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Influenza Pandemics and Macroeconomic Fluctuations in Recent Economic History[*]

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Abstract

COVID-19 and the associated economic disruption is not a unique pairing. Catastrophic health events including the Black Death and the Spanish Flu also featured major economic disruptions. This paper focuses on significant health shocks during 1870-2016 from a singular virus: influenza. Our analysis builds on a literature dominated by long-run analyses by documenting the causal impact of influenza pandemics on short-run macroeconomic fluctuations. We examine 16 developed economies combining the Jordà-Schularick-Taylor Macro History Database with the Human Mortality Database. Our results reveal important negative impacts. Further, we illustrate that these effects operate through different channels over time. Prior to vaccines, pandemic-induced mortality was responsible for economic contractions while modern flu-induced cycles appear to arise because of pandemic-induced consumption decreases.

JEL Classification: E32; I18

Keywords: Pandemics; Business Cycles; Mortality; Consumption; GDP Fluctuations

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1 Introduction

COVID-19 and the accompanying international economic disruption appear unprecedented to current observers. Yet, similar shocks have happened before and they will happen again. The short and long-run impacts of other considerable health shocks are well documented in historical case studies. The Black Death (1347-1352) was paired with a considerable economic disruption (Jedwab et al., 2021) and the Spanish Flu caused economic disaster in many developed countries (Barro et al., 2020; Barro and Ursúa, 2008).

For the past 150 years influenza has been a recurring source of disruption among developed economies. Yet, many influenza pandemics have received comparatively less attention in the literature even if they were characterized as serious health shocks. The careful observer will note that along with the Spanish Flu, most influenza pandemics appear to coincide with economic downturns. The Asian Flu (1957−58), for example, coincides with a major downturn in April of 1958 and the comparatively recent H1N1 flu accompanied a particularly slow recovery from the 2008 financial crisis. Because influenza eradication remains a distant goal, identifying the systematic economic impacts of influenza pandemics is an important empirical exercise. Rapid technological change and medical advancements since the nineteenth suggest scope for analysis of these relatively recent health shocks to inform macroeconomic stabilization policy

The current analysis examines influenza pandemic impacts on business cycle fluctuations in 16 developed countries from 1871-2016. Our contribution to the rapidly evolving pandemic literature[1] is two-fold. First, our analysis builds on a strong record of pandemic case studies by providing systematic cross-country evidence specific to the influenza virus. Our sample spans the most recent 150 years and thus, includes several less-studied health shocks. In focusing on influenza pandemics, we extend the analysis of Barro et al. (2020); Karlsson et al. (2014) and others who document macroeconomic impacts from the Spanish flu. Because we examine panel data, we also account for the unmeasured contextual factors described by Alfani (2021) that mediate pandemic effects. Second, whereas the majority of the literature examines long-term outcomes, such as economic growth, our emphasis is short-term macro-economic performance. The mechanisms whereby disease affects the economy are laid out in Bloom et al. (2021): short-run behavioural effects decrease consumption and reduce labour supply partly due to mortality. Our analysis follows directly from these insights.[2]

Identifying the economic effects of pandemics in historical data is challenging. Historical data are granular relative to modern data, being available annually rather than quarterly or monthly. Furthermore, pandemic severity varies across countries and by pandemic event. Alfani (2013) demonstrates the magnitude of a health shock is particularly important and may reveal economic consequences not evident in studies of pandemic timing alone. Understanding the underlying mechanisms is therefore important. Advancements in medical technology and living standards may have allowed pandemics to propagate differently over time. One might expect less excess mortality but stronger disruptions to consumer behaviour in more

[1]See the recent symposium on epidemic diseases in economic history forthcoming in the Journal of Economic Literature, available at: https://www.aeaweb.org/journals/jel/forthcoming.

[2]Specific to Influenza, Bloom et al. (2021) write that ". . . major outbreaks are likely to trigger strong behavioural policy-induced reductions in labour supply and consumption."

modern pandemics, for example. The data support this intuition, suggesting an important shift in the role of consumerism overlapping the discovery of vaccines circa 1946. Our analysis exploits this information to identify separate pandemic impacts before and after this turning point.

We estimate a simple model of short-term GDP fluctuations based on an augmented national accounting identity especially suitable for the aggregate data at hand.[3] Our results show that pandemics have important impacts on year-over-year GDP changes via effects on mortality and consumption expenditure. Two Stage Least Squares (2SLS) estimates identify pandemic impacts through their effects on these intermediaries, enabling our results to account for differential pandemic severity across countries and events. Our approach additionally addresses any endogeneity in the relationships between economic performance and mortality or consumption. This is an important consideration in any pandemic study since wealth may be a determinant of public health and thus mortality. Also, the circular nature of the economy means that consumption expenditure is also endogenous with respect to GDP.

