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ORIGINAL PAPER

Influenza pandemics and macroeconomic fluctuations 1871–2016

Fraser Summerfield[1] · Livio Di Matteo[2]

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Abstract
This paper documents the short-run macroeconomic impacts of influenza pandemics across 16 countries spanning 1871–2016 using the Jordà–Schularick–Taylor Macrohistory Database and the Human Mortality Database. We find pandemic-induced mortality contributed meaningfully to business cycle fluctuations in the post 1870 era. We identify negative causal impacts on the cyclical component of GDP using pandemics to instrument for working-age mortality. The analysis of short-run economic outcomes extends literature dominated by long-run economic growth outcomes and case studies of several specific health shocks such as the Black Death, Spanish Flu or COVID-19. Our findings illustrate that less catastrophic pandemics still have important economic implications.

Keywords Pandemics · Business cycles · Mortality · GDP fluctuations · Health shocks

JEL Classification I18 · E32 · N10 · N30

1 Introduction

Economic fallout following major health shocks is well documented in historical case studies. The Black Death was paired with a considerable economic disruption and change (Jedwab et al. 2022; Alfani 2013) and the Spanish Flu caused economic disaster in many developed countries (Barro et al. 2020; Barro and Ursúa 2008).

✉ Fraser Summerfield
fsummerf@stfx.ca

Livio Di Matteo
livio.dimatteo@lakeheadu.ca

1 Department of Economics, St Francis Xavier University, Antigonish, NS B2G 2W5, Canada

2 Department of Economics, Lakehead University, 955 Oliver Road, Thunder Bay, ON P7B5E1, Canada

Pandemics are some of the most insidious health shocks as they often arrive unexpectedly with wide-reaching effects. Their economic impacts are a broad field of inquiry since pandemics can arise from many different viruses and can propagate through several economic channels including investment, employment and consumption, though the prime mover is the prospect of mortality.

The causal link between health and long-term economic outcomes has been established in the literature (Sharma 2018) and its dynamics well known (Swift 2011). Less understood are the short-run economic impacts of shocks to population health. Strauss and Thomas (1998) review a related literature on health and individual productivity and yet, the extent to which these, or other, health shocks combine to cause recessions is not well documented. This is, perhaps, surprising given the attention paid to business cycle mitigation by governments and central banks worldwide.

This paper offers insights from numerous influenza shocks occurring for the past 150 years which appear to coincide with economic slowdowns in developed economies. Examples include the Asian Flu (1957–58) and the Swine Flu that accompanied the slow recovery from the 2008 financial crisis. Specific to the USA, several economic downturns or slowdowns appear to coincide with influenza pandemics that strike every 28 years on average (Mackellar 2007: 430).[1] Major troughs in the USA business cycle occur in March of 1919, April 1958 and June 2009. As well, Italy experienced approximately 20 business cycles between 1861 and 2000 and saw major troughs in 1920 and 1958 (Delli Gatti et al. 2005: 83) and additionally was quite hard hit in the aftermath of the 2008–09 Great Recession by the 2009–2011 Sovereign Debt Crisis.[2]

To provide evidence with a causal interpretation, we constrain our study to a single channel by which these pandemics are plausibly exogenous in our context in terms of their contribution to business cycles: mortality.[3] The causal mechanism we examine is appropriate for an analysis of short-run pandemic effects which can be expected to propagate through reductions in labour supply (Bloom et al. 2022). Because the scientific community recognizes influenza as a continued threat for future pandemics (Palese 2004), learning from past influenza pandemics remains an important empirical endeavour. Our analysis of less-studied influenza shocks is also motivated by literature showing that different health shocks (i.e. different causal pathways) can have different impacts; For example, Sharma (2018) finds a strong causal effect of population health on GDP through human capital, while Acemoglu and Johnson (2007) find no meaningful effect from epidemiological improvements.

[1] Appendix Table 6 lists USA recessions that also occur frequently, on average every 5 years since the mid-nineteenth century.

[2] Modern integrated economies may be more susceptible to small disruptions. Consumer spending was less developed in the nineteenth century with an explosion of durable consumption occurring in the 1920s (Greasley et. al. 2001).

[3] We do not identify impacts that propagate through investment, for example. Short-run stock market effects of the Spanish Flu were relatively inconsequential in the USA and UK (Beach et al. 2022; Velde 2020). Bloom et al. (2022) suggest that physical and human capital impacts occur in the long run and are best captured through multisector growth models like Kuhn and Prettner (2016).

Our contribution to the literature[4] is twofold. First, we establish the causal impact of pandemics as one type of exogenous health event on the business cycle. This analysis of short-run economic fallout adds to the broader literature linking health to economic performance, including Weil (2007). Aside from case studies of pandemics, existing causal analyses focus on the long-run and obscure the short-run impacts we measure here. For example, Sharma (2018) uses 10-year averaged data while Acemoglu and Johnson (2007) study 40- and 60-year spans. Second, our analysis extends the historical record of pandemic case studies by documenting the importance of several less-studied health shocks. In focusing on influenza pandemics, our analysis complements evidence on the macroeconomic impacts from the Spanish Flu (Barro et al. 2020; Karlsson et al. 2014). Whereas large-scale health shocks (e.g. the Black Death 1347–1352) had obvious economic consequences, we show that mortality from numerous smaller, but nonetheless serious, pandemics caused GDP to decrease from trend by about 0.3% for each additional death per 1000 persons of working age, on average.

Identifying the economic impacts of historical pandemic events is challenging because data surrounding these shocks are available with limited frequency: annual, rather than quarterly or monthly. Pandemics are also likely to have heterogeneous effects across countries and by pandemic event (Alfani 2013). For example, Clay et al. (2018) find regional pollution differences to be a factor in Spanish Flu mortality. Our data combine the Jordà–Schularick–Taylor (JST) Macrohistory Database (Jordà et al. 2017) with the Human Mortality Database (2020), hereafter the HMD, to form an unbalanced panel across 16 countries spanning 1870–2016. One advantage of these historical panel data is to capture effects across several countries and several events. This exercise will identify a causal parameter that represents a weighted local average treatment effect (LATE) across pandemics. Because Abadie (2003) and others highlight the difficulty interpreting weighted LATE parameters, we supplement our main findings with details on which events weigh most heavily in our causal framework, that is, when and where influenza pandemics induce mortality the most.

Our estimates address endogeneity between economic performance and mortality—an important consideration since national wealth may also affect public health. We first demonstrate considerable drops in real log GDP per capital coincident with influenza pandemics that are evident in the raw data and then provide two-stage least squares (2SLS) estimates of pandemic-induced mortality shocks on the cyclical component of log GDP. The pandemic-induced mortality effects we measure using our instrumental variable approach are larger than the GDP–mortality relationship suggested by OLS regressions that may suffer from endogeneity. Our specifications include a wide range of controls under which case we are confident that pandemic timing is a plausibly exogenous instrument. However, we also present Conley et al. (2012) bounds for our estimates under departures from the exclusion restriction. Where data permit, we also provide ancillary evidence in favour of the causal channel we identify. Pandemic-induced mortality effects on the cyclical component of

[4] See the recent symposium on epidemic diseases in economic history in the *Journal of Economic Literature* and the collection of articles on pandemics and health shocks in the *Journal of Economic History*.

GDP can be expected to propagate through reductions in labour supply. Estimates suggest that influenza pandemics may cause meaningful decreases in the employment-to-population ratio. In addition, our results are robust to several important considerations, alternative measures of the cyclical component of GDP, alternative mortality measures and a variety of covariates.

2 Literature review

A substantial literature details the contribution of health status and pandemics to historical economic events. Our focus on historical short-run effects situates the current analysis in a relatively sparser literature. Alfani and Murphy (2017), Alfani and Percoco (2019) and Jedwab et al. (2022) note that major pre-industrial events including the Black Death caused asymmetric economic shocks across Europe because of differences in population density and economic development. Important immediate effects are also evident from the COVID-19 pandemic (Baker et al. 2020). Our empirical approach is most like Barro et al. (2020), where Spanish Flu mortality is shown to have decreased short-run real GDP per capita by 3%. In a review of empirical approaches, Bloom et al. (2022) argue that these growth-type regressions may be a suitable strategy when panel data are available. Barro and Ursúa (2008) use similar data to study economic crises. Their results suggest that the Spanish Flu was the fourth-worst contraction in recent history after the two World Wars and the Great Depression.

The Spanish Flu receives particular attention in the literature. Karlsson et al. (2014), for example, find little discernible effect on earnings but increased poorhouse rates and a reduced return to capital across Swedish regions. Garrett (2008, 2009) finds that mortality decreased the supply of manufacturing workers and increased the marginal product of labour, the marginal product of capital and real wages in the USA. Brainerd and Siegler (2003) argue that USA states with higher influenza mortality during the Spanish Flu era subsequently experienced higher per capita income growth rates. Beach et al. (2022) revisit the Spanish Flu's impact to provide lessons for COVID-19, noting deeper recessions in countries with higher 1918 influenza mortality. Aassve et al. (2021) using respondent attitudes to a general social survey also find that experiencing the Spanish Flu likely had permanent impacts on the level of social trust that was passed on to the descendants of Flu survivors which can also impact economic development.

Our focus on short-run or business cycle effects differs from the larger literature on long-run impacts of health shocks (e.g. Acemoglu and Johnson 2007; Barro 2013; Bloom et al. 2004). Pamuk (2007) argues that the great divergence in economic growth among western economies may be rooted in the effects of the Black Death. Arora (2001) finds that long-term health measures including stature and life expectancy appear to have permanently altered the growth paths for major industrialized countries over the course of 125 years. Jordà et al. (2020a, b) link pandemics and the natural rate of interest since the fourteenth century, finding that interest rates fall by about 1.5 per cent—lasting 20 years because pandemics reduce labour relative to capital.

Pandemic effects on the macroeconomy manifest through several channels. Following the insights from Bloom et al. (2022), our approach will examine one such channel that is associated with short-run impacts: mortality. Grimm (2010) notes that mortality shocks induce expenses and income loss but also reduce the number of household consumption units. Given that influenza pandemics effects differ across age cohorts, this latter point would particularly apply to the Spanish Flu which had high mortality among prime working-age adults. The 2009 pandemic had short-run hospitalization costs exceeding 20 million GBP in the UK (Lau et al. 2019) and decreased labour supply considerably in Chile (Duarte et al. 2017).

Our analysis also relates to the wider literature relating health to economic growth that is often summarized by the Preston curve (Preston 1975) which noted a long-term relationship between life expectancy and per capita income over time with recent research noting more than proportional increases in life expectancy at higher per capita income levels (de la Escosura 2023). Fogel (1994) noted the positive long-run relationship between nutrition improvements, human health capital and economic growth. Indeed, this literature is not settled with regard to causality. For example, Ye and Zhang (2018) examine 15 OECD countries and 5 developing countries from 1971 to 2015 and find a range of results from no causality to a unidirectional relationship in either direction to bi-directional causality using Granger tests. Bloom et al. (2019) also consider bi-directional causality between health status and per capita GDP as well as the presence of confounding factors noted by Deaton (2013) including education, technological progress and institutional quality. Further nuances include whether specific diseases are communicable (e.g. influenza pandemics) or non-communicable (e.g. cardiovascular, diabetes) and whether longer-term effects on health will arise through life expectancy or infant mortality (Bloom et al. 2019; Suhrcke and Urban 2010).

Finally, our findings contribute to understanding the historical influence of pandemic health shocks in the broader literature on the causes of business cycles. This literature is primarily structural models that parameterize the economy. The current analysis can be seen as preliminary causal evidence to assist with the inclusion of health shocks, specifically recurring influenza pandemics. Known factors affecting the business cycle are many, including interest rates, financial crises and oil prices, all of which may propagate differently through consumption, investment and other components of GDP. Some reviews of this literature are available in Stock and Watson (1999), for the USA and Sensier et al. (2004) for Europe.

3 Pandemic events

Influenza pandemics worldwide since 1870 are presented in Table 1. These pandemics are, by definition, global events, and we model them as such in the subsequent analysis. The influenza pandemic during 1873 to 1875 was preceded by equine influenza in the USA and Canada (Judson 1873). The loss of working animals in the nineteenth century in addition to any animal to human transmission was a serious economic effect, and it

Table 1 List of major influenza events 1870–2016. *Sources*: Judson (1873); Mamelund (2008); Centre for Disease Control and Prevention (2020)

Date	Event
1873–1875	Equine Influenza and Possible Pandemic
1889–1892	Flu Pandemic (Russian Flu)
1899–1900	Possible Pandemic
1918–1920	Spanish Flu
1946	Possible Pandemic
1957–1958	Asian Flu (H2N2 virus)
1968–1970	Hong Kong Flu (H3N2 virus)
2009–2010	Swine Flu (H1N1 virus)

We exclude the 1977–1978 H1N1 flu event, because there is uncertainty as to whether this event was indeed a pandemic (Mamelund 2008). The CDC in the USA does note the outbreak and a vaccination programme was implemented that prevented a pandemic

should be noted the contraction of the 1870s was particularly severe in some countries.[5] The 1889–1892 Russian Flu pandemic had an estimated global death toll of 1 million people, and its spread was facilitated by the rapid population growth and urbanization of the nineteenth century. However, recent evidence asks the question whether this event may have been a coronavirus rather than influenza (Brüssow and Brüssow 2021).[6] The 1918–1920 Spanish Flu is the most devastating pandemic event of recent history infecting nearly one-third of the world's population and killing an estimated 50 to 100 million people (Mamelund 2008, p 601). These pandemics spread globally given transportation improvements over the course of the nineteenth and early twentieth century. Thus, while the severity of these pandemics certainly differed by country, the timing of pandemic onset in annual data does not. In the post-World War II period, the spread of air travel made the rapid spread of pandemics an even greater concern and pandemic declaration by the WHO can be considered particularly definitive during this period. The 1957–1958 Asian Flu and the 1968–1970 Hong Kong Flu were major events with global death tolls estimated at 2 million and 1 million, respectively.

