, or in the non-linear specifications.

The effects of pandemics differ from those of war and weather, the latter being proxied with tree rings. Both wars and higher tree ring growth depress GDP per capita in the first 10-15 years, with no long-run effects. Having said that, the negative effect of higher tree ring growth and its persistence 10-15 years afterwards is somewhat puzzling.

Economically, it seems that in the short run the positive impact of pandemics on land and capital per worker is offset by disruptions to economic activity and perhaps a rise in risk aversion. In the medium term, negative effects dissipate and the positive effects in the spirit of Malthus (higher per capita income following population decline) and the neoclassical growth model (higher land and capital per worker) begin to dominate. As population rebuilds itself through demographic compensation, these effects should ultimately dissipate as well. However, in some specifications, including baseline, positive impact of pandemics persists even after 40 years, particularly after large events. This suggests that large pandemics can lead to structural changes - in particular, they could make institutions more conducive to growth. The Black Death as one of the main drivers of enclosure in England is one such example.

Are the results of this paper in any way relevant in the context of the COVID-19 pandemic? COVID-19 significantly differs from the pandemics studied in this paper as its effects stem mostly from restrictions imposed on social and economic activity, while in the past the impacts were related mostly to population losses. Having said that, quarantines were used on a locally significant scale already during e.g. the Great Northern War of early 18th century, and have been growing increasingly important with advances in medical knowledge. Moreover, the specification non-linear with respect to time does not indicate that medium- and longer-run positive effects of pandemics decrease over time – the opposite is true, in fact – while the short-run effect is found to be negative, as expected.

Thus, while the studies focusing on post-WW2 pandemics (such as Ma et al. 2020) are clearly more relevant when one aims to study particularly the short-run effects of COVID-19, this paper could be regarded as an optimistic indication that unlike e.g. financial crises, the pandemic is unlikely to have negative effects in the longer run. Quite the contrary, these effects could be positive if COVID-19 speeds up innovation and structural shifts related to e.g. remote work, automation, or e-commerce.

There are numerous caveats to these results, however. First and foremost, there are many issues with the data. The pandemic death tolls are often no more than rough estimates, frequently limited to certain cities or regions. Even though the Black Death has been extensively studied and there is some relatively precise local data from parishes, estimates for the whole countries remain quite tentative. This is even more the case for the recurring plague epidemics or the first New World pandemics, while historical accounts tend to exaggerate death tolls. In the 17th-18th centuries the data and accounts are already more precise, but they are often confined to big cities. Thus, death toll estimates from this period are likely to be substantially biased downwards (think of e.g. the Great Plagues of Seville, London, Vienna, or Marseille).

Population estimates, to which the pandemic death tolls are related to obtain the main variable of interest, are also quite tentative prior to the 19th century. At the same time, they are quite sparse, therefore interpolation is often used to obtain a rough estimate for a given year. In the eras of wars and pandemics, these interpolations might be quite imprecise.

Other variables also suffer from data issues. In particular, GDP per capita estimates are quite tentative as well. They are constructed in the following way: at first, an estimate of GDP per capita is obtained for one or several specific years, using data on population size, its structure, urbanisation and incomes by social groups from one region. Later, these estimates are projected backwards and forwards using data on real wages from a major city and estimates of urbanisation, assuming that certain relations remain constant, to obtain a continuous GDP per capita series (see e.g. Malinowski and van Zanden 2017 for more details).

Thus, while GDP per capita estimates are relatively reliable for benchmark years (though still very imprecise compared to modern national accounts data), the in-between continuous estimates are very tentative. They are based on population interpolations, and hence do not account for large shifts in population due to pandemics and wars. Since in practice these are estimates for specific regions or even cities, they are influenced by local factors and might substantially diverge from the real values for the country as a whole, especially in the short run. Thus, GDP per capita estimates are most reliable in the longer run, while short run deviations should be interpreted with great caution.

Another problem with GDP per capita estimates is the constant price assumption. As relative prices change over time, which they are bound to do over such a long time frame, relative levels of GDP per capita become biased, and this bias might be substantial (see Bolt and van Zanden 2020 for a discussion). However, this bias concerns per capita income comparisons across countries at a given point in time, while in this paper the focus is on GDP growth over time. Actually, differences in GDP per capita levels across countries are not even taken into account in the fixed effects estimation utilised in this paper. Therefore, the constant PPP bias is not a major issue here, though it might have some effect on impulse responses in the longer run, when changes in price structure are likely to become more significant.