2 Literature Review

A substantial literature details the contribution of both health and historical pandemics to economic events. Our focus on short-run effects situates the current analysis in a more sparse literature. Alfani and Murphy (2017), Alfani and Percoco (2019) and Jedwab et al. (2021) note that major pre-industrial events including the Black Death caused asymmetric economic shocks across European countries because of differences in population density and economic development. Results for the current COVID-19 pandemic also suggest important immediate effects (Baker et al., 2020). Our empirical approach is most similar to Barro et al. (2020), where the Spanish Flu mortality is shown to have decreased short-run real GDP per capita by 3% in regressions featuring health shock variables. In a review of empirical approaches, Bloom et al. (2021) 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 and draw important distinctions between wartime and non-wartime contractions. Their results suggest that the Spanish Flu was the fourth-worst contraction in recent history.[4]

The Spanish Flu receives particular attention in the literature. Karlsson et al. (2014) find little discernible effect on earnings but increased poorhouse rates and a reduced return to capital across Swedish regions. Garrett (2008, 2009) find that mortalities from this pandemic decreased the supply of manufacturing workers, increased the marginal products of labour and capital per worker and increased real wages in the US. Brainerd and Siegler (2003) argue US states with higher influenza mortality during the Spanish Flu era subsequently experienced higher per capita income growth rates. Beach et al. (2021) revisits the Spanish Flu's impact to provide lessons for COVID-19, noting deeper recessions in countries with higher influenza mortality in 1918.

[3] Alternative approaches using microeconomic data in a production function framework may be more suitable when the aim is estimating long-run growth, given the important complementarities between investments in health, fertility and other long-term outcomes (Bloom et al., 2019, 2021; Shastry and Weil, 2003; Weil, 2007).

[4] The two World Wars and the Great Depression are found to be more severe.

Our focus on short-run or business cycle effects differs from the larger literature on long-run impacts of health shocks (Acemoglu and Johnson, 2007; Barro, 2013; Bloom et al., 2004, for example). Pamuk (2007) argues that the great divergence in the economic growth of 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 slope of growth paths for ten major industrialized countries over the course of 100 to 125 years. Jordà et al. (2020) link pandemics and the natural rate of interest since the 14th century, finding that interest rate fall by about 1.5 percent for as much as twenty years afterwards since pandemics reduce labour relative to capital.

Pandemic effects on the macroeconomy manifest through several channels. Following the insights from Bloom et al. (2021) our approach will examine the two channels associated with short-run impacts: consumption and mortality. Baker et al. (2020) find these channels to be important for the COVID-19 pandemic and Eichenbaum et al. (2020) also consider consumption in their model of the interaction between economic decisions and rates of infection. They find that decisions to reduce work and consumption increase recession severity but reduce deaths. Grimm (2010) notes that mortality shocks induce expenses and income loss but also reduce the number of household consumption units. Given that flu pandemics effects differ across age cohorts, this latter point would particularly apply to the Spanish Flu which had high mortality amongst 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).

An important factor in the economic effects of a flu pandemic is the potential interplay between health status or health spending and economic growth. The literature demonstrates countercyclical mortality in the US and Europe (Ruhm, 2000; Toffolutti and Suhrcke, 2014), with persistent decreases in some health-negative behaviours such as binge drinking (Ásgeirsdóttir et al., 2016).The Preston curve illustrates bi-directional causality in any relationship between health status and economic growth. Fogel (1994) noted the positive long-run relationship between nutrition improvements, human health capital and economic growth, suggesting that health affects a nation's GDP. 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. (2018) 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 (eg. Flu pandemics) or non-communicable (eg. Cardiovascular, diabetes) and whether longer term effects on health will arise through life expectancy or infant mortality. (Bloom et al., 2018; Suhrcke and Urban, 2010).

Our identification strategy adopts these lessons and accounts for reverse causality. We use the exogenous timing of pandemics as instruments for changes in mortality and consumption expenditure. Since pandemic timing is arguably exogenous in annual data, our estimates should capture causal effects from pandemic induced changes to mortality and consumption. Our instrumental variables account for supply-side effects through mortality of the labour force and for demand-side effects through reduced consumption. Thus, our estimation strategy addresses concerns noted by Bazzi and Clemens (2013) that many instrumental variables for health status in macroeconomic data often have difficulty fulfilling exclusion restrictions. Indeed, it is difficult to imagine how pandemics affect short-run GDP fluctuations aside from these two channels when holding constant other standard macroeconomic variables.

3 Data

3.1 Economic Panel Data

The economic data used are from the Jordà-Schularick-Taylor Macrohistory Database, a comprehensive macro-financial panel dataset including 16 developed countries spanning the period 1870 to 2016 (Jordà et al., 2017). Countries are: Australia, Belgium, Canada, Denmark, Finland, France, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK, and the US.[5] These 16 countries are relatively similar in their development during the period of analysis and Deaton (2003) shows that all are found on the relatively flat portion of the Preston (1975) Curve. This homogeneity is important for our analysis because it suggests that our estimates will not be confounded by a systematic cross-country relationship between GDP and mortality.

Our analysis examines the year-over-year change in the index of real Gross Domestic Product per capita. Because the outcome variable ΔGDP is a difference, the analysis sidesteps concerns about unit roots common in macroeconomic series.[6] Further, the simple difference in GDP is a straightforward way to examine short-term fluctuations in GDP that might be expected following health shocks such as pandemics.

Consumption is the most important single component of GDP, accounting for close to two thirds of GDP in most developed countries (Attanasio, 1999). Short-term GDP fluctuations then, should depend heavily on consumer behaviour. Indeed, pandemics can be expected to affect consumption. Prior to online shopping, incapacitation or quarantine would invariably reduce the ability to spend disposable income. Further, concerns about employment stability would likely lead individuals to defer consumption in the short-run. A prominent example is the loss of 2.8 Billion USD by the Mexican tourism sector during H1N1 (Rassy and Smith, 2013). Thus, our analysis considers consumption expenditure to be one important mechanism by which a pandemic could affect year-over-year GDP fluctuations.