4 Data

4.1 Economic panel data

Our analysis employs release 5 of the JST Database, which spans 16 developed countries during 1870–2016. Countries are: Australia, Belgium, Canada, Denmark, Finland, France, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the USA.[7] These data form an unbalanced panel

[5] Until the 1930s, the period of the 1870s was seen as the start of a Great Depression. See Beales (1934) and Musson (1959).

[6] For additional references on pandemics through time and space see Kilbourne (2006), Patterson (1986) and Taubenberger and Morens (2010).

[7] JST data also include Germany; however, German mortality data were unavailable for most years.

since some covariates are not available for some countries in earlier years or during war years. Appendix Table 7 summarizes these limitations. Fortunately, our outcomes are constructed from real gross domestic product (GDP) per capita, which is continuously available for all countries from 1870 through 2016.

Our analysis examines the cyclical component of log GDP per capita, denoted $\widetilde{lGDP}$. We take the natural log of the JST variable "real GDP per capita index" (2005 = 100) and detrend the resulting variable three different ways: using the HP (Hodrick and Prescott 1997) filter,[8] the BK bandpass filter (Baxter and King 1999),[9] and linear detrending (LDT) that allows for a break mid-series in 1946. This break allows for the considerable change observed in the average GDP series around the time of the first influenza vaccine. Our preferred estimates use the HP filter, since our results are then more comparable to the broader business cycle literature. However, the HP filter has been criticized as potentially being arbitrary (Hamilton 2018).[10] Presenting HP results alongside others, particularly the BK band pass filter, demonstrates the robustness of our findings to the particulars of any one detrending procedure and builds confidence in our findings.

The $\widetilde{lGDP}$ measure is advantageous for capturing the business cycle in our data. Changes in log GDP approximate percentage change, which aids in cross-country comparisons since larger economies experience larger nominal GDP fluctuations. Furthermore, the HP and BK filters isolate precisely those high-frequency movements in the time series that we wish to examine, separately by country.[11] Both of these filters isolate the cyclical component from a potentially nonlinear trend and thus may remove more persistent periods of growth that a linear detrending procedure would not. Measured deviations in these series, then, might be expected to be smaller than measured deviations in the LDT series.

To illustrate the net effect of influenza pandemic onset on economies in our raw data, we reorganize the data into pandemic spells. We then plot average log GDP across years to pandemic onset. Because advancements in medical technology and living standards may have allowed pandemics to propagate differently over time, we break the data into two large spans. A natural break point is 1946, in the light of the importance of the 1940s "international epidemiological transition" for population growth (Omran 1971), economic growth (Acemoglu and Johnson 2007) and because of the onset of flu vaccines.[12] A precipitous drop in log GDP at pandemic onset is evident in Fig. 1. These

[8] Following Ravn and Uhlig (2002), our annual data smoothing parameter is 6.25. Appendix Fig. 8 presents the cross-country averaged time series of $\widetilde{lGDP}$.

[9] We follow Stock and Watson (1999) to set the parameters of our band pass to use 3 leads and lags for smoothing and to filter out cycles smaller than 2 years or larger than 8 years. Values for the first and last 3 years in each series are thus, unavailable. No influenza pandemic events overlap these missing years.

[10] Still others defend the HP filter (Drehmann and Yetman 2018). Our approach is robust to different detrending measures. Hamilton (2018) proposes an alternative that is preferable particularly in forecasting applications with quarterly data.

[11] Averaged HP and BK detrended series are presented in Appendix Figs. 8 and 9. Im et al. (2003) unit root tests, available upon request, confirm that both these series and our mortality series are stationary.

[12] Spell data are centred at zero for pandemic onset. We use spell data because the observations leading up to and away from some pandemic events overlap.

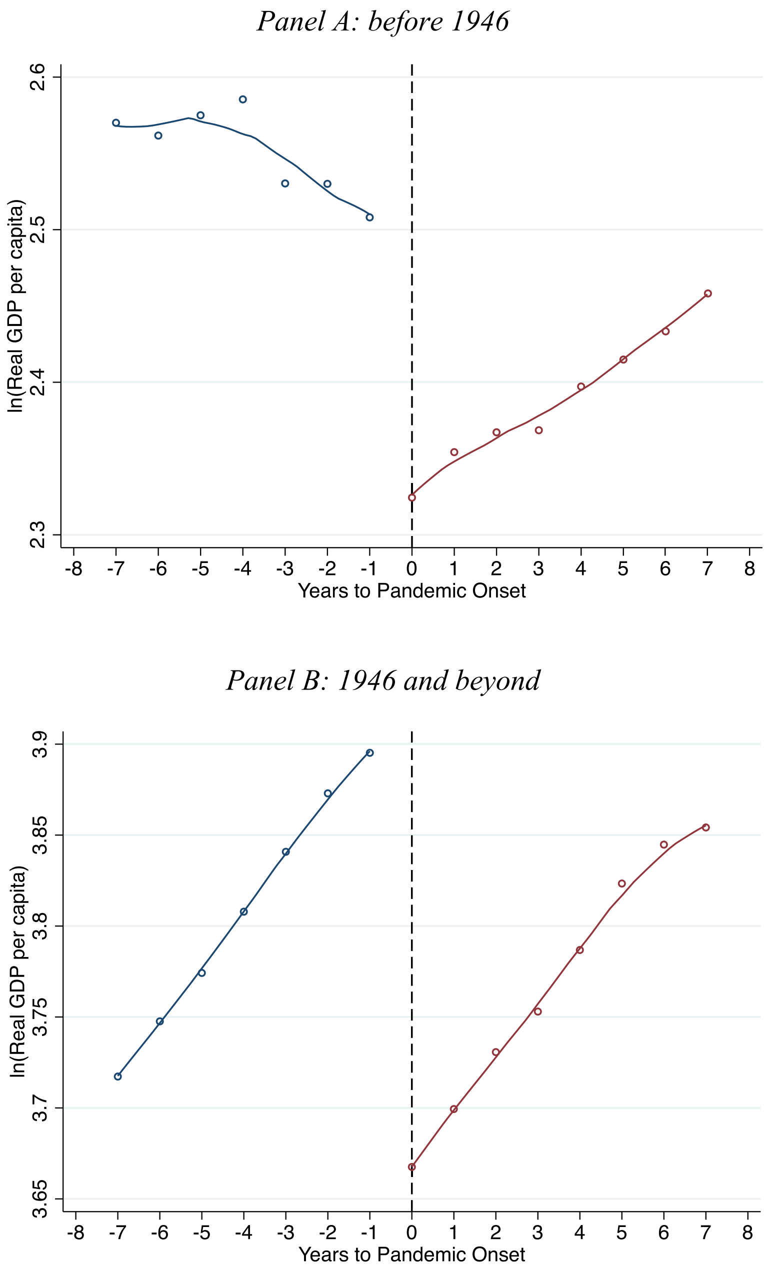


Fig. 1 Average log GDP and pandemic onset, before and after 1946. Data source: Jordà et al. (2017). Author calculations on spell level data centred with zero at pandemic onset averaged by year-to-pandemic. Local linear regression (bandwidth of 1) overlaid

data are highly suggestive of pandemic-induced downturns. The dynamics of log GDP differ somewhat in the lead-up to the pandemic, primarily because of war effects in the pre-1946 era that we will account for fully in regression models to follow.

Examining pandemic effects through mortality permits an imperfect measure of the intensity of a pandemic. Pandemics may differ following improvements in public health and medical technologies that vary across countries and have reduced infectious disease mortality during the years 1870–2016 (Cutler et al. (2006) discuss mortality determinants). Annual death rates by sex and age are available from the Human Mortality Database (HMD) for most of the time series: Sweden, France, Belgium, Denmark, the Netherlands and Norway start from 1870. Italy, Switzerland and Spain start from 1872, 1876 and 1908, respectively.

We construct two mortality measures pertinent to the question at hand. The first is an annual death rate among working-age males (D^{M}), generated for each of the 16 countries (j) using counts of age-specific (a) deaths among males (MD) and male population (MPOP):

$$D_{jt}^{\mathrm{M}} = \frac{\left(\sum_{a=16}^{65} \mathrm{MD}_{jt}(a)\right)}{\left(\sum_{a=16}^{65} \mathrm{MPOP}_{jt}(a)\right)} \tag{1}$$

D^{M} captures mortality among men ages $16-65$ providing a measure that should capture effects on the population most directly responsible for labour supply during the period of analysis.[13] Figure 2 illustrates that, in the spell-arranged data, pandemic onset coincides with a considerable jump in D^{M}. The increase is particularly evident pre-1946, when medical interventions were more limited. However, even after 1946 the increase in death rates is much larger than any other year-over-year increase observed in the data.

The focus on male mortality is more defendable earlier in the time series. Because female labour force participation has risen dramatically starting in the mid twentieth century, we also generate a working-age population mortality rate D^{P} (for both sexes combined) following an equivalent formula. A considerable jump in this variable at pandemic onset is also seen in Fig. 3. It will turn out that our results are largely immune to sex differences in mortality rates.

5 Model and identification

Conditional on disruptions to consumption and investment, pandemics can be expected to influence the economy through mortality. Indeed, mortality is identified as a key short-run mechanism in a recent review of empirical approaches (Bloom et al. 2022). This mechanism manifests in lower GDP largely through decreased labour supply, for which there is evidence where data exist (see correlation plots for

[13] Male labour supply is the most consistent variable over the entire 1870–2016 period, whereas formal female labour supply grows after 1950. Female and male mortality rates are highly correlated.

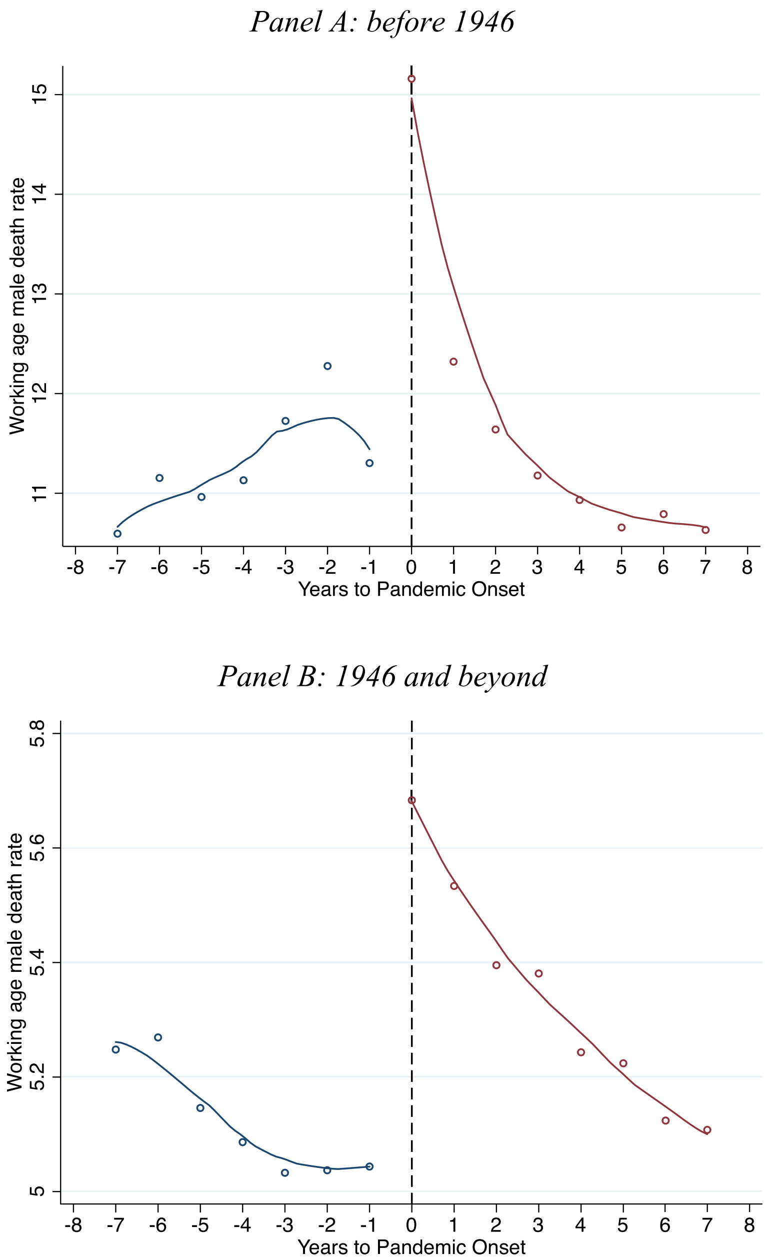


Fig. 2 Mortality among working-age males and pandemic onset. Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Author calculations on spell level data centred with zero at pandemic onset averaged by year-to-pandemic. Local linear regression (bandwidth of 1) overlaid