The data on tree rings is plagued with similar issues as the GDP per capita data. These are estimates for a particular place, sometimes – when no better location is available – from not a very central region, not necessarily representative for a country as a whole. Moreover, observations are derived from various tree species, and thus are not entirely comparable between each other. The quality of the data is not constant over time, as early observations tend to be derived from fewer trees, leading to higher variation in tree ring growth. Finally, tree ring growth is not a perfect proxy for agricultural conditions, as weather conditions that are conducive to tree growth are not necessarily conducive also to crop growth.

Econometrically, all these data issues are likely to cause a measurement error in both the dependent and independent variables. As a result, parameter (IRF) estimates are likely to be biased towards zero and standard errors are likely to be inflated. Both issues make it more difficult to obtain statistically significant results. However, if the measurement error is not random – and for reasons presented above one might believe that in some cases it is not – then the results might as well be biased in another direction. Therefore, quantitative results should be treated with great caution.

Moving on from data issues, another important question is the stability of model parameters, particularly over time, which is related to the question whether the results of this study are relevant for the current policy debates. That the stability assumption is true seems highly doubtful, given the time span of the study, which includes evolving economic structures, improving knowledge about epidemic diseases and changing responses to them. While the stability assumption is eased in the non-linear specification, the results of this model specification are quite counterintuitive and difficult to interpret, potentially due to data issues. Hence, while there is some evidence that the main conclusions of this paper remain true even today, this result should be taken with more than a pinch of salt.

Omitted variables are another potential issue. The economic consequences of a pandemic might depend not only on its death toll, but also – as we have seen recently – on containment measures, whether it is a more local or nationwide event, infectiousness of the disease and its death rate, duration of the pandemic etc. There are also other variables that might be correlated with the likelihood of a pandemic outbreak and GDP per capita, e.g. hygiene practices, which are likely to have varied not only over time, but also across time, affecting pandemic outbreak and spread. Another such variable is trade linkages, which could have been conducive to pandemic spread, while boosting per capita income.

Going forward, more work is to be done on the data front, including the coverage of additional countries and a further selection of sources to make the data more comparable across time and countries. This relates not only to the pandemic variable, but also controls. It would also be desirable to scale the war variable in a similar fashion as the pandemic variable, either by casualties or the number of engaged troops. On the top of that, accounting for various other characteristics of pandemics other than the death toll, such as regional distribution and time scope, infectiousness, death rates, and containment measures, would definitely help to obtain more accurate and nuanced estimates of the economic consequences of pandemics.

At the same time, further investigation into non-linear effects of pandemics, both with respect to their size and time, and differences across countries in those effects, seems necessary to better understand the results obtained in this paper.

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Appendix

A. Pandemic data

Data on the incidence and the death toll of pandemics has been compiled from a large variety of sources, including – but not limited to – internet sources. When a range of or several death toll estimates are provided, the midpoint of the range/an average is calculated. When no death toll estimate is available, but a given epidemic is assessed to be significant, it is not included in the baseline pandemic variable, but it is covered by the binary variable measure. Death estimates are divided by population estimates from the Maddison Project Database (interpolated when necessary). Only pandemics estimated to have killed at least 0.1% of the population are included in the sample. Endemic diseases are included only in the years of notable spikes in deaths. When pandemics are reported to have lasted for several years, the death toll is spread evenly over time, unless data suggests otherwise.

Table A. 1 lists data sources by the types of pandemics.