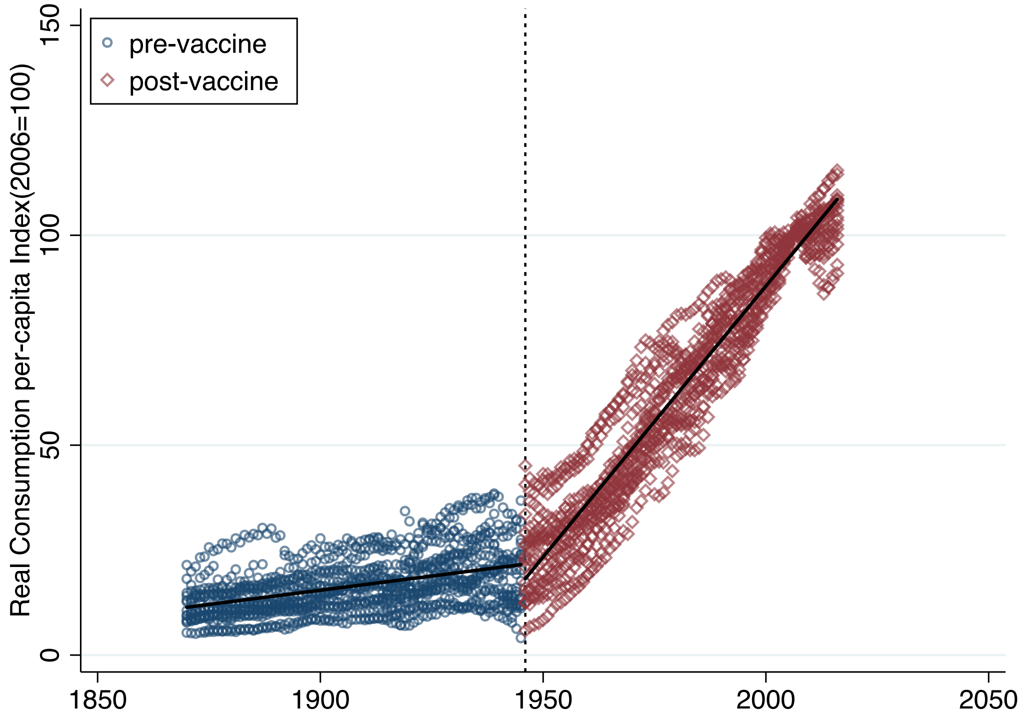
The data contain measures of real consumption expenditure per-capita, normalized to 100 during the year 2006. This line of expenditure differs considerably in our data, falling from an average of 46.3 during non-pandemic years to 37.7 in pandemic years. Examining the trends in this line of expenditure suggests a considerable change in behaviour around the time of the first influenza vaccine in 1946.[7] Figure 1 illustrates

[5] Macroeconomic data also available for Germany but are excluded due to unavailable mortality data throughout most of the series.

[6] Unit root tests, available upon request, confirm that ΔGDP is stationary. Our data series effectively start in 1871 because ΔGDP is not defined for 1870. GDP per-capita index = 100 in 2005.

[7] The influenza virus was isolated in the United States in 1933 and the first vaccine developed in 1938 and approved for military use in the United States in 1945 and civilian use in 1946 citepNVIC:20,CPP:20. It was not until 1960 that the US Surgeon General, in response to substantial morbidity and mortality during the 1957−58 pandemic, 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).

Figure 1: Real consumption per capita over time (pre and post-vaccine)



Data Source: Jordà et al. (2017). Vaccine date is 1946. Linear fit overlaid separately pre and post vaccine.

consumption patterns for these two separate periods. After years of very low growth, consumption trends upwards sharply starting in the mid 1940s. This apparent change suggests that the pandemic effects on GDP through consumption may be more salient in the post-WW2 and/or post-vaccine era. Indeed, evidence from economic history suggests that mass consumption expenditure becomes more important as an economic driver during the course of the twentieth century.

3.2 Pandemic Timing

Data on major influenza pandemics worldwide since 1870 is collected from Mamelund (2008) and is listed in Table 1. In the post-war period, pandemic declaration by the WHO can be considered particularly definitive. The flu pandemic over the period 1873 to 1875 was preceded by equine influenza in the United States and Canada that sickened horses (Judson, 1873). The loss of working animals in the 19th century had serious economic consequences in addition to any animal to human transmission. The 1889-92 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 19th century.[8] The 1918-20 Spanish Flu pandemic is the most famous and 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, p601). All these pandemics spread globally given the improvements in transportation over the course of the 19th and early 20th century.

[8]For a listing of serious pandemics see MPHOnline (2020).

Table 1: List of Major Influenza Events 1870 to 2016

Date	Event
1873-75	Equine Influenza & Possible Pandemic
1889-92	Flu Pandemic (Russian Flu)
1899-1900	Possible Pandemic
1918-1920	Spanish Flu
1946	Possible Pandemic
1957-58	Asian flu (H2N2 virus)
1968-70	Hong Kong Flu (H3N2 virus)
1977-78*	Possible pandemic (H1N1 virus)
2009-10	H1N1 Swine Flu

Sources: Judson (1873); Mamelund (2008); Centre for Disease Control and Prevention (2020). *Mamelund (2008) notes there is some debate over whether this was a pandemic. The CDC in the United States does note the outbreak and a vaccination program was implemented that prevented a pandemic.