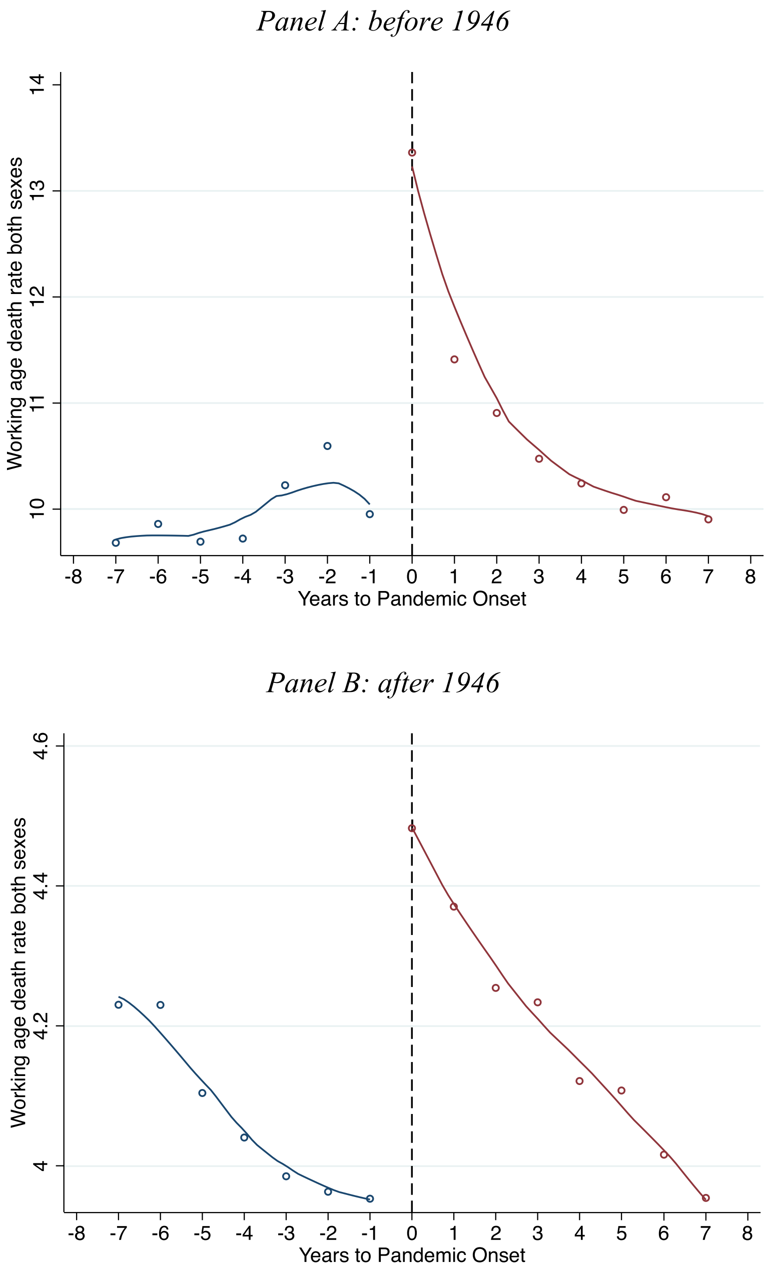


Fig. 3 Mortality among working-age population (both sexes) and pandemic onset. Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Author calculations on spell level data centred with zero at pandemic onset averaged by year-to-pandemic. Local linear regression (bandwidth of 1) overlaid

Sweden, the USA and the UK in Appendix Figure 7).[14] We cannot rule out the existence of other mechanisms behind this causal channel, however, including the possibility of behavioural changes in workplaces and the like, that might follow from mortality or accompanying morbidity.[15]

Equations (2) and (3) detail our empirical model, to be estimated by 2SLS. Mortality measures (D) are instrumented by binary pandemic timing indicators (Flu). The parameter we wish to identify is β, the pandemic-induced effect of mortality on various measures of the cyclical component of log GDP per capita, $\widetilde{lGDP}$. Wald (1940) notes that β effectively compares the correlation of $\widetilde{lGDP}$ and mortality in pandemic periods to non-pandemic periods. Our estimates will embody the magnitude of the pandemic by measuring the differential mortality rates induced by pandemics across countries.

$$D_{jt} = \psi_j + \delta \mathrm{Flu}_t + \boldsymbol{X}'_{1jt}\boldsymbol{\pi} + \boldsymbol{X}'_{2jt}\boldsymbol{\phi} + \boldsymbol{\varepsilon}_{jt} \tag{2}$$

$$\widetilde{lGDP}_{jt} = \alpha_j + \beta D_{jt} + \boldsymbol{X}'_{1jt}\boldsymbol{\eta} + \boldsymbol{X}'_{2jt}\boldsymbol{\theta} + u_{jt} \tag{3}$$

All specifications include country-specific fixed effects (α_j),[16] which may help account for unmeasured contextual factors important to pandemics (Alfani 2022). Time-varying covariates include the vector $\boldsymbol{X}_1$ comprising dummies for the two world wars, the real short-term interest rate and exchange rate adjusted wheat and oil prices.[17] We also include a dummy variable to allow for a break in the GDP series in 1946, which is circa the introduction of vaccines.[18] We further include the vector $\boldsymbol{X}_2$ in some specifications, which includes shares of GDP components from

[14] Employment to population ratios calculated from: Sweden tables "*C* mean population" and "*O* total aggregate" from Edvinsson (2004); UK tables "A.50 Total Employment in Heads with S.Ireland break retained in 1920" and "A.18 Population in the UK and Ireland, Kingdom of Great Britain" (to 1920) and the "bottom-up measure for Great Britain and Norther Ireland" from 1921 onward from Thomas and Dimsdale (2017); USA tables Ba470 "Civilian Labor Force Total" and Aa7 "Resident Population" from Carter et al. (2006).

[15] Acemoglu and Johnson (2007) note that mortality and life expectancy may broadly capture population health.

[16] Specifications without fixed effects suggest broadly similar results. We also estimated models separately by rough continental grouping, finding strongest impacts for Scandinavia, although instruments were weak for some groupings. These are available upon request.

[17] Annual wheat prices constructed from monthly USA and foreign wheat prices (in dollars per metric ton obtained from the Wheat Data Yearbook Tables, USA Department of Agriculture Economic Research Service (https://www.ers.usda.gov). Similarly constructed oil prices are sourced from the USA Energy Information Administration (https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=F000000__3&f=A).

[18] Specifically, the influenza virus was isolated in the USA in 1933. The first vaccine was developed in 1938, approved for US military use in 1945 and civilian use in 1946 (National Vaccine Information Centre 2020; College of Physicians of Philadelphia 2020). In response to substantial morbidity and mortality during the subsequent 1957–1958 pandemic, the USA Surgeon General recommended annual influenza vaccination for people with chronic debilitating disease, people aged 65 years or older and pregnant women (Centre for Disease Control and Prevention 2020).

the national accounting identity and the debt-to-GDP ratio.[19] We cluster standard errors by country because the disturbance term in Eq. (2) may be subject to serial correlation. Because the number of clusters in our data (16) may be too low for reliable inference, we also compute clustered p-values using the wild restricted efficient (WRE) bootstrap method (Davidson and MacKinnon 2010).[20]

Our identification strategy requires that *Flu* induce a natural experiment in mortality rates. Pandemics are certainly exogenous events. This is particularly true in annual data where the speed at which pandemics propagate or the order in which they spread across countries does not vary; these world events affect all countries in the data in the same years. One limitation of any pandemic study where all countries are "treated" together is that accounting for time effects becomes challenging. We largely sidestep this concern by estimating $\widetilde{lGDP}$, which is already stripped of any trend. It will also turn out that our results are robust to international or country-specific time trends.

Instrumental variables in macroeconomic analyses often fail to fulfil exclusion restrictions (Bazzi and Clemens 2013). In our case, $\boldsymbol{X}_2$ controls may be particularly important to ensuring the exclusion restriction holds. It is difficult to imagine other ways, aside from health (i.e. mortality), that pandemic timing in annual data could affect the cyclical component of GDP when holding constant consumption, investment, exports and government spending. Nevertheless, we illustrate the impact of possible departures from the exclusion restriction on confidence intervals for β.

The influenza-induced shocks we measure with β comprise a weighted local average treatment effect (LATE) because pandemic impacts are not homogeneous events. Angrist and Imbens (1995) show that monotonicity is required to identify a weighted LATE. Figure 4 illustrates that pandemic timing has a monotonic effect on our mortality measures, D^{M} and D^{P}, by confirming that the cumulative density function (CDF) of the endogenous variable during pandemics is always to the right of the CDF for non-pandemics.[21]

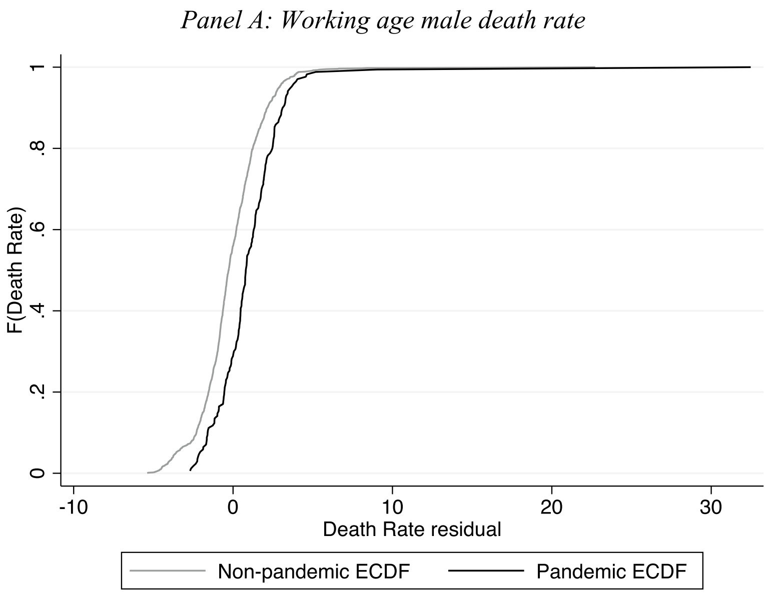
The weighed LATE we identify can be challenging to interpret because the weights vary by country and by event. Because the weights are proportional to the distance between the CDFs, we illustrate which countries and time periods can be expected to receive higher weight in by plotting the difference in CDFs (shaded) against kernel density estimates for different countries and decades in Figs. 5 and 6. All countries have considerable coverage over the shaded range, suggesting all contribute considerably to β. Weights are largest over the range $(-1.5, 1.5)$, and over this range countries that contribute more than their share of observations include Finland, France, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK.[22] Thus, we identify a LATE more heavily reflective of Europe. The decadal analysis, in Fig. 6, suggests that the LATE we identify is reflective more heavily of the 1880–1910s and the 1940–1990s than other decades. The former is

[19] Consumption is also a channel for short-run influenza impacts (See Bloom et al. 2022).

[20] Mackinnon (2019) suggests no fewer than 50 clusters. We implement the Roodman et al. (2019) WRE bootstrap code employing the weighting distribution suggested by Webb (2014).

[21] CDFs of mortality measures have first-stage covariates partialed out, precisely as our estimates will.

[22] Plots are for D^{M} with covariates partialed out. This range comprises 63% of the values.



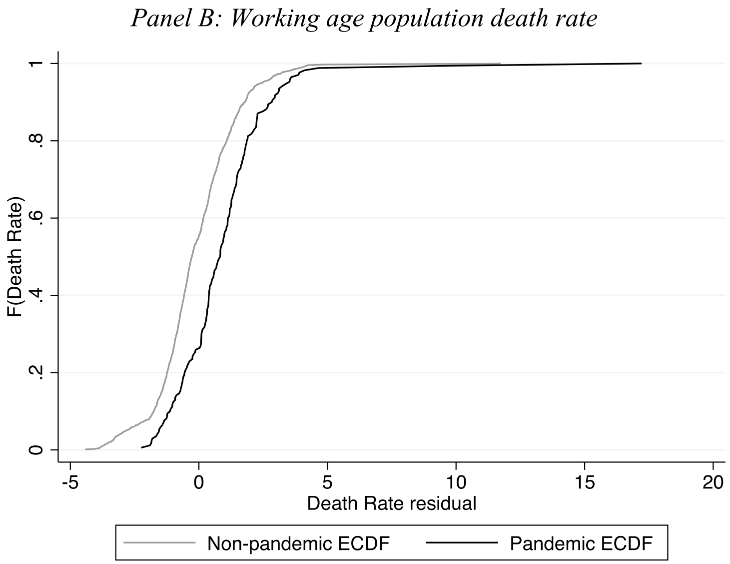


Fig. 4 Empirical CDFs of endogenous variables conditional on covariates. Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Plots illustrate the monotonicity principle of Angrist and Imbens (1995) for both endogenous measures of mortality. ECDF's generated from using control variables from the first stage (Eq. 2)

particularly sensible, as the Spanish Flu (1918) is the most substantive pandemic event in our data.