Table A. 1. Data sources used in the construction of the pandemic variables

Pandemic/disease	Data sources
The Black Death and the recurring plague epidemics (Second plague pandemic)	"Black Death", "Black Death migration", "Bubonic plague", "List of epidemics", "Pandemic" and "Second plague pandemic" Wikipedia articles; Gould and Pyle (1896), Payne (1911), Biraben (1976), Horrox (1994), Austin Alchon (2003), Benedictow (2004), Bray (2004), Hays (2005), Deleo and Hinnebusch (2005), Hays (2009), Cohn (2010), Gottfried (2010), Hatcher (2010), Welford and Bossak (2010), Byrne (2012), Aberth (2013), Ziegler (2013), Cesana et al. (2017), Karlsson (2020). **Austria**: "Great Plague of Vienna" Wikipedia article. **France**: "Great Plague of Marseille" Wikipedia article, Jones (1996), Parker (2001), Duchene and Contrucci (2004). **Germany**: Eckert (1978). **Italy**: "1629-1631 Italian plague" and "Naples Plague" Wikipedia articles, Wyman (1897), Beloch (1937), Morrison et al. (1985), Scasciamacchia et al. (2012), Tognotti (2013), White (2014). **Romania**: "Caragea's plague" and "Great Plague of 1738" Wikipedia articles, Ionescu (1974). **Russia**: Collins (1671), Melikishvili (2006). **Spain**: "Great Plague of Seville" Wikipedia article, Payne (1973). **Sweden**: "Black Death in Sweden" Wikipedia article, Alexander (2002), Myrdal (2003), Griffiths (2009). **UK**: "1563 London plague", "1592-1593 London plague", "Black Death in England" and "The Great Plague of London" Wikipedia articles; Nichols (1823), Creighton (1891), Russell (1948), Appleby (1980), Goldberg (1996), Moote and Moote (2004), Porter (2009), Newman (2012), Lewis (2016).
Great Northern War plague outbreak (a part of the second plague pandemic)	"Great Northern War plague outbreak" Wikipedia article, Lorinser (1837), Sticker (1908), Helleiner (1967), Bohn (1989), bei der Wieden (1999), Kossert (2005), Kroll and Kruger (2006), Vuorinen (2007), Burchardt et al. (2009), Frandsen (2010), Gose (2009).
Sweating sickness	"Sweating sickness" Wikipedia article.