In the post-World War II period, the spread of air travel made the rapid spread of pandemics an even greater concern. The 1957-58 Asian Flu and the 1968-70 Hong Kong flu were major events with global death tolls estimated at 2 million and 1 million respectively.

Differences in GDP fluctuations across pandemic timing are visible in the raw data. Table 2 presents the average change in real GDP in our 16 countries of analysis for flu pandemic and non-pandemic years. Fluctuations were generally more positive during non-pandemic years. This difference is statistically significant in the United States, United Kingdom, Norway, Canada, Spain and Finland. Only for Switzerland and Belgium is this difference meaningfully negative. This may reflect WWI effects that coincided with the Spanish Flu, which we address through various robustness checks.[9]

3.3 Mortality Data

Examining pandemic effects through mortality allows us to have an imperfect measure of the intensity of a pandemic as determined, in part, by improvements in public health and medical technologies which have reduced mortality due to infectious diseases during the years 1870-2016 (see Cutler et al. (2006) for a discussion of mortality determinants). Our mortality data come from the Human Mortality Database (HMD), where annual death rates are available by sex and age for most of the time series (Human Mortality Database, 2020).

We construct a Death Rate among Working Age Males ($DRWAM$) for all 16 countries (j) using deaths for males (MD) by age and male population ($MPOP$) by age (a):

$$DRWAM_{jt} = \left(\sum_{a=16}^{65} MD_{jt}(a) \right) \bigg/ \left(\sum_{a=16}^{65} MPOP_{jt}(a) \right) \tag{1}$$

[9] Switzerland, which remained neutral, likely experienced post-war boom differently than other European nations. A similar explanation does not automatically extend to Belgium, which was occupied during both conflicts.

Table 2: Average Annual change in GDP, 1870 to 2016

	Pandemic Years	**Non-Pandemic Years**	**Difference**
Australia	0.31	0.74	0.43**
Belgium	1.06	0.60	-0.47
Canada	-0.09	0.80	0.89***
Denmark	0.53	0.66	0.13
Finland	0.17	0.73	0.56*
France	0.64	0.65	0.01
Italy	0.23	0.64	0.4
Japan	0.50	0.74	0.24
Netherlands	0.70	0.66	-0.04
Norway	0.13	0.75	0.61***
Portugal	0.40	0.69	0.29
Spain	0.19	0.72	0.53
Sweden	0.52	0.77	0.25
Switzerland	0.83	0.62	-0.21
UK	-0.22	0.76	0.98***
USA	-0.16	0.82	0.97***
Total	0.36	0.71	0.35***

Data Source: Jordà et al. (2017). Difference is Non-pandemic year average minus Pandemic year average. t-Test for difference of means with H_0: Difference$>$ 0. *** p$<$0.01, ** p$<$0.05, * p$<$0.1

$DRWAM$ 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. This age group is also less affected by considerable medical advances during the first half of the 1900s that prolonged the lives of elderly or decreased infant mortality. Indeed, the average value of $DRWAM$ over our entire time series varies considerably with the onset of a pandemic, rising from 6.9 to 8.2 per 1,000 persons. We present scatterplots of $DRWAM$ against real GDP per capita in Appendix Figure A1, revealing the expected negative relationship in all countries.

Mortality data are not available for all countries in all years, although several countries do have full coverage. Sweden, France, Belgium, Denmark the Netherlands and Norway start from 1870, whereas Italy, Switzerland and Spain start from 1872, 1876, and 1908, respectively. The macroeconomic series also have breaks. Several European countries are missing war years, and there are several occasional years where covariates in our main specification are no available. Our main estimates employ the full unbalanced panel of 1599 observations described in Appendix Table A1. However, it will turn out that the results are robust to numerous restrictions, including estimation on only the 9 European countries with unbroken series spanning 1908-2016 and to estimation on a more comprehensive unbalanced panel of 1881 observations without the macroeconomic covariates that often limit available observations.

Another important consideration for the mortality data is the coinciding events of WW1 and the Spanish Flu. Barro and Ursúa (2008)) note that war contractions during our period of analysis are more than twice as large as non-wartime contractions among OECD countries. Thus, it is important to ensure our estimates are not unduly influenced by WW1. We provide additional estimates using mortality series that are adjusted by the ratio of pandemic to war deaths reported in Barro et al. (2020). It will turn out that our results are largely unchanged.

4 Model and Estimates

Our model supposes that the short-run growth in GDP depends on several factors. Country-specific fixed factors including geography, political institutions and endowed natural resource wealth, $\boldsymbol{J}$, as well as particularities of the period in time $\boldsymbol{T}$, both contribute to differences in national income across countries and over time, respectively. Further, GDP fluctuations in the short-run depend on expenditure and on production, as suggested by the standard national accounting identity. Expenditure, all of which may vary in the short-run, is decomposed into Consumption expenditure C, the largest component, and other components including government expenditure contained in the vector $\boldsymbol{Y}$. Production in the short-run depends only on Labour L,[10] which can be measured as the size of the labour force if we assume homogeneous workers and contract hours.