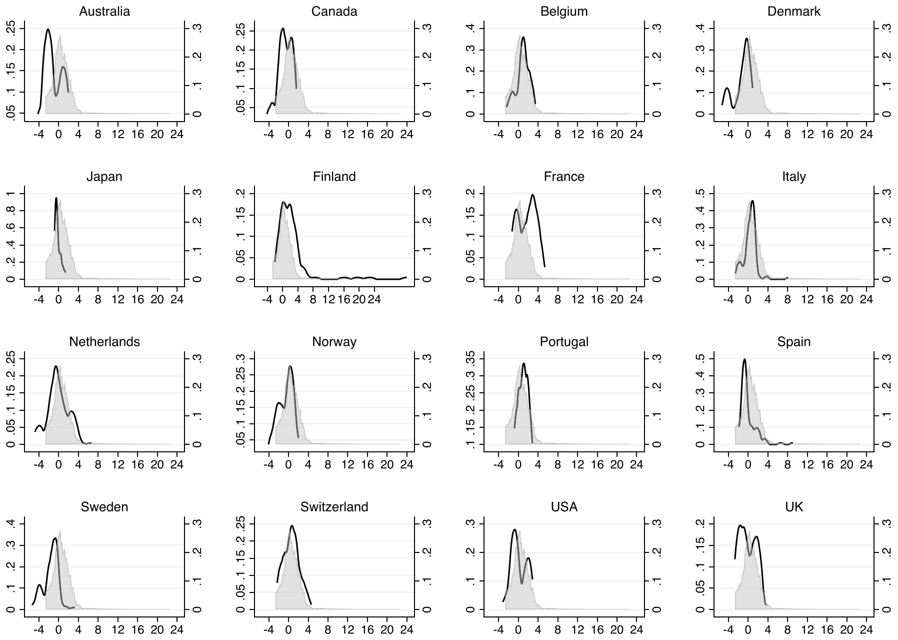


Fig. 5 Analysis of influenza pandemic timing as an instrumental variable, by country. Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Shaded grey area is the difference in empirical CDFs of the residual working-age male death rate from Fig. 4a (non-pandemic–pandemic), scaled on the right vertical axis. Overlaid is the density of residual working-age male death rate by country, scaled on the left vertical axis

6 Results

Our findings establish a robust causal impact of pandemic-induced mortality on the business cycle. Mortality shocks identified by our pandemic timing instrument decrease $\widetilde{lGDP}$ across different measures of the cycle and different mortality rates. Estimates of pandemic-induced mortality among working-age males are summarized in Panel A of Table 2.[23] In columns 1–3, the business cycle is captured using HP-filtered $\widetilde{lGDP}$. Column 1 is the baseline specification with only fixed effects as controls. In columns 2 and 3, we add vectors $\boldsymbol{X}_1$ and $\boldsymbol{X}_2$ successively. Estimates are very stable across all three columns; however, we interpret column 3 as it is the most conservative in the sense that our exclusion restriction is mostly likely to be satisfied in this case. The coefficient of -0.003 can be interpreted as follows: each additional death per 1000 (among working-age males) causes a contemporaneous average decrease in GDP per capita of about 0.3 per cent. To put this magnitude in the context, from 1917 to 1918 the average mortality rate in our data rose by about 8 deaths per 1000, suggesting that influenza-induced mortality alone would have contracted

[23] We include only coefficients of interest. For full results, see Appendix (Tables 8, 9 for OLS; Tables 10, 11, 12, 13, 14 for 2SLS.

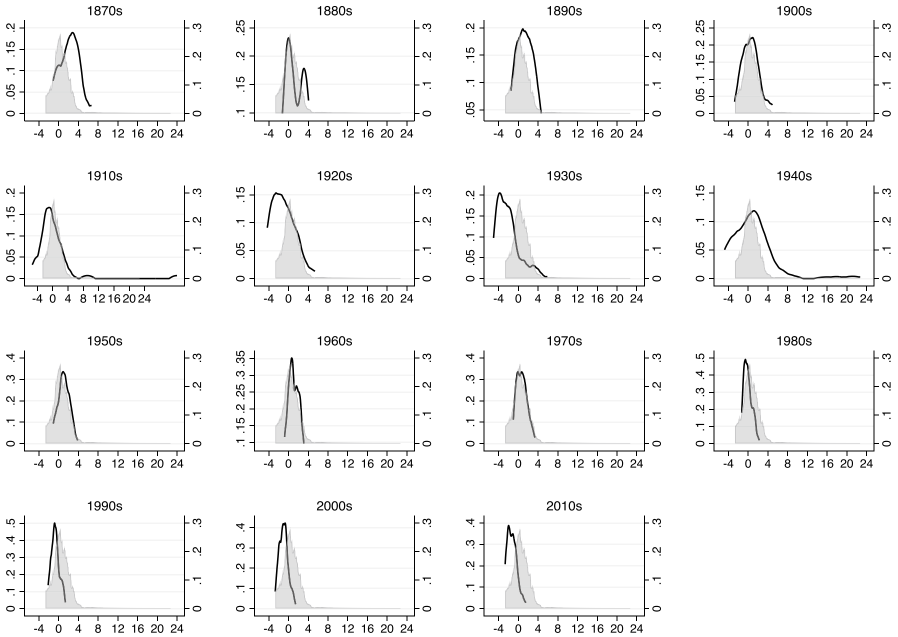


Fig. 6 Analysis of influenza pandemic timing as an instrumental variable, by decade. Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Shaded grey area is the difference in empirical CDFs of the residual working-age male death rate from Fig. 4a (non-pandemic–pandemic), scaled on the right vertical axis. Overlaid is the density of residual working-age male death rate by decade, scaled on the left vertical axis

GDP from trend by an average of about 2.4%, which is about half the observed contraction from trend in our data for this period.[24]

Columns 4–6 repeat with an alternative outcome measure: the BK-filtered $\widetilde{lGDP}$. The results are highly similar despite the differences in how these two filters capture the business cycle. All specifications are statistically significant based on cluster-robust inference. The WRE bootstrap provides 2SLS inference that is more conservative with few clusters. Resulting p-values suggest statistical significance for all specifications aside from column 1 and allow us to be specific about the probability of a type 1 error in our preferred specifications: statistical significance is attained at the 6.7 and 7.2 per cent levels in columns 3 and 6, respectively.

First-stage results in Panel *B* of Table 2 suggest that our instruments are strong. As expected, pandemic timing has a strong positive impact on D^{M}, conditional on whichever covariates are included. We assess instrument weakness following Montiel Olea and Pflueger (2013) by comparing the effective *F*-statistic for exclusion of Flu to critical values at the 5% level, where these critical values indicate a fraction of the "worst-case" bias that remains after instrumenting. Our instrument is sufficiently strong that we are able to reject a worst-case bias of 10% or more in the most

[24] HP-detrended log GDP decreases by 0.053 over this period in our estimation sample.

Table 2 Working-age male mortality effects on cyclical log real GDP per capita

	HP-filtered log GDP per capita			BK-filtered log GDP per capita		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2SLS estimates						
D^M	−0.0021*	−0.0029*	−0.0029*	−0.0022*	−0.0030**	−0.0026*
	(0.0012)	(0.0016)	(0.0015)	(0.0011)	(0.0014)	(0.0014)
	[0.1121]	[0.0921]	[0.0661]	[0.0611]	[0.0591]	[0.0721]
Panel B: First-stage estimates						
Flu	1.5894***	1.3159***	1.2878***	1.5626***	1.3001***	1.2561***
	(0.2184)	(0.1610)	(0.2310)	(0.2223)	(0.1594)	(0.2309)
rK	9.399***	11.05***	9.622***	9.148***	10.88***	9.385***
F	$52.98^{\dagger\dagger\dagger}$	$66.80^{\dagger\dagger\dagger}$	$31.09^{\dagger\dagger}$	$49.39^{\dagger\dagger\dagger}$	$66.54^{\dagger\dagger\dagger}$	$29.58^{\dagger\dagger}$
Panel C: OLS estimates						
D^M	−0.0007*	−0.0017***	−0.0009	−0.0009**	−0.0020***	−0.0010
	(0.0004)	(0.0004)	(0.0009)	(0.0004)	(0.0004)	(0.0010)
FE	Yes	Yes	Yes	Yes	Yes	Yes
$\boldsymbol{X}_1$	No	Yes	Yes	No	Yes	Yes
$\boldsymbol{X}_2$	No	No	Yes	No	No	Yes
N	1929	1803	1600	1862	1745	1548

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Working-age male mortality is constructed for males aged 16–65 as in Eq. 1. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2,8 and 3. FE are country fixed effects, vector $\boldsymbol{X}_1$ includes dummies for the two world wars, the introduction of vaccines in 1946, the real short-term interest rate and exchange rate adjusted wheat and oil prices, and vector $\boldsymbol{X}_2$ includes the following shares of GDP: investment, consumption, exports, government expenditure and the debt-to-GDP ratio. Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation. Wild restricted efficient bootstrap p-values in square brackets. *F*-statistic is the SW cluster-robust weak instrument *F*-statistic for excluding the pandemic instrument. We tested against the "worst-case" bias at the 5% level using the test for clustered standard errors following (Montiel Olea and Pflueger 2013). Rejection of the null hypothesis that our bias exceeds certain thresholds of the worst-case bias is indicated by the symbols: $^{\dagger\dagger\dagger}<5\%$, $^{\dagger\dagger}<10\%$, $^{\dagger}<20\%$. Corresponding critical values are 37.42, 23.11 and 15.06. This table is a summary of OLS and 2SLS regression results. Full results displaying all covariates are available in Appendix Tables 7, 8, 9, 10, 11 and 12

conservative specifications (columns 3 and 6) and to reject a bias of 5% or more elsewhere. Thus, we are confident that our instrument is sufficiently strong to identify pandemic-induced impacts on mortality in our data.[25]

For comparison, OLS estimates in Panel *C* illustrate the correlation, pandemic or not, between mortality among working-age males and the business cycle. Unlike 2SLS estimates that exploit the exogenous pandemic shocks to identify mortality impacts, OLS estimates may suffer from identification concerns mentioned earlier

[25] The Kleibergen and Paap (2006) robust rk statistic also rejects underidentification across all our estimates.

so we believe our identification strategy to be important. OLS estimates are about one-third of the size and are not statistically significant in specifications that hold constant the covariates $\boldsymbol{X}_2$. A weaker relationship when including non-pandemic mortality is expected as pandemics likely may have a stronger impact for a host of reasons, including their unexpected nature and considerable increases in unmeasurable morbidity challenges. Outside of a major health shock, national wealth is less correlated with life expectancy in the countries we study. Deaton (2003) shows that all are found on the flat portion of the Preston curve.

We now examine the same models through the lens of pandemic-induced mortality among both sexes. This alternative measure, D^P, may be important because our time series span periods from the past where the workforce was male dominated and periods closer to the present where the workforce is much more evenly distributed across the sexes. 2SLS impacts in Panel A of Table 3 are highly similar to those based on D^{M}, too alike to draw any conclusions about nuances in mortality across the sexes. Instead, it appears that pandemic-induced working-age mortality, broadly defined, has a robust negative impact on the business cycle.

Our estimates suggest that mortality is one causal channel through which influenza pandemics contribute meaningfully to the business cycle. On average, these events increase mortality rates in our data by 1.73 deaths per 1000. The mortality consequences alone, then, suggest that influenza pandemics over the past 150 years decreased GDP per capita below its trend by half a percentage point on average. While modest compared with the drop in US GDP during the COVID pandemic or the Spanish Flu, it is not a trivial effect. Our 2SLS framework does not model the dynamics of how these shocks propagate over time once they hit. Such an analysis is better explored in a structural model, which would be motivated by the causal findings of this paper. Furthermore, while our analysis does include the Spanish Flu, several other influenza pandemics might be considered less-severe health shocks and the data available cover industrialized countries where, from a global perspective, impacts may have been less drastic.