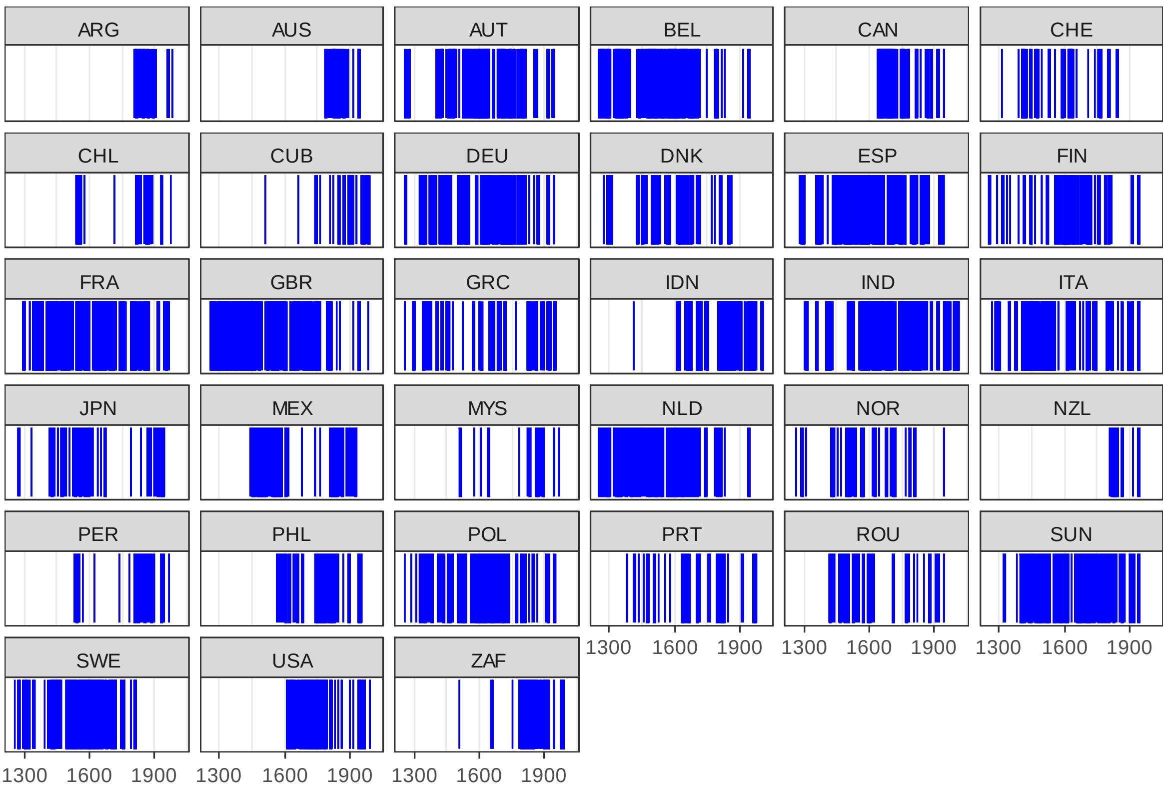
Typhus	"List of epidemics" and "Pandemic" Wikipedia article, Patterson (1993), Conlon (2014). **Canada**: "1847 North American typhus epidemic" Wikipedia article, Gallagher (1936). **Poland**: Szukała (2020).
Early flu pandemics	"1510 influenza pandemic" and "1557 influenza pandemic" Wikipedia articles, Bergeron (1872), Morens et al. (2010).
New World pandemics	"List of epidemics" and "Pandemic" Wikipedia articles. **Australia**: Cumpston (1914). **Canada**: "1837 Great Plains smallpox epidemic" Wikipedia article, Desjardins (1996). **Mexico**: "Cocoliztli epidemics" Wikipedia article, Acuna-Soto et al. (2000), Acuna-Soto et al. (2002). **Peru**: Cook (2004), Kiracofe and Marr (2009). **US**: "1721 Boston smallpox outbreak", "1775-1782 North American smallpox epidemic", "1793 Philadelphia yellow fever epidemic", "1837 Great Plains smallpox epidemic" and "Massachusetts smallpox epidemic" Wikipedia articles; Carey (1793), Thatcher (1828), Kelly and Burrage (1920), Krebsbach (1996), Houston and Houston (2000), Marr and Cathey (2010), Daschuk (2013), Purvis (2014).
Yellow fever	"List of epidemics" and "Yellow fever in Buenos Aires" Wikipedia articles, Chisholm (1911).
Cholera	"Cholera outbreaks and pandemics", "List of epidemics" and "Pandemic" Wikipedia articles; Hays (2005), Byrne (2008), Rosenberg (2009). **First pandemic**: "1817-1824 cholera pandemic" Wikipedia article, Moreau de Jonnes (1831), McGrew (1960), Arnold (1993). **Second pandemic**: "1826-1837 cholera pandemic" Wikipedia article, Raymond Durand (1980), Beardslee (2000). **Third pandemic**: "1846-1860 cholera pandemic", "1853 Copenhagen cholera outbreak**"** and "Nashville, Tennessee cholera epidemic (1849–1850)" Wikipedia articles; Bowling (1866), Unruh (1993), Sugihara et al. (1996), Hosking (2001), Kohn (2008). **Fourth pandemic**: "1863-1875 cholera pandemic" Wikipedia article, Barua and Greenough (1992), Smallman-Raynor and Cliff (2004). **Fifth pandemic**: "1881-1896 cholera pandemic" Wikipedia article. **Sixth pandemic**: "1899-1923 cholera pandemic" Wikipedia article. **Seventh pandemic**: "1961–1975 cholera pandemic**"** Wikipedia article, Kotar and Gessler (2014).
Malaria	"Groningen epidemic" Wikipedia article.
Third plague pandemic	"Bombay plague epidemic" and "Third plague pandemic" Wikipedia articles, Low (1899), Low (1902), Eager (1908).
Russian flu	"1889-1890 pandemic" Wikipedia article, Parsons (1891), Mouritz (1921), Ryan (2008), Charles River Editors (2020).
Polio	"List of epidemics" Wikipedia article, Ochman and Roser (2017).
Spanish flu	"Spanish flu" Wikipedia article, US Census Bureau (1920), Warren (1921), Jordan (1927), Aman (1990), Patterson and Pyle (1991), Mayor (2000), Johnson and Mueller (2002), Barry (2004), Knobler et al. (2005), Ansart et al. (2009), Carbonetti (2010), Erkoreka (2010), Killingray and Phillips (2011), Chandra et al. (2012), Radusin (2012), Chowell et al. (2014), Yang et al. (2014), Grabowski et al. (2017), Spinney (2018), Spreeuwenberg et al. (2018), Arnold (2019), Mata (2020).
Asian flu	"1957–1958 influenza pandemic" Wikipedia article, Clark (2008), Jackson (2009),

	Viboud et al. (2016), Nickol and Kindrachuk (2019), Kutzner (2020).
Hong Kong flu	"Hong Kong flu" Wikipedia article.
Smallpox in India	"1974 smallpox epidemic in India" Wikipedia article.