Equation (2) illustrates our model of short-run changes in GDP:

$$\Delta GDP_{jt} = f(\boldsymbol{T}, \boldsymbol{J}, \boldsymbol{Y}, C, L) \tag{2}$$

The model suggests that, conditional on $\boldsymbol{Y}$, $\boldsymbol{T}$ and $\boldsymbol{J}$, pandemics can be expected to have their impact on the economy solely through their effects on production via the available labour supply and on expenditure through consumption behaviour. These two channels are precisely those outlined the recent review of empirical approaches to measuring macro-effects of disease in Bloom et al. (2021). Short-run impacts are expected to manifest in reduced labour supply and consumption expenditure through mortality through changes in consumer behaviour.[11] The latter effect can arise through curtailment of social freedoms as well as through precautionary saving by consumers. The raw data at hand suggest these two channels are indeed important and further supports our modeling decisions. Appendix Figure A2 illustrates that, on average, sudden drops in GDP coincide with drops in consumption and spikes in mortality at the onset of pandemics.

The model equations (3) and (4) illustrate the former channel. The labour supply available, L, to contribute to economic output depends on the working age population, events in time such as the world wars and country-specific fixed factors including institutional environment and so forth. Thus, the working age population is modelled as function of mortality rates, D, which are directly influenced by some flu pandemics, P^O. Modelling the working age population as a function of mortality may imperfectly reflect the extent of associated labour supply reductions from morbidity, with its associated quarantine and recovery periods. Our empirical approach measures the local average treatment effect of mortality rates, suggesting

[10] The assumption that capital is fixed in the short-run is standard in basic models of the macroeconomy.

[11] Bloom et al. (2021) notes that uncertainty in the short-run will also manifest itself through these two channels.

that our estimates of the overall possible effects are, if anything, conservative estimates.

$$L_{jt} = h(D, \boldsymbol{T}, \boldsymbol{J}) \tag{3}$$

$$D_{jt} = g(P^O, \boldsymbol{T}, \boldsymbol{J}) \tag{4}$$

$$C_{jt} = k(P^N, \boldsymbol{T}, \boldsymbol{J}) \tag{5}$$

In equation (5), the model accounts for the possibility that some pandemic events, P^N, affect consumption by decreasing shopping behaviour, and/or because of imposed changes to consumption possibilities including quarantine and retail closures.

We propose a just-identified two-stage empirical model based on the equations above. The structural equation, (6), estimates the impact of pandemic-induced mortality rates among working-age males ($DRWAM$) on short-run GDP fluctuations with the parameter β and the impact of pandemic-induced decreases in real consumption per capita ($rCONSpc$) on short-run GDP changes, θ.

$$\Delta GDP_{jt} = \alpha_j + \beta DRWAM_{jt} + \theta rCONSpc_{jt} + \boldsymbol{Y'}_{jt}\gamma + \delta W_{jt} + t + u_{jt} \tag{6}$$

Covariates are chosen to reflect the basic model above. These include country-specific fixed effects (α_j) and important time-series controls. The former is expected to address institutional differences across countries and the latter, which include linear and quadratic time variables and binary war variables, will capture trends in macroeconomic growth and consumption and the non-linear effects of the two world-wars W_{jt}.[12] Non-consumption expenditure components of GDP from the national accounting identity are included in the vector $\boldsymbol{Y}_{jt}$, along with the real short-term interest rate. Investment, for example, enters our model as a control variable. Thus, we account for its effects on GDP, though we do not identify pandemic impacts that propagate through investment fluctuations as capital investment is unlikely to vary significantly in the short-run. Bloom et al. (2021) suggest that impacts on physical capital, human capital through education, and structural changes comprise long-run impacts that would be captured only through a multisector growth model similar to Kuhn and Prettner (2016). The empirical record supports this modeling decision: short-run stock market effects of the Spanish Flu were relatively inconsequential in the US and UK (Beach et al., 2021; Velde, 2020).

Death rates and consumption, which may each be partly endogenous, are instrumented with separate indicators for major flu pandemics in the first stage equation. To address technological changes over time we separately examine pandemic effects for two broad eras. Older pandemics (P^O) provide exogenous variation in death rates prior to 1946, an era prior to influenza vaccines when mortality effects of pandemics were likely to be particularly strong. For example, this era captures the Spanish Flu, which was noted for its high death rate. Newer pandemics (P^N) comprise exogenous health shocks post 1946, the era in which consumption trends upward and thus when pandemics may have more substantial effects on consumer behaviour. First stage equations (7) and (8) are detailed below.

[12] It should also be noted that investment spending is affected by expectations and investment plans can be dramatically affected by a pandemic. However, given that ultimately consumption is the ultimate end of economic activity and requires productive investment and labour supply is an input into both consumption and investment activities, we believe that all the channels whereby a pandemic affects the economy is accounted for in our framework.

$$DRWAM_{jt} = \pi_j + \rho^O P^O_{jt} + \rho^N P^N_{jt} + \boldsymbol{Y'}_{jt}\gamma + \delta W_{jt} + t + u_{jt} \tag{7}$$

$$rCONSpc_{jt} = \pi_j + \rho^O P^O_{jt} + \rho^N P^N_{jt} + \boldsymbol{Y'}_{jt}\gamma + \delta W_{jt} + t + u_{jt} \tag{8}$$

Because both instruments are binary, our estimates amount to Wald estimates which identify the effect of the flu pandemic on GDP by comparing the correlation of $\Delta GDP_j t$ and mortality in periods with exogenous flu-induced mortality rates to periods without this shock. One limitation of pandemics as a source of exogenous variation is that they do not differ cross-sectionally reflecting the reality of a pandemic. By their nature, pandemics proliferate world-wide quickly and generally within the same calendar year, and even quarter. Thus, while we will be unable to examine the robustness of our estimates to year or decade dummies, we are nonetheless capturing pandemic variation in a suitable way.