Our interpretation of $\widehat{\beta}$ depends on the argument that pandemic events are exogenous. Although we believe it to be so, particularly with covariates $\boldsymbol{X}_2$, this assumption is fundamentally untestable. Conley et al. (2012) provide a "local to zero" method to estimate confidence intervals around β in cases where the exclusion restriction does not hold perfectly (where *Flu* affects $\widetilde{lGDP}$ through channels other than D, captured by some parameter γ). The distribution for γ is assumed to be $\gamma \sim N(0, 0.001)$, which is conservative in the sense that it allows γ to approach the full size of our measured effect of β.[26] For our preferred specification, column (3) of Tables 2 and 3, 90% local to zero confidence intervals are presented alongside cluster-robust confidence intervals that assume the exclusion restriction holds ($\gamma = 0$) in Table 4.[27] The bounds for β do not change significantly, which suggests that our estimates are reliable even in the unlikely case that $\gamma \neq 0$. This is to be expected

[26] The standard deviation of γ is one-third the size of $\widehat{\beta}$

[27] We present 90% confidence intervals because estimates are statistically significant at the 10% level. A similar comparison of 95% confidence intervals is available upon request.

Table 3 Working-age population mortality effects on cyclical log real GDP per capita

	HP-filtered log GDP per capita			BK-filtered log GDP per capita		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2SLS estimates						
D^P	− 0.0022	− 0.0032*	− 0.0034*	− 0.0023*	− 0.0033*	− 0.0031*
	(0.0014)	(0.0019)	(0.0020)	(0.0013)	(0.0017)	(0.0018)
	[0.1331]	[0.1151]	[0.0921]	[0.0781]	[0.0751]	[0.0861]
Panel B: First-stage estimates						
Flu	1.4718***	1.1844***	1.0847***	1.4576***	1.1788***	1.0630***
	(0.2100)	(0.0935)	(0.1416)	(0.2169)	(0.0954)	(0.1445)
rK	9.109***	12.23***	10.92***	8.850***	12.00***	10.63***
F	$49.14^{\dagger\dagger\dagger}$	$160.4^{\dagger\dagger\dagger}$	$58.71^{\dagger\dagger\dagger}$	$45.17^{\dagger\dagger\dagger}$	$152.7^{\dagger\dagger\dagger}$	$54.09^{\dagger\dagger\dagger}$
Panel C: OLS estimates						
D^P	− 0.0006*	− 0.0018***	− 0.0005	− 0.0008*	− 0.0022***	− 0.0006
	(0.0003)	(0.0006)	(0.0011)	(0.0004)	(0.0006)	(0.0011)
FE	Yes	Yes	Yes	Yes	Yes	Yes
X_1	No	Yes	Yes	No	Yes	Yes
X_2	No	No	Yes	No	No	Yes
N	1929	1803	1600	1862	1745	1548

*** p < 0.01, ** p < 0.05, * p < 0.1

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Working-age population mortality is constructed for both sexes age 16–65. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2,8 and 3. FEare country fixed effects, vector X_1 includes dummies for the two world wars, the introduction of vaccines in 1946, the real short-term interest rate and exchange rate adjusted wheat and oil prices, and vector X_2 includes the following shares of GDP: investment, consumption, exports, government expenditure and the debt-to-GDP ratio. Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation. Wild restricted efficient bootstrap p-values in square brackets. *F*-statistic is the SW cluster-robust weak instrument *F*-statistic for excluding the pandemic instrument. We tested against the "worst-case" bias at the 5% level using the test for clustered standard errors following (Montiel Olea and Pflueger 2013). Rejection of the null hypothesis that our bias exceeds certain thresholds of the worst-case bias is indicated by the symbols: $^{\dagger\dagger\dagger}<5\%$, $^{\dagger\dagger}<10\%$, $^{\dagger}<20\%$. Corresponding critical values are 37.42, 23.11 and 15.06. This table is a summary of OLS and 2SLS regression results. Full results displaying all covariates are available in Appendix Tables 7, 8, 9, 10, 11 and 12

Table 4 Comparison of 90% confidence intervals for β if exclusion restriction fails

	D^M HP filter	D^P HP filter
Original	[− .0054,− .0004]	[− .0067, − .0002]
LTZ N(0,0.001)	[− .0056,− .0002]	[− .0067, − .0002]

Data sources: Jordà et al. (2017), Human Mortality Database (2020). Original confidence intervals from estimates in column 3 of Tables 2 and 3 for respective endogenous variables. D^M and $D^{P.}$ LTZ are local to zero confidence intervals computed using the methods of Conly (2012); the exclusion restriction ($\gamma = 0$) is relaxed allowing for $\gamma \sim N(0, 0.001)$

as violations of the exclusion restriction are most egregious when instruments are weak, which is not our case.

6.1 Further robustness checks

Our findings are robust to the choice of business cycle measure. Both the HP and BK filters isolate particular frequencies in the data and thus generate cyclical measures that is relative to a nonlinear trend. However, we also illustrate that our results hold when using a linear detrending procedure (LDT) whereby $\widetilde{lGDP}$ is comprised of residuals from country-specific regressions of log GDP on the year of observation and the 1946 dummy variable. This measure is impacted negatively in all specifications (columns 5–8 of Tables 9 and 11 in the Appendix). Coefficients are much larger, which is to be expected as deviations from a linear trend over such a long period are necessarily larger than deviations from the nonlinear HP or BK trends that fluctuate slowly to capture sustained periods of higher growth.

We also consider more carefully the context of our most significant pandemic. The year 1918 overlaps both WW1 and the Spanish Flu. This matters because wartime contractions during our period of analysis are more than twice as large as non-wartime contractions among OECD countries (Barro and Ursúa 2008). WW1, in particular, was among the most significant contractions in the period of analysis with total deaths of combatants and civilians of about 20 million (Mougel 2011).[28]Although the vector $\boldsymbol{X}_1$ includes a WW1 timing control, we may not fully disentangle differential mortality impacts of the during this crucial year. To provide some evidence that WW1 is not confounding the results, we adjust D^{M} for the year 1918 using estimates from Barro et al. (2020), where separate death rates for the Spanish Flu and WW1 are available for all countries in our data aside from Finland.[29] The results using these adjusted mortality numbers are virtually unchanged (see Appendix Table 14).

An alternative way to measure pandemic-induced mortality is to examine excess mortality from influenza pandemics. Measurement concerns prevent us from adopting this as our main approach; any estimate of excess mortality introduces further uncertainty. Nevertheless, OLS estimates using excess mortality should be broadly similar to our IV results. Following Murray et al. (2006), we use the mean of adjacent year values twice the duration of the pandemic to establish a baseline mortality rate, separately for each pandemic in each country.[30] Excess mortality (EM_{jt}) is the difference between this baseline and original mortality data. Equation (4) details our calculation for a pandemic of duration S beginning in year T, using the mortality rate D^{M} as an example.

[28] See also, Willcox (1923) who notes the larger impact of the Spanish Flu.

[29] Finland is given the un-adjusted value. Results that omit this missing value were very similar.

[30] Alternative estimation methods for excess mortality often employ harmonic regression models (e.g. Ansart et al.2009). However, such methodology is more suited to capturing seasonal flu mortality in monthly data. We thank an anonymous referee for suggesting the use of an excess mortality measure.

$$\mathrm{EM}_{jt}^{M} = \left(D_{jt}^{\mathrm{M}} - \left[\frac{\sum_{t=T-S}^{T-1} D_{jt}^{\mathrm{M}} + \sum_{t=T+S}^{T+2S-1} D_{jt}^{\mathrm{M}}}{2S} \right] \right) \tag{4}$$

Estimates of the effect of excess mortality on the cyclical component of GDP in Appendix Table 15 suggest very similar impacts to the IV estimates in Tables 2 and 3. Point estimates using EM_{jt} exceed IV estimates somewhat but fall well within the confidence interval of the IV estimates, and so, we cannot rule out that the IV estimate might exceed these estimates with stronger instruments.

We consider the possibility that any subtle trends in any of our covariates and/or mortality rates might lead to spurious findings, even if it is unlikely given that our outcome is detrended. 2SLS estimates in Appendix Table 16 present results, for both the HP- and BK-filtered outcomes and for both mortality measures D^{M} and D^{P}, that include overall time trends (columns 1–4) and country-specific time trends (columns 5–8). The results are very similar, if not slightly larger. However, as the instruments are also slightly weaker, we cannot rule out that this difference is the result of a small increase in bias.

The impact measured above represents an average effect across all pandemics. However, not all events were equally severe. In particular, the flu events spanning 1873–75, 1899–1900 and 1946 may not be considered by some to have been full-fledged pandemics. A LATE that is not identified using the variation across these events might be expected to measure a stronger response. We redefine our instrument to treat these years as non-pandemic events and present 2SLS estimates in Table 17. As expected, point estimates are indeed larger although confidence intervals overlap. These results are suggestive that stronger pandemics had stronger effects, although it is worth noting that the indicator for more severe pandemics, while still a strong predictor of D^{P} is somewhat weaker as an instrument for D^{M}.

Finally, we rule out the possibility that our results are driven entirely by the most severe pandemic in the data, the Spanish Flu. Appendix Table 18 reports 2SLS results excluding the years 1918–1920. The results are broadly similar, particularly in columns 3 and 6 which are conditional on covariates that account for the overlapping world war events and their economic impacts, which might be particularly problematic as confounders during this period.

6.2 Employment

Labour supply is expected to be the main mechanism behind the causal link between mortality and GDP. In this section, we examine the potential intermediate effect that pandemic-induced mortality has on the employment-to-population ratio, E, where data permit (USA 1890–1990, UK 1870–2011 and Sweden 1870–2000). While Appendix Figure 7 illustrates correlation between E and D^{M}, this is merely suggestive of an intermediating role. Instead, we re-estimate Eqs. (2) and (3), replacing E as the outcome variable. Table 5 shows results for D^{M} and D^{P} mortality measures. Point estimates suggest a considerable negative impact on the employment ratio in these three countries for each additional death per 1000. However, the instrument is

Table 5 2SLS estimates: mortality effects on the employment-to-population ratio

	(1)	(2)
	E	*E*
Panel A: Second stage		
D^{M}	−0.0076**	
	(0.0033)	
	[0.1892]	
D^{P}		−0.0091**
		(0.0042)
		[0.1992]
Panel B: First stage		
Flu	1.2143**	1.0163
	(0.5257)	(0.4749)
F	$15.388^{\dagger}$	12.203
N	275	275

*** p < 0.01, ** p < 0.05, * p < 0.1

Data sources: Jordà et al. (2017), Human Mortality Database (2020), Edvinsson (2004), Thomas and Dimsdale (2017), Carter et al. (2006). Working-age population mortality is constructed for both sexes age 16–65. Employment to population ratios constructed for Sweden the UK and the USA only. All specifications include country fixed effects, vector $\boldsymbol{X}_1$ (dummies for the two world wars, the introduction of vaccines in 1946, the real short-term interest rate and exchange rate adjusted wheat and oil prices), and vector $\boldsymbol{X}_2$ (the following shares of GDP: investment, consumption, exports, government expenditure and the debt-to-GDP ratio). Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation. Wild restricted efficient bootstrap *p*-values in square brackets. *F*-statistic is the effective *F*-statistic for excluding the pandemic instrument. We tested against the "worst-case" bias at the 5% level using the test for clustered standard errors following (Montiel Olea and Pflueger 2013). Rejection of the null hypothesis that our bias exceeds certain thresholds of the worst-case bias is indicated by the symbols: $^{\dagger\dagger\dagger}<5\%$, $^{\dagger\dagger}<10\%$, $^{\dagger}<20\%$. Corresponding critical values are 37.42, 23.11 and 15.06. This table is a summary of OLS and 2SLS regression results

not strong enough to consider these estimates anything beyond suggestive. This is not surprising since $N = 275$ with covariates. Further, inference based on three clusters is certainly unreliable and WRE bootstrapped p-values suggest statistical significance well above the 10% level. Thus, we cannot as confidently place any emphasis on causal results for employment.

7 Discussion and conclusion

Our results suggest that over the course of the period 1870–2016, influenza shocks decreased the short-run (cyclical) component of GDP by increasing mortality rates among the working-age population. In addition to contributing to a growing knowledge of pandemic events, the influenza shocks we examine comprise a quasi-experimental setting under which we can identify causal effects of mortality on the business cycle. This causal channel appears to act, in part, through a reduction of labour supply, though it may capture other population health effects from these pandemic events. These events on average increased mortality rates in our data by 1.73 deaths per 1000 and suggest that influenza pandemics over the past 150 years decreased GDP per capita below its trend by half a percentage point on average.

While meaningful and significant, the effects we identify are modest enough that we would not claim mortality as the only channel by which pandemics contribute to the business cycle. Mortality effects from influenza pandemic shocks were predominant in the late nineteenth century and early twentieth century, which featured more rudimentary medical technology and treatments. Yet, our findings suggest that they continue to be worth consideration even after the introduction of vaccines. Even where mortality from influenza is not particularly egregious, behavioural responses in the workforce from attempts to reduce mortality impact from infection spread or accompanying morbidity (Bloom et al. 2022) are also likely to be important in the short run. Given that mortality may only be the tip of the proverbial iceberg, it should be noted that comparing morbidity and mortality shocks remains a promising avenue for further research pending the availability of long-run data on illnesses and pandemics as may certainly be the case in the wake of the COVID-19 pandemic and the evidence regarding the effects of "Long Covid" (Bach 2022; World Bank 2022). Indeed, going forward the macroeconomic effects of COVID will be an interesting area of further research given the novelty of the coronavirus, the extent of lockdowns, the rapid development and deployment of vaccines as well the magnitude of fiscal and monetary responses relative to previous pandemic periods.