B. War data

Data on the incidence of wars has been gathered mostly from the very rich internet sources – Wikipedia lists of wars ("List of wars: 1000-1499", "List of wars: 1500-1799", "List of wars: 1800-1899", "List of wars: 1900-1944", "List of wars: 1945-1989", "List of wars: 1990-2002", "List of wars: 2003-present"), country-specific Wikipedia lists of wars ("List of wars involving Argentina", "List of wars involving Australia", "List of wars involving Austria", "List of wars involving Belgium", "List of wars involving Canada", "List of wars involving Switzerland", "List of wars involving Chile", "List of wars involving Cuba", "List of wars involving Germany", "List of wars involving Netherlands", "List of wars involving France"), all the Wikipedia articles linked there, and references therein. The second major source is the Conflict Catalog (Brecke 1999).

Figure A. 1 Data on the incidence of wars



Source: Own compilation based on various sources.

Included are conflicts that are judged to have caused major destruction of physical capital and/or disruption of social and economic activity, or have required a substantial military effort from a given country, i.e. a substantial part of its military force was used and actively engaged in warfare (rather than only deployed to an area of conflict). For countries that did not exist as independent entities at the time of conflicts, they are reported to have taken part in a war if warfare had taken place on their territory or the population of the country had taken part in the conflict (by being drafted into the military in significant numbers).

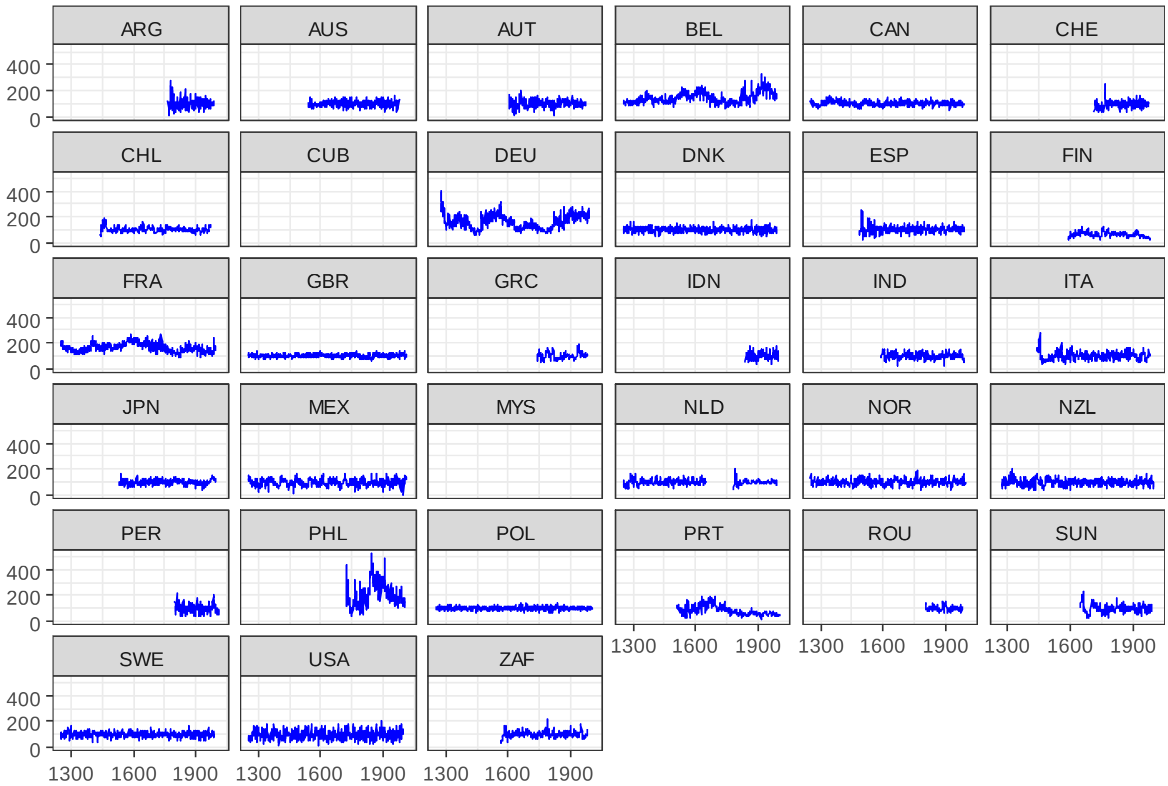
Figure A. 1 presents the data on the incidence of wars.