Because our dependent variable is differenced, the error term can be expected to auto-correlate. Thus, we estimate all models with conservative standard errors that are clustered by country. This approach to inference is robust to within-country serial correlation

5 Results

We examine the reduced-form relationship relating exogenous pandemic timing directly to fluctuations in real GDP per capita to see the realized pandemic-GDP relationship over the historical period. As expected, the relationship is negative. Estimates suggest that fluctuations in Real GDP per capita fluctuations are on average 0.4 to 0.45 percentage points lower during pandemics since 1870,[13] a considerable effect since the mean year-over-year fluctuation is about 0.67 percentage points. Table 3 presents separate reduced form estimates with and without indicators for the two world wars in order to evaluate the importance of considering the overlap of WW1 with the particularly significant Spanish Flu pandemic during 1918. The similarity of the pandemic coefficients suggests a meaningful pandemic effect, even conditional on these wars. In column 3 we restrict the data to match our structural estimation sample by excluding observations with missing mortality rates. This strengthens the pandemic coefficient, however not by a statistically significant amount. Finally, in column 4 we deconstruct pandemics into two parts, reflecting the pre and post-influenza vaccine eras. Both point estimates remain negative, although only post-vaccine pandemics are statistically significant with our (conservative) cluster-robust inference. The smaller estimate for pre-1946 pandemics can be understood by appealing to the interpretation of reduced form coefficients as Intent To Treat (ITT) effects. These coefficients include the meaningful effects where pandemics manifested and the non-effects where they did not. Some pre-1946 pandemics, occurring in a less-globalized society, did not manifest as strongly in some countries.[14] Thus, while it appears that pandemic timing may be a somewhat more robust determinant of pandemic-induced economic fluctuations from 1946 onward, our 2SLS approach will

[13] Real GDP per capita is an index, with value 100 in the year 2005.

[14] Antràs et al. (2020) note that more global integration can either increase or decrease the range of parameters for which a pandemic occurs generating multiple waves of infection as opposed to a single wave in a closed economy.

Table 3: Reduced-form Estimates, Pandemics and real GDP fluctuations

	(1)	(2)	(3)	(4)
	Δ rGDP$_{pc}$	Δ rGDP$_{pc}$	Δ rGDP$_{pc}$	Δ rGDP$_{pc}$
Pandemic (All)	-0.399***	-0.394***	-0.445***	
	(0.111)	(0.104)	(0.125)	
Pandemic$\geq$ 1946				-0.623***
				(0.148)
Pandemic $<$ 1946				-0.040
				(0.085)
INV/GDP	6.138***	6.022***	5.462***	6.213***
	(1.401)	(1.354)	(1.379)	(1.327)
EXPORT/GDP	0.206	0.224	0.268	0.148
	(0.329)	(0.341)	(0.414)	(0.316)
rSTIR	0.004	0.004	0.005	0.004
	(0.002)	(0.002)	(0.004)	(0.002)
DEBT/GDP	-0.301***	-0.316***	-0.464***	-0.311***
	(0.099)	(0.101)	(0.137)	(0.101)
EXPEND/GDP	1.210**	1.225*	1.470*	1.175*
	(0.541)	(0.615)	(0.705)	(0.591)
WW1		-0.310**	-0.462***	-0.342**
		(0.137)	(0.152)	(0.141)
WW2		0.037	-0.038	0.055
		(0.373)	(0.351)	(0.375)
Trend	0.002	0.002	0.001	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-4.657	-4.521	-2.218	-5.905
	(3.454)	(3.720)	(3.799)	(3.688)
Country FE	YES	YES	YES	YES
N	1,796	1,796	1,599	1,796
R^2	0.143	0.144	0.116	0.149

Data Sources: Jordà et al. (2017) and Human Mortality Database (2020). OLS estimates of the reduced form model. Clustered standard errors in parentheses are robust to arbitrary serial correlation by country. $rSTIR$ is the short-term real interest rate, coefficient scaled $\times$100. Time trend is linear. *** p<0.01, ** p<0.05, * p<0.1.

identify pandemic effects where they occurred by accounting for their differential influence on mortality and consumption.

We now consider the full empirical model examining the pandemic effects on year-over-year changes in GDP via effects on consumption and mortality − the two primary channels by which disease can be expected to have short-run macroeconomic impacts Bloom et al. (2021). By examining effects through these two channels we are identifying causal effects that result from the differential strength of pandemics according to their ability to propagate through various economies. The results of this model show the effect of pandemic-induced economic influences and thus are applicable to policymakers interested in mitigating the adverse economic effects of pandemics. Put another way, since our instruments are binary indicators for pandemic timing, the coefficients measure Local Average Treatment Effects (LATEs) specific to pandemic-induced mortality and pandemic-induced decreases in consumption expenditure.