Other important channels are at play which we hold constant in our analysis. Consider disruptions to trade, investment and particularly consumption, which comprises close to two-thirds of GDP in most developed countries (Attanasio 1999). For example, interplay between consumption and mortality might follow from reduced mobility due to taking private measures, lockdowns that are implemented in response to rising mortality, or from deferred consumerism when employment is less stable. A prominent example is the loss of 2.8 billion USD by the Mexican tourism sector during H1N1 (Rassy and Smith 2013). Ultimately, our results also motivate the inclusion of influenza pandemics as an overlooked health shock in structural models of health and the business cycle, building on such as those proposed by Bloom et al. (2022), which have been motivated by the recent and severe COVID-19 pandemic. The impact of influenza pandemics on business cycle fluctuations, while moderate is nevertheless of significance and important to appreciate given that economic history shows they have happened before and will inevitably happen again.

Appendix A

See Figs. 7, 8, 9 and Tables 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18

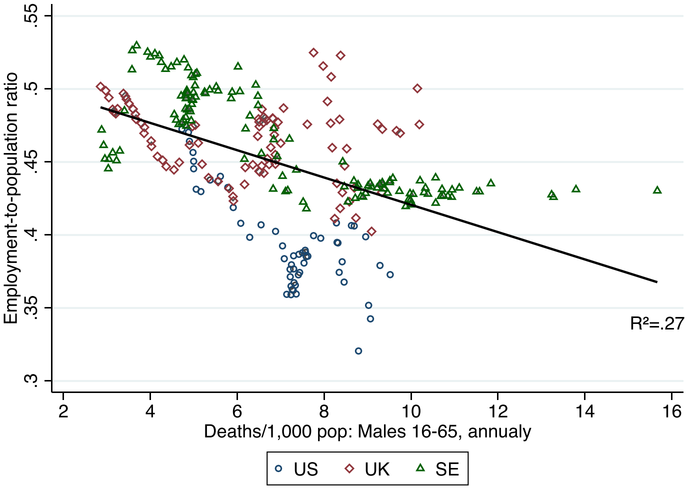


Fig. 7 Correlation of working-age male mortality and employment in three countries. Data sources: Jordà et al. (2017), Human Mortality Database (2020), Edvinsson (2004), Thomas and Dimsdale (2017), Carter et al. (2006). Correlation between the employment-to-population ratio and the working-age male death rate in the USA, the UK and Sweden.

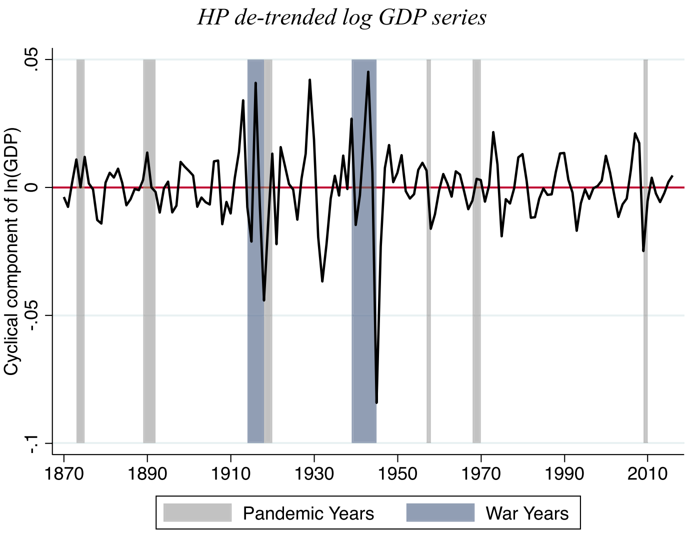


Fig. 8 HP-detrended log GDP series. Data source: Jordà et al. (2017). Log GDP per capita index, 2005 = 100 series are detrended Hodrick and Prescott (1997) filter using the smoothing parameter 6.25

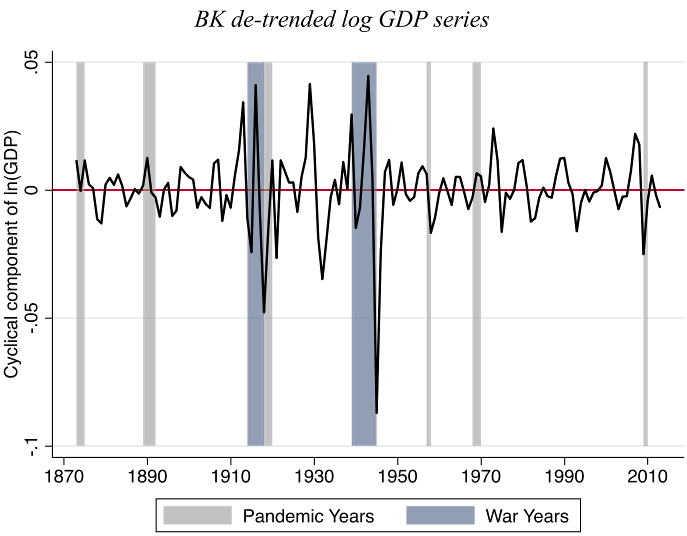


Fig. 9 BK detrended log GDP series. Data source: Jordà et al. (2017). Log GDP per capita index, 2005 = 100 series are detrended using the Baxter and King (1999) band pass filter with parameters 2, 8 and 3

Table 6 Major economic contractions, US economy. *Source*: NBER https://www.nber.org/cycles.html

Peak month	Trough month	Duration (months)
October 1873	March 1879	65
March 1882	May 1885	38
March 1887	April 1888	13
July 1890	May 1891	10
January 1893	June 1894	17
December 1895	June 1897	18
June 1899	December 1900	18
September 1902	August 1904	23
May 1907	June 1908	13
January 1910	January 1912	24
January 1913	December 1914	23
August 1918	March 1919	7
January 1920	July 1921	18
May 1923	July 1924	14
October 1926	November 1927	13
August 1929	March 1933	43
May 1937	June 1938	13
February 1945	October 1945	8
November 1948	October 1949	11
July 1953	May 1954	10

Table 6 (continued)

Peak month	Trough month	Duration (months)
August 1957	April 1958	8
April 1960	February 1961	10
December 1969	November 1970	11
November 1973	March 1975	16
January 1980	July 1980	6
July 1981	November 1982	16
July 1990	March 1991	8
March 2001	November 2001	8
December 2007	June 2009	18

Table 7 Data availability

Country	Macro variables			Mortality rates	
Australia	1902–2016			1921–2016	
Belgium	1919–2016			1870–1913	1919–2016
Canada	1934–2016			1921–2016	
Denmark	1880–1946	1953–1956	1960–2016	1870–2016	
Finland	1914–2016			1878–2016	
France	1880–1913	1920–1938	1949–2016	1870–2016	
Italy	1886–1914	1922–2016		1872–2016	
Japan	1885–1838	1957–2016		1946–2016	
Netherlands	1870–1914	1921–1939	1948–2016	1870–2016	
Norway	1880–1939	1947–2016		1870–2016	
Portugal	1953–2016			1940–2016	
Spain	1880–1935	1940–2016		1908–2016	
Sweden	1870–2016			1870–2016	
Switzerland	1885–1913	1948–2016		1876–2016	
UK	1870–2016			1922–2016	
USA	1870–2016			1933–2016	

Data sources: Jordà et al (2017) and Human Mortality Database (2020)

Table 8 OLS regressions of working-age male mortality effects on cyclical log real GDP per capita

	(1) HP filter	(2) HP filter	(3) HP filter	(4) BK filter	(5) BK filter	(6) BK filter	(7) LDT	(8) LDT	(9) LDT
Deaths/1k	−0.0007*	−0.0017***	−0.0009	−0.0009**	−0.0020***	−0.0010	−0.0021	−0.0051***	−0.0011
	(0.0004)	(0.0004)	(0.0009)	(0.0004)	(0.0004)	(0.0010)	(0.0012)	(0.0017)	(0.0041)
WW1		−0.0080*	−0.0045		−0.0095**	−0.0056		−0.0571*	−0.0462*
		(0.0039)	(0.0043)		(0.0041)	(0.0040)		(0.0276)	(0.0262)
WW2		−0.0109*	0.0009		−0.0135*	−0.0004		−0.0340	−0.0623
		(0.0057)	(0.0052)		(0.0071)	(0.0048)		(0.0457)	(0.0361)
Year ≥ 1946		−0.0098***	−0.0194***		−0.0110***	−0.0222***		−0.0385*	−0.2379***
		(0.0023)	(0.0059)		(0.0024)	(0.0053)		(0.0195)	(0.0422)
rSTIR		0.0000	0.0000		0.0000	0.0000		−0.0001	−0.0001
		(0.0000)	(0.0000)		(0.0001)	(0.0001)		(0.0004)	(0.0003)
Wheat price adj		0.0000	0.0000**		0.0000	0.0000**		0.0000**	0.0000***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Oil price adj		−0.0000**	−0.0000*		−0.0000	−0.0000		−0.0000***	−0.0000***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Invest/GDP			0.0964***			0.1084***			1.1042***
			(0.0235)			(0.0177)			(0.2624)
Cons/GDP			−0.0160			−0.0220*			−0.1964***
			(0.0115)			(0.0111)			(0.0572)
Export/GDP			−0.0095			−0.0086			−0.0850**
			(0.0079)			(0.0079)			(0.0343)
Debt/GDP			0.0015			0.0004			−0.1057**
			(0.0022)			(0.0018)			(0.0399)
Expend/GDP			0.0040			0.0041			0.4585**
			(0.0222)			(0.0204)			(0.1578)

Table 8 (continued)

	(1) HP filter	(2) HP filter	(3) HP filter	(4) BK filter	(5) BK filter	(6) BK filter	(7) LDT	(8) LDT	(9) LDT
Constant	0.0055*	0.0192***	0.0184	0.0069**	0.0219***	0.0259	0.0152*	0.0624**	0.1545
	(0.0027)	(0.0041)	(0.0217)	(0.0029)	(0.0042)	(0.0182)	(0.0087)	(0.0255)	(0.1149)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1929	1803	1600	1862	1745	1548	1929	1803	1600
R-squared	0.0094	0.0280	0.0431	0.0143	0.0395	0.0597	0.0040	0.0582	0.3533

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Working-age population mortality is constructed for males age 16–65. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2,8 and 3. FE are country fixed effects. Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation

Table 9 OLS regressions of working-age population mortality effects on cyclical log real GDP per capita

	(1) HP filter	(2) HP filter	(3) HP filter	(4) BK filter	(5) BK filter	(6) BK filter	(7) LDT	(8) LDT	(9) LDT
Deaths/1k	−0.0006*	−0.0018***	−0.0005	−0.0008*	−0.0022***	−0.0006	−0.0026**	−0.0093***	−0.0015
	(0.0003)	(0.0006)	(0.0011)	(0.0004)	(0.0006)	(0.0011)	(0.0012)	(0.0024)	(0.0050)
WW1		−0.0097**	−0.0061		−0.0112**	−0.0072		−0.0543*	−0.0459
		(0.0042)	(0.0051)		(0.0043)	(0.0048)		(0.0277)	(0.0283)
WW2		−0.0130**	0.0008		−0.0160**	−0.0006		−0.0477	−0.0639
		(0.0057)	(0.0053)		(0.0072)	(0.0048)		(0.0485)	(0.0369)
Year ≥ 1946		−0.0106***	−0.0177**		−0.0125***	−0.0206***		−0.0643**	−0.2399***
		(0.0035)	(0.0061)		(0.0037)	(0.0055)		(0.0251)	(0.0437)
rSTIR		0.0000	0.0000		0.0000	0.0000		−0.0002	−0.0001
		(0.0000)	(0.0000)		(0.0001)	(0.0001)		(0.0004)	(0.0003)
Wheat Price adj		0.0000	0.0000*		−0.0000	0.0000*		0.0000**	0.0000***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Oil Price adj		−0.0000**	−0.0000		−0.0000	−0.0000		−0.0000***	−0.0000***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Invest/GDP			0.1007***			0.1125***			1.0992***
			(0.0259)			(0.0198)			(0.2678)
Cons/GDP			−0.0161			−0.0221*			−0.1955***
			(0.0113)			(0.0109)			(0.0575)
Export/GDP			−0.0083			−0.0075			−0.0849**
			(0.0075)			(0.0078)			(0.0353)
Debt/GDP			0.0019			0.0008			−0.1059**
			(0.0023)			(0.0019)			(0.0399)
Expend/GDP			0.0030			0.0028			0.4567**
			(0.0236)			(0.0220)			(0.1585)