C. Tree ring data

Tree ring data is gathered from the NOAA Paleoclimatology database and expressed in terms of the standardised growth index, computed according to the standard chronology method. When several locations are available for a given country, one of them is picked, taking into account time coverage and proximity in distance and altitude to most densely populated areas. When data is not available for a given country, a proximate location from a neighbouring country is chosen. For Cuba and Malaysia this is not possible, though, and thus the tree ring data covers only 31 countries.

Tree ring data details are shown in Table A. 2 and the data itself is presented in Figure A. 2.

Figure A. 2 Tree ring growth data



Source: Own compilation based on the sources from the NOAA Paleoclimatology database (for details see Table A.2).

Table A. 2 Tree ring data details

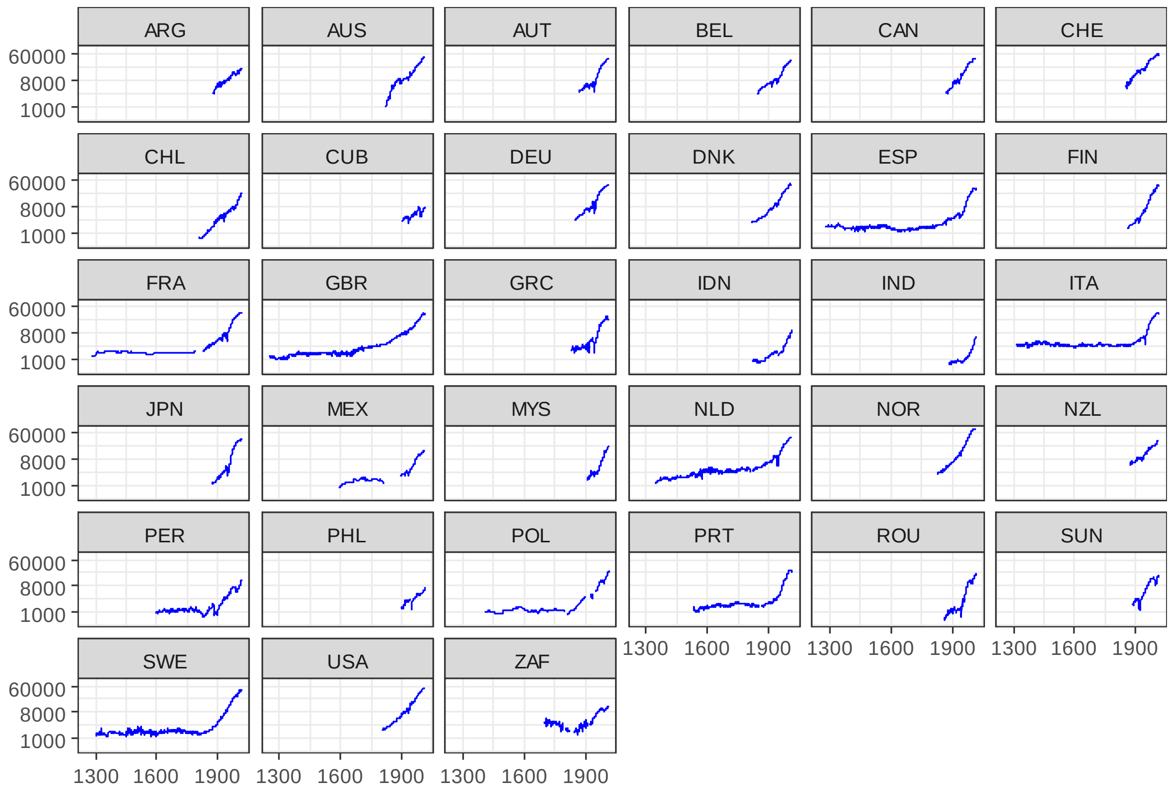
Country	Author/study	Location	Altitude	Tree type	Time coverage
Argentina	Villalba	El Arrasayal	880 m	JGAU	1766-1985
Australia	Lamarche	Bruny Island	380 m	PHAS	1542-1975
Austria	Giertz	Obergurgl	2000 m	LADE	1604-1972
Belgium	Hoffsummer	Meuse Valley	0 m	QUSP	1252-1989
Canada	Archambault and Bergeron	Lac Duparquet	274 m	THOC	1252-1987
Switzerland	Schweingruber	Krauchtal BE	550 m	PISY	1714-1976
Chile	Holmes	Caramavida	900 m	ARAR	1440-1972
Germany	Billamboz	Bodensee	450 m	QUSP	1275-1986
Denmark	Schweingruber	Gotland, Sweden	50 m	PISY	1252-1987
Spain	Genova Fuster, Fernandez-Cancio and Perez Antelo	Torreton	1500 m	PINI	1485-1988
Finland	Eronen	Lieksa Koivujoki	150 m	PISY	1588-1983
France	Lambert, Lavier and Trenard	Bourgogne 29 Master	0 m	QUSP	1252-1991
United Kingdom	Wilson et al. (2013)	Southern-Central England	45-185 m	QUSP	1252-2009
Greece	Kuniholm	Chalkidiki Arnaia Barbara	600 m	QUFR	1740-1979
Indonesia	D'Arrigo, Krusic, Jacoby and Buckley	Bigin, Java	75 m	TEGR	1839-1995
India	Borgaonkar, Pant, and Rupa Kumar	Narkhanda	3000 m	ABPI	1590-1989
Italy	Schweingruber	Sierra de Crispo	2000 m	PILE	1441-1980
Japan	Davi, D'Arrigo, Jacoby, Buckley and Kobayashi	Mount Asahidake, Hokkaido	1350 m	PCGN	1532-1997
Mexico	Stahle et al. (2011)	Barranca de Amealco	1970 m	Montezuma baldcypress	1252-2008
Netherlands	Jansma and van Rijn (1252-1457), Jansma (1458-1650), Maessen (1783-1990)	Maastricht St. Jan's Church (1252-1457), Oegstgeest (1458-1650), whole Netherlands (1783-1990)	0-20 m	QUSP (1252-1650), PISY (1783-1990)	1252-1650, 1783-1990
Norway	Kirchhefer	Forfjorddalen 2	110 m	PISY	1252-1994
New Zealand	Ahmed, Boswijk and Ogden	Manaia Sanctuary	350 m	AGAU	1269-1998
Peru	Lopez et al. (2017)	Purubi, Bolivia	446 m	CEMC	1798-2010
Philippines	Cook et al. (2010)	Bakun	-	PIKE	1721-2005
Poland	Wazny	East Pomerania	20 m	QURO	1252-1985
Portugal	Shestakova et al. (2019)	Pinar de Lillo, Spain	1600 m	PISY	1511-2002
Romania	Schweingruber	Novaci	1650 m	PCAB	1804-1981
Russia	Schweingruber	Nyuchpas	160 m	LASI	1649-1991