Model (1) in Table 4 presents 2SLS estimates of equations (6−8). Measured effects in the second stage equation show that Pandemics have significant effects on GDP through mortality and consumption behaviour. Increases in working-age male death rates have a negative impact. The coefficient suggests that each percentage point increase in the working age male death rate has a causal negative impact the year-over-year change in real GDP per capita of about 0.84 percentage points.[15] The positive coefficient on consumption suggests that consumption decreases also have a negative causal impact on short-run real GDP changes. Each percentage point increase in the consumption per-capita index generates a change of about 0.16 percentage points. Thus, pandemics may be important contributors to business cycles through these two economic channels. Standard t-tests using our cluster-robust standard errors suggest that the coefficients are statistically significant (at the 5% level).

Our confidence in the effects measured above is justified only if instruments are strong. Fortunately, our instruments seem strong enough with first-stage estimates suggesting that neither instrument is weak.[16] However, in light of the leniency of the $F > 10$ rule noted by Lee et al. (2020) we employ additional tests to support the strength of our instruments.[17] We conduct underidentification tests for each of the first-stage regressions and for the structural model using Sanderson and Windmeijer (2016) F-statistics for and the Kleibergen and Paap (2006) robust rk statistic, respectively. We reject underidentification at the 1% level in all cases. Further, we report the corresponding Sanderson Windmeijer F-statistics and Kleibergen and Paap F-statistics for weak instruments. The robust first-stage F-statistics are moderate in size (26 and 27). However, critical values suitable for formal hypothesis testing in our case remain an ongoing area of research. We follow the literature (Baum et al., 2007) and employ the Stock et al. (2005) critical values with full acknowledgment that they are, at best, suggestive in the absence of iid errors. Bazzi and Clemens (2013) further suggest computing p-values to reject the null hypothesis of actual t-test sizes due to instrument strength that are associated with a nominal 5% t-test. We implement this suggestion using replication files

[15] $DRWAM$ is measured from 0 to 100 so that the raw coefficient represents a 1% change in death rates.

[16] The signs of the coefficients for exogenous pandemic indicators are also as expected: pandemics correlate negatively with de-trended real consumption per capita and positively with the mortality rates among working-age males. Post-vaccine pandemics do not have a measurable relationship with mortality, which is sensible given that broad flu vaccination programs have reduced the likelihood of severe pandemics.

[17] Lee et al. (2020) provide suggested practice for inference in the case of just-identified models with a single instrument and a single endogenous variable, which is not the case for the current analysis.

Table 4: Pandemics and real GDP fluctuations in 16 Advanced Economies

	(1)			(2)	(3)			(4)
	2SLS			OLS	2SLS			OLS
VARIABLES	ΔrGDP$_{pc}$	DRWAM	rCON$_{pc}$	ΔrGDP$_{pc}$	ΔrGDP$_{pc}$	DRWAM	rCON$_{pc}$	ΔrGDP$_{pc}$
DRWAM	-0.838**			-0.041***	-0.895**			-0.041***
	(0.338)			(0.015)	(0.355)			(0.015)
rCON$_{pc}$	15.872***			0.020	16.896***			0.029
	(5.639)			(0.374)	(6.017)			(0.376)
INVEST/GDP	13.093***	-4.936*	-0.727***	5.168***	13.535***	-4.940*	-0.727***	5.153***
	(4.217)	(2.732)	(0.228)	(1.479)	(4.586)	(2.734)	(0.228)	(1.490)
EXPORT/GDP	-4.088*	0.250	0.283***	0.313	-4.351*	0.251	0.283***	0.320
	(2.192)	(0.536)	(0.098)	(0.480)	(2.354)	(0.535)	(0.098)	(0.480)
rSTIR	0.008*	-0.000	-0.000*	0.005	0.008*	-0.000	-0.000*	0.005
	(0.005)	(0.002)	(0.000)	(0.004)	(0.005)	(0.002)	(0.000)	(0.004)
DEBT/GDP	-1.273**	-0.053	0.049	-0.449***	-1.332**	-0.054	0.049	-0.452***
	(0.617)	(0.422)	(0.039)	(0.123)	(0.656)	(0.422)	(0.039)	(0.123)
EXPEND/GDP	11.963**	8.232***	-0.229*	1.728**	12.727**	8.241***	-0.230*	1.760**
	(4.877)	(3.111)	(0.136)	(0.784)	(5.275)	(3.118)	(0.137)	(0.783)
WW1	3.064**	3.607***	-0.035	-0.336**	3.257**	3.601***	-0.034	-0.355**
	(1.361)	(1.205)	(0.029)	(0.148)	(1.459)	(1.204)	(0.029)	(0.148)
WW2	2.453**	0.642	-0.121***	0.043	2.630**	0.644	-0.122***	0.053
	(1.042)	(0.935)	(0.025)	(0.337)	(1.121)	(0.935)	(0.025)	(0.338)
TREND	-0.209***	-0.083***	0.009***	-0.002	-0.195***	-0.079***	0.009***	0.011
	(0.073)	(0.007)	(0.000)	(0.005)	(0.073)	(0.006)	(0.000)	(0.009)
TREND^2					-0.281**	-0.037	0.002	-0.130
					(0.116)	(0.054)	(0.003)	(0.083)
Pandemic <1946		2.041***	0.111***			2.041***	0.111***	
		(0.704)	(0.018)			(0.703)	(0.018)	
Pandemic ≥1946		0.071	-0.037***			0.065	-0.037***	
		(0.069)	(0.007)			(0.070)	(0.007)	
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
N	1,599	1,599	1,599	1,599	1,599	1,599	1,599	1,599