Table 9 (continued)

	(1) HP filter	(2) HP filter	(3) HP filter	(4) BK filter	(5) BK filter	(6) BK filter	(7) LDT	(8) LDT	(9) LDT
Constant	0.0037*	0.0183***	0.0132	0.0049**	0.0220***	0.0206	0.0167**	0.0992***	0.1579
	(0.0020)	(0.0055)	(0.0224)	(0.0023)	(0.0060)	(0.0188)	(0.0074)	(0.0323)	(0.1185)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1929	1803	1600	1862	1745	1548	1929	1803	1600
R-squared	0.0046	0.0211	0.0387	0.0076	0.0317	0.0544	0.0052	0.0667	0.3534

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Working-age population mortality is constructed for both sexes age 16–65. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2,8 and 3. FE are country fixed effects. Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation

Table 10 2SLS second-stage results for working-age male mortality effects on cyclical log real GDP per capita

	(1) HP filter	(2) HP filter	(3) HP filter	(4) BK filter	(5) BK filter	(6) BK filter	(7) LDT	(8) LDT	(9) LDT
Deaths/1k	−0.0021*	−0.0029*	−0.0029*	−0.0022*	−0.0030**	−0.0026*	−0.0239***	−0.0314***	−0.0235***
	(0.0012)	(0.0016)	(0.0015)	(0.0011)	(0.0014)	(0.0014)	(0.0046)	(0.0055)	(0.0069)
WW1		−0.0048	0.0016		−0.0067	−0.0005		0.0188	0.0221
		(0.0057)	(0.0051)		(0.0056)	(0.0047)		(0.0419)	(0.0203)
WW2		−0.0117**	−0.0008		−0.0141**	−0.0017		−0.0533	−0.0818*
		(0.0052)	(0.0064)		(0.0065)	(0.0057)		(0.0537)	(0.0452)
Year $\geq$ 1946		−0.0160*	−0.0282***		−0.0160**	−0.0292***		−0.1823***	−0.3370***
		(0.0082)	(0.0078)		(0.0070)	(0.0065)		(0.0436)	(0.0639)
rSTIR		0.0000	0.0000		0.0000	0.0000		−0.0003	−0.0002
		(0.0000)	(0.0000)		(0.0001)	(0.0001)		(0.0004)	(0.0004)
Wheat price adj		0.0000	0.0000**		0.0000	0.0000**		0.0000***	0.0000***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Oil price adj		−0.0000**	−0.0000**		−0.0000*	−0.0000**		−0.0000***	−0.0000***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Invest/GDP			0.0742**			0.0903***			0.8567***
			(0.0321)			(0.0262)			(0.2604)
Cons/GDP			−0.0148			−0.0203*			−0.1829***
			(0.0116)			(0.0108)			(0.0686)
Export/GDP			−0.0139			−0.0116			−0.1336*
			(0.0089)			(0.0082)			(0.0759)
Debt/GDP			−0.0003			−0.0009			−0.1264***
			(0.0027)			(0.0021)			(0.0477)
Expend/GDP			0.0055			0.0060			0.4754***
			(0.0188)			(0.0169)			(0.1737)

Table 10 (continued)

	(1) HP filter	(2) HP filter	(3) HP filter	(4) BK filter	(5) BK filter	(6) BK filter	(7) LDT	(8) LDT	(9) LDT
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1929	1803	1600	1862	1745	1548	1929	1803	1600
K–P UnderID LM	9.399***	11.05***	9.622***	9.148***	10.88***	9.385***	9.399***	11.05***	9.622***
Weak IV *F* stat	52.98	66.80	31.09	49.39	66.54	29.58	52.98	66.80	31.09

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Working-age population mortality is constructed for males age 16–65. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2,8 and 3. FE are country fixed effects. SEs in parentheses clustered by country. *K–P* stat is the Kleibergen and Paap (2006) robust LM statistic. Weak IV *F*-stat is the Sanderson and Windmeijer (2016) *F*-statistic for the excluded instrument in the first stage

Table 11 2SLS first-stage results for working-age male mortality effects on cyclical log real GDP per capita

	(1) HP/LDT Death rate	(2) HP/LDT Death rate	(3) HP/LDT Death rate	(4) BK filter Death rate	(5) BK filter Death rate	(6) BK filter Death rate
Flu Pandemic	1.5894***	1.3159***	1.2878***	1.5626***	1.3001***	1.2561***
	(0.2184)	(0.1610)	(0.2310)	(0.2223)	(0.1594)	(0.2309)
WW1		2.7746**	2.9363**		2.8513**	2.9904**
		(1.3437)	(1.2819)		(1.3531)	(1.2705)
WW2		−0.5771	−0.8178		−0.4904	−0.7361
		(0.9120)	(1.0545)		(0.9176)	(1.0626)
Year ≥ 1946		−5.4543***	−4.5527***		−5.2881***	−4.4016***
		(0.3942)	(0.9795)		(0.3913)	(0.9668)
rSTIR		−0.0076**	−0.0080***		−0.0083	−0.0098*
		(0.0032)	(0.0026)		(0.0100)	(0.0052)
Wheat price adj		0.0000	0.0000		0.0000	0.0000
		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Oil price adj		−0.0000***	−0.0000***		−0.0000***	−0.0000**
		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Invest/GDP			−10.4763**			−10.3772**
			(5.3393)			(5.1867)
Cons/GDP			0.3743			0.7671
			(1.6000)			(1.6367)
Export/GDP			−2.0439			−1.7107
			(2.3992)			(2.4123)
Debt/GDP			−0.8593			−0.7581
			(0.5818)			(0.6171)
Expend/GDP			0.9580			1.3675
			(4.0150)			(4.0425)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1929	1803	1600	1862	1745	1548

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). First-stage estimates for estimates in Table 10. Working-age population mortality is constructed for males age 16–65. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2, 8 and 3. FE are country fixed effects. Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation

Table 12 2SLS second-stage results for working-age population mortality effects on cyclical log real GDP per capita

	(1) HP filter	(2) HP filter	(3) HP filter	(4) BK filter	(5) BK filter	(6) BK filter	(7) LDT	(8) LDT	(9) LDT
Deaths/1k	−0.0022	−0.0032*	−0.0034*	−0.0023*	−0.0033*	−0.0031*	−0.0258***	−0.0349***	−0.0279***
	(0.0014)	(0.0019)	(0.0020)	(0.0013)	(0.0017)	(0.0018)	(0.0053)	(0.0055)	(0.0082)
WW1		−0.0071	0.0006		−0.0091*	−0.0014		−0.0064	0.0140
		(0.0050)	(0.0049)		(0.0050)	(0.0046)		(0.0320)	(0.0232)
WW2		−0.0156***	−0.0039		−0.0180***	−0.0044		−0.0955*	−0.1069**
		(0.0045)	(0.0069)		(0.0056)	(0.0059)		(0.0521)	(0.0478)
Year ≥ 1946		−0.0186*	−0.0304***		−0.0185**	−0.0311***		−0.2109***	−0.3544***
		(0.0102)	(0.0092)		(0.0090)	(0.0077)		(0.0449)	(0.0685)
rSTIR		0.0000	−0.0000		0.0000	0.0000		−0.0003	−0.0003
		(0.0000)	(0.0000)		(0.0001)	(0.0001)		(0.0004)	(0.0004)
Wheat price adj		−0.0000	0.0000		−0.0000	0.0000		0.0000***	0.0000***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Oil price adj		−0.0000**	−0.0000**		−0.0000	−0.0000*		−0.0000***	−0.0000***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Invest/GDP			0.0688*			0.0855***			0.8124***
			(0.0357)			(0.0292)			(0.2484)
Cons/GDP			−0.0131			−0.0188*			−0.1689**
			(0.0107)			(0.0101)			(0.0677)
Export/GDP			−0.0123			−0.0102			−0.1210*
			(0.0084)			(0.0080)			(0.0670)
Debt/GDP			−0.0003			−0.0009			−0.1258***
			(0.0028)			(0.0023)			(0.0467)
Expend/GDP			0.0011			0.0020			0.4399***
			(0.0203)			(0.0185)			(0.1638)

Table 12 (continued)

	(1) HP filter	(2) HP filter	(3) HP filter	(4) BK filter	(5) BK filter	(6) BK filter	(7) LDT	(8) LDT	(9) LDT
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1929	1803	1600	1862	1745	1548	1929	1803	1600
K–P UnderID LM	9.109***	12.23***	10.92***	8.850***	12.00***	10.63***	9.109***	12.23***	10.92***
WeakIV *F* stat	49.14	160.4	58.71	45.17	152.7	54.09	49.14	160.4	58.71

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Working-age population mortality is constructed for both sexes age 16–65. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2,8 and 3. FE are country fixed effects. Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation. *K–P* statist is the Kleibergen and Paap (2006) robust LM statistic testing the null hypothesis that the model is not identified. Weak IV *F*-stat is the Sanderson and Windmeijer (2016) *F*-statistic for the excluded instrument in the first stage

Table 13 2SLS first-stage results for working-age population mortality effects on cyclical log real GDP per capita

	(1) HP/LDT Death rate	(2) HP/LDT Death rate	(3) HP/LDT Death rate	(4) BK filter Death rate	(5) BK filter Death rate	(6) BK filter Death rate
Flu Pandemic	1.4718***	1.1844***	1.0847***	1.4576***	1.1788***	1.0630***
	(0.2100)	(0.0935)	(0.1416)	(0.2169)	(0.0954)	(0.1445)
WW1		1.7769**	2.1837***		1.8464**	2.2326***
		(0.7957)	(0.8052)		(0.7991)	(0.7984)
WW2		−1.7257***	−1.5881**		−1.6446***	−1.5107**
		(0.4903)	(0.7248)		(0.4970)	(0.7379)
Year ≥ 1946		−5.7258***	−4.4571***		−5.5835***	−4.3293***
		(0.3614)	(0.7740)		(0.3588)	(0.7685)
rSTIR		−0.0074**	−0.0078***		−0.0097	−0.0109**
		(0.0029)	(0.0020)		(0.0094)	(0.0048)
Wheat price adj		−0.0000	−0.0000		−0.0000	−0.0000
		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Oil price adj		−0.0000**	−0.0000		−0.0000**	−0.0000
		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Invest/GDP			−10.4087**			−10.3184**
			(4.7371)			(4.6060)
Cons/GDP			0.8132			1.1516
			(1.3211)			(1.3547)
Export/GDP			−1.2705			−0.9870
			(1.6572)			(1.6700)
Debt/GDP			−0.7026			−0.6187
			(0.5022)			(0.5396)
Expend/GDP			−0.4631			−0.1330
			(2.7290)			(2.7083)
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	1929	1803	1600	1862	1745	1548

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). First-stage estimates for estimates in Table 12. Working-age population mortality is constructed for males age 16–65. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2, 8 and 3. FE are country fixed effects. Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation

Table 14 2SLS second-stage results for adjusted working-age population mortality effects on cyclical log real GDP per capita

	(1) HP filter	(2) HP filter	(3) HP filter	(4) BK filter	(5) BK filter	(6) BK filter	(7) LDT	(8) LDT	(9) LDT
Deaths/1k	−0.0022*	−0.0029*	−0.0029*	−0.0023*	−0.0030**	−0.0026*	−0.0250***	−0.0314***	−0.0235***
	(0.0013)	(0.0016)	(0.0015)	(0.0012)	(0.0014)	(0.0014)	(0.0049)	(0.0055)	(0.0069)
WW1		−0.0048	0.0016		−0.0067	−0.0005		0.0188	0.0221
		(0.0057)	(0.0051)		(0.0056)	(0.0047)		(0.0419)	(0.0203)
WW2		−0.0117**	−0.0008		−0.0141**	−0.0017		−0.0533	−0.0818*
		(0.0052)	(0.0064)		(0.0065)	(0.0057)		(0.0537)	(0.0452)
Year ≥ 1946		−0.0160*	−0.0282***		−0.0160**	−0.0292***		−0.1823***	−0.3370***
		(0.0082)	(0.0078)		(0.0070)	(0.0065)		(0.0436)	(0.0639)
rSTIR		0.0000	0.0000		0.0000	0.0000		−0.0003	−0.0002
		(0.0000)	(0.0000)		(0.0001)	(0.0001)		(0.0004)	(0.0004)
Wheat price adj		0.0000	0.0000**		0.0000	0.0000**		0.0000***	0.0000***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Oil price adj		−0.0000**	−0.0000**		−0.0000*	−0.0000**		−0.0000***	−0.0000***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Invest/GDP			0.0742**			0.0903***			0.8567***
			(0.0321)			(0.0262)			(0.2604)
Cons/GDP			−0.0148			−0.0203*			−0.1829***
			(0.0116)			(0.0108)			(0.0686)
Export/GDP			−0.0139			−0.0116			−0.1336*
			(0.0089)			(0.0082)			(0.0759)
Debt/GDP			−0.0003			−0.0009			−0.1264***
			(0.0027)			(0.0021)			(0.0477)
Expend/GDP			0.0055			0.0060			0.4754***
			(0.0188)			(0.0169)			(0.1737)