Sweden	Schweingruber	Gotland	50 m	PISY	1252-1987
United States	Stahle et al. (2013)	Average of Blackwater River and Devil's Gut	-	Baldcypress	1252-1993
South Africa	Lamarche and Dunwiddie	Die Boss	1330 m	WICE	1564-1976

D. GDP data

GDP per capita data comes primarily from the 2018 version of the Maddison Project Database (Bolt et al. 2018)[10]. As I am interested in GDP growth over time, rather than the comparison of relative GDP per capita levels across countries, the 2011 PPP benchmark series (rgdpnapc) is used. Data for the Netherlands and the UK is projected backwards with estimates for Holland and England, respectively, assuming a constant relation of income levels between these regions and whole countries. Data for Italy is extended with estimates for North and Central Italy from Malanima (2011) in the same fashion. For Spain, recent estimates by Prados de la Escosura et al. (2020) are used.

Figure A. 3 GDP per capita data (log scale)



Source: Maddison Project Database (2018 edition), Malanima (2011), Prados de la Escosura et al. (2020).

[10] The 2020 edition of the database has been published recently, but it does not include important new time series. The main modification is the change back to the 1990 PPP benchmark, which does not have any effect on pre-1950 growth estimates and thus should not substantially influence the results of this paper.

GDP per capita data is presented in Figure A. 3.

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