Table 14 (continued)

	(1) HP filter	(2) HP filter	(3) HP filter	(4) BK filter	(5) BK filter	(6) BK filter	(7) LDT	(8) LDT	(9) LDT
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1929	1803	1600	1862	1745	1548	1929	1803	1600
K–P UnderID LM	9.263***	11.05***	9.622***	9.024***	10.88***	9.385***	9.263***	11.05***	9.622***
WeakIV *F* stat	49.14	160.4	58.71	45.17	152.7	54.09	49.14	160.4	58.71

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Working-age population mortality is constructed for males age 16–65 and adjusted in 1918 to remove the share of WW1 deaths as documented by Barro et al. (2020). HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2, 8 and 3. FE are country fixed effects. Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation. *K–P* statist is the Kleibergen and Paap (2006) robust LM statistic the null hypothesis that the model is not identified Weak IV *F*-stat is the Sanderson and Windmeijer (2016) *F*-statistic for the excluded instrument in the first stage

Table 15 OLS estimates: excess mortality effects on cyclical log real GDP per capita

	HP-filtered log GDP per capita			BK-filtered log GDP per capita		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Excess mortality among working-age males						
EM^M	−0.0021	−0.0041***	−0.0038***	−0.0023	−0.0042***	−0.0039***
	(0.0016)	(0.0006)	(0.0008)	(0.0016)	(0.0006)	(0.0007)
Panel B: Excess mortality among working-age population						
EM^P	−0.0024	−0.0041***	−0.0038***	−0.0028	−0.0054***	−0.0048**
	(0.0017)	(0.0006)	(0.0008)	(0.0023)	(0.0016)	(0.0019)
FE	Yes	Yes	Yes	Yes	Yes	Yes
$\boldsymbol{X}_1$	No	Yes	Yes	No	Yes	Yes
$\boldsymbol{X}_2$	No	No	Yes	No	No	Yes
N	1929	1803	1600	1862	1745	1548

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Excess mortality is constructed for working males aged 16–65 and the working-age population following Eq. 4. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2, 8 and 3. FE are country fixed effects, vector $\boldsymbol{X}_1$ includes dummies for the two world wars, the introduction of vaccines in 1946, the real short-term interest rate and exchange rate adjusted wheat and oil prices, and vector $\boldsymbol{X}_2$ includes the following shares of GDP: investment, consumption, exports, government expenditure and the debt-to-GDP ratio. Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation

Table 16 Robustness of main results to various time trends

	(1) HP filter	(2) BK filter	(3) HP filter	(4) BK filter	(5) HP filter	(6) BK filter	(7) HP filter	(8) BK filter
Male Deaths/1k (D^M)	−0.0059**	−0.0052**			−0.0054**	−0.0045**		
	(0.0024)	(0.0020)			(0.0025)	(0.0021)		
All Deaths/1k (D^P)			−0.0071**	−0.0061**			−0.0065**	−0.0054*
			(0.0032)	(0.0028)			(0.0033)	(0.0028)
WW1	0.0150	0.0107	0.0132	0.0091	0.0084	0.0043	0.0076	0.0035
	(0.0105)	(0.0089)	(0.0090)	(0.0076)	(0.0093)	(0.0083)	(0.0082)	(0.0074)
WW2	0.0019	0.0007	−0.0045	−0.0047	0.0058	0.0040	0.0014	0.0005
	(0.0068)	(0.0055)	(0.0072)	(0.0056)	(0.0064)	(0.0046)	(0.0063)	(0.0047)
Year ≥ 1946	−0.0185***	−0.0203***	−0.0228***	−0.0239***	−0.0160***	−0.0180***	−0.0195***	−0.0208***
	(0.0059)	(0.0047)	(0.0075)	(0.0060)	(0.0058)	(0.0046)	(0.0071)	(0.0058)
rSTIR	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Wheat price adj	0.0000	0.0000	−0.0000	−0.0000	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Oil price adj	0.0000	0.0000	0.0000	0.0000	−0.0000*	−0.0000**	−0.0000**	−0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Invest/GDP	0.0935***	0.1100***	0.0825***	0.1010***	0.1133***	0.1269***	0.1028***	0.1188***
	(0.0249)	(0.0210)	(0.0294)	(0.0238)	(0.0262)	(0.0217)	(0.0322)	(0.0258)
Cons/GDP	−0.0207*	−0.0265**	−0.0172*	−0.0235**	−0.0452***	−0.0557***	−0.0425***	−0.0535***
	(0.0124)	(0.0121)	(0.0104)	(0.0104)	(0.0162)	(0.0158)	(0.0152)	(0.0148)
Export/GDP	−0.0042	−0.0038	−0.0008	−0.0009	0.0136	0.0155	0.0158	0.0175
	(0.0066)	(0.0068)	(0.0083)	(0.0086)	(0.0094)	(0.0110)	(0.0124)	(0.0137)
Debt/GDP	0.0015	0.0000	0.0017	0.0002	0.0043	0.0025	0.0049	0.0030
	(0.0032)	(0.0030)	(0.0035)	(0.0033)	(0.0036)	(0.0033)	(0.0035)	(0.0032)

Table 16 (continued)

	(1) HP filter	(2) BK filter	(3) HP filter	(4) BK filter	(5) HP filter	(6) BK filter	(7) HP filter	(8) BK filter
Expend/GDP	0.0667**	0.0610***	0.0588**	0.0542**	0.0441*	0.0368	0.0301	0.0253
	(0.0264)	(0.0236)	(0.0237)	(0.0213)	(0.0260)	(0.0231)	(0.0221)	(0.0197)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trend	Yes	Yes	Yes	Yes	No	No	No	No
Country × Trend	No	No	No	No	Yes	Yes	Yes	Yes
Observations	1600	1548	1600	1548	1600	1548	1600	1548
K–P UnderID LM	6.861***	6.979***	8.261***	8.391***	6.702***	6.837***	7.846***	7.997***
WeakIV *F* stat	13.35	13.81	22.26	23.15	12.90	13.43	19.78	20.77

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). Working-age population mortality is constructed for males age 16–65. Trend is a single international linear trend for all series. Country × trend is a country-specific linear trend. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2, 8 and 3. FE are country fixed effects. SEs in parentheses clustered by country. *K–P* stat is the Kleibergen and Paap (2006) robust LM statistic the null hypothesis that the model is not identified Weak IV *F*-stat is the Sanderson and Windmeijer (2016) *F*-statistic for the excluded instrument in the first stage

Table 17 Robustness of main results to use of stronger pandemics only

	HP-filtered log GDP per capita			BK-filtered log GDP per capita		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2SLS estimates, working-age male mortality						
D^M	−0.0061***	−0.0064***	−0.0046***	−0.0062***	−0.0064***	−0.0042***
	(0.0018)	(0.0018)	(0.0013)	(0.0018)	(0.0017)	(0.0012)
Panel B: First-stage estimates						
Flu	1.0159***	1.0194***	1.0642***	0.9795***	0.9911***	1.0272***
	(0.2246)	(0.1843)	(0.2324)	(0.2193)	(0.1804)	(0.2302)
rK	7.459***	9.475***	8.883***	6.916***	9.330***	8.669***
F	$20.46^{\dagger}$	$30.58^{\dagger\dagger}$	$20.97^{\dagger}$	$17.28^{\dagger}$	$30.18^{\dagger\dagger}$	$19.92^{\dagger}$
Panel C: 2SLS estimates, working-age population mortality						
D^P	−0.0074***	−0.0073***	−0.0055***	−0.0076***	−0.0072***	−0.0051***
	(0.0024)	(0.0022)	(0.0019)	(0.0024)	(0.0021)	(0.0018)
Panel D: First-stage estimates						
Flu	0.8304***	0.8917***	0.8785***	0.8062***	0.8751***	0.8521***
	(0.1834)	(0.1127)	(0.1351)	(0.1795)	(0.1096)	(0.1340)
rK	7.346***	11.24***	10.81***	7.192***	11.13***	10.63***
F	$20.51^{\dagger}$	$62.65^{\dagger\dagger\dagger}$	$42.29^{\dagger\dagger\dagger}$	$20.18^{\dagger}$	$63.77^{\dagger\dagger\dagger}$	$40.42^{\dagger\dagger\dagger}$
FE	Yes	Yes	Yes	Yes	Yes	Yes
$\boldsymbol{X}_1$	No	Yes	Yes	No	Yes	Yes
$\boldsymbol{X}_2$	No	No	Yes	No	No	Yes
N	1929	1803	1600	1862	1745	1548

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). 2SLS Estimates in this table are comparable to those in Tables 2 and 3 but treat 1873–75, 1899–1900 and 1946 as non-pandemic years. Working-age population mortality is constructed for both sexes age 16–65. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2, 8and 3. FE are country fixed effects, vector $\boldsymbol{X}_1$ includes dummies for the two world wars, the introduction of vaccines in 1946, the real short-term interest rate and exchange rate adjusted wheat and oil prices, and vector $\boldsymbol{X}_2$ includes the following shares of GDP: investment, consumption, exports, government expenditure and the debt-to-GDP ratio. Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation. Wild restricted efficient bootstrap p-values in square brackets. F-statistic is the SW cluster-robust weak instrument F-statistic for excluding the pandemic instrument. We tested against the "worst-case" bias at the 5% level using the test for clustered standard errors following (Montiel Olea and Pflueger 2013). Rejection of the null hypothesis that our bias exceeds certain thresholds of the worst-case bias is indicated by the symbols: $^{\dagger\dagger\dagger} < 5\%$, $^{\dagger\dagger} < 10\%$, $^{\dagger} < 20\%$. Corresponding critical values are 37.42, 23.11 and 15.06

Table 18 Robustness of main results to the exclusion of the Spanish Flu years

	HP-filtered log GDP per capita			BK-filtered log GDP per capita		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2SLS estimates, working-age male mortality						
D^M	−0.0022	−0.0021	−0.0036***	−0.0019	−0.0021	−0.0032***
	(0.0029)	(0.0014)	(0.0012)	(0.0027)	(0.0013)	(0.0010)
Panel B: First-stage estimates						
Flu	0.6853***	1.1054***	0.9905***	0.6573**	1.0803***	0.9555***
	(0.2571)	(0.1066)	(0.1336)	(0.2721)	(0.1171)	(0.1396)
rK	4.309**	11.74***	10.52***	3.774*	11.23***	10.03***
F	7.104	$107.6^{†††}$	$54.95^{†††}$	5.835	$85.11^{†††}$	$46.86^{†††}$
Panel C: 2SLS estimates, working-age population mortality						
D^P	−0.0021	−0.0022	−0.0041***	−0.0018	−0.0022	−0.0036***
	(0.0028)	(0.0015)	(0.0014)	(0.0025)	(0.0014)	(0.0011)
Panel D: First-stage estimates						
Flu	0.7253***	1.0372***	0.8709***	0.7101***	1.0242***	0.8465***
	(0.2252)	(0.0864)	(0.1137)	(0.2412)	(0.0981)	(0.1214)
rK	5.180**	12.08***	10.51***	4.669**	11.58***	9.988***
F	10.37	$144.1^{†††}$	$58.65^{†††}$	8.669	$109^{†††}$	$48.60^{†††}$
FE	Yes	Yes	Yes	Yes	Yes	Yes
$\boldsymbol{X}_1$	No	Yes	Yes	No	Yes	Yes
$\boldsymbol{X}_2$	No	No	Yes	No	No	Yes
N	1900	1782	1588	1833	1724	1536

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Data sources: Jordà et al. (2017) and the Human Mortality Database (2020). 2SLS Estimates in this table are comparable to those in Tables 2 and 3 but drop years 1918–1920. Working-age population mortality is constructed for both sexes age 16–65. HP-filtered log GDP per capita uses smoothing parameter 6.25, Baxter King bandpass filter of the same uses parameters 2,8 and 3. FE are country fixed effects, vector $\boldsymbol{X}_1$ includes dummies for the two world wars, the introduction of vaccines in 1946, the real short-term interest rate and exchange rate adjusted wheat and oil prices, and vector $\boldsymbol{X}_2$ includes the following shares of GDP: investment, consumption, exports, government expenditure and the debt-to-GDP ratio. Standard errors in parentheses clustered by country are robust to heteroskedasticity and serial correlation. Wild restricted efficient bootstrap p-values in square brackets. F-statistic is the SW cluster-robust weak instrument F-statistic for excluding the pandemic instrument. We tested against the "worst-case" bias at the 5% level using the test for clustered standard errors following (Montiel Olea and Pflueger 2013). Rejection of the null hypothesis that our bias exceeds certain thresholds of the worst-case bias is indicated by the symbols: $^{†††}<5\%$, $^{††}<10\%$, $^{†}<20\%$. Corresponding critical values are 37.42, 23.11 and 15.06. This table is a summary of OLS and 2SLS regression results

Declarations

Conflict of interest The authors declare that they have no conflicts of interest to disclose.

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