	KP rk Stats	**SW stats**			**KP rk Stats**	**SW stats**	
F UnderID	10.01***	28.94***	28.08***		9.804***	27.15***	26.21***
F Weak IV	13.09	26.98	26.18		12.33	25.29	24.42
(p-value): t-test size>10%	0.331	0.0036	0.0050		0.388	0.0072	0.0101
(p-value): t-test size>15%	0.0255	<0.0001	<0.0001		0.0361	<0.0001	<0.0001
(p-value): t-test size>20%	0.0047	<0.0001	<0.0001		0.0073	<0.0001	<0.0001
(p-value): t-test size>25%	0.0014	<0.0001	<0.0001		0.0023	<0.0001	<0.0001

Data Sources: Jordà et al. (2017) and Human Mortality Database (2020). Countries include Australia, Belgium, Canada, Denmark, Finland, France, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States. 2SLS estimates of equations (6−8). Clustered standard errors in parentheses are robust to arbitrary serial correlation by country. $DRWAM$ is the annual death rate per 1,000 population among males age 16-65. $rCONpc$ is an index of real consumption per capital, normalized to 100 in the year 2006. $rSTIR$ is the short-term real interest rate, coefficient scaled ×100. F-statistics for Underidenfitication and Weak Instruments in second-stage columns are Kleibergen and Paap (2006) robust rk statistics for the full model. F-statistics for Underidenfitication and Weak Instruments in first-stage columns are Sanderson and Windmeijer (2016) multivariate statistics for individual regressors. Underidentification test statistics are distributed χ^2. For these and for coefficient t-tests, $p < 0.01^{***}; p < 0.05^{**}; p < 0.1^{*}$. p-Values for weak instrument tests with non-i.i.d. errors are the subject of ongoing research and are presently unavailable to the research community. We follow Bazzi and Clemens (2013) and compute p-values for maximal test sizes based on Stock et al. (2005) critical values, acknowledging the limits of the conclusions drawn from these.

provided by the authors and find that we can reject the null hypothesis of actual t-test sizes exceeding 10% at the 1% level. Thus, we are confident that our estimates are significant at the 10% level, and likely at the 5% level.

Model (2) in Table 4 presents OLS estimates for comparison. These results suggest much weaker correlation between mortality and GDP when not isolating pandemic-induced changes. A weaker measured relationship is expected given the potential endogeneity of mortality. Other factors present in the error term, such as public health expenditure, likely correlate positively with GDP and death rates positively biasing the OLS estimates. For example, countries experiencing short-run GDP growth and countries experiencing higher mortality rates may spend differently on public health or pandemic countermeasures. Further, there is essentially no correlation observed in the OLS estimates between the short-run GDP fluctuations and consumption. Since these estimates do not isolate pandemic-induced consumption changes, the covariates are free to correlate. Decreases in GDP may not necessarily affect consumer spending when holding constant investment, interest rates and exports. It is also true that, in the absence of pandemic-induced constraints on the retail sector, a considerable portion of consumption spending is income inelastic (food, shelter, clothing).

We also provide estimates conditional on a quadratic trend in light of Figure 1, which suggests that the trend in real consumption per capita is not linear when considering the entire series. 2SLS estimates are presented in model (3) of Table 4. Results are very similar, and if anything, the measured effects are slightly stronger. Model (4) presents a comparable OLS estimation, which again is similar to OLS estimates of Model (2) that has a linear trend.

Our findings are robust to several important data-related considerations. First, we consider more carefully the 1918 overlap of WW1 overlaps with the Spanish Flu. WW1 was among the most significant contractions in the period of analysis and the Spanish Flu was arguably the largest mortality event. Although we control for WW1 timing in all our specifications, we cannot be certain that we are accounting for these separate sources of mortality during this crucial year. Fortunately, Barro et al. (2020) produces separate death rates for the Spanish flu and for WW1 during this year for all countries in our data except for Finland. We generate adjusted 1918 data using the ratio of these flu to war mortality rates and present estimates using this adjusted mortality instrument in the first three columns of Table 5. The point estimate increases considerably in size.

We also address missing data considerations with two additional robustness checks. In the middle three columns we restrict our analysis to a set of 9 countries for which mortality data are available prior to 1908, all of which are European. This change results in a much smaller sample but returns a causal estimate quite close to those in table 4, if not slightly larger. Finally, we present results without covariates in the final three columns. In light of the exogenous nature of pandemic timing, covariates may not be strictly necessary for identification. The primary effect in our case is the inclusion of an additional 290 observations that are lost due to missing covariates in the JST data. Including these years decreases the size of both $\hat{\beta}$ and $\hat{\theta}$ considerably. The likely reason is that many missing datapoints coincide with war years in Europe and other periods of instability, when macroeconomic conditions may have been poor for reasons other than influenza pandemics. Nevertheless, all specifications we estimated found robust negative effects of pandemic-induced

Table 5: Robustness Checks for Pandemics and real GDP fluctuations

	Adjusted 1918 Death Rates			9 Nations with Data <1908			No Control Variables		
	ΔrGDP$_{pc}$	DRWAM	rCON$_{pc}$	ΔrGDP$_{pc}$	DRWAM	rCON$_{pc}$	ΔrGDP$_{pc}$	DRWAM	rCON$_{pc}$
DRWAM	-1.177**			-0.919***			-0.321**		
	(0.464)			(0.296)			(0.160)		
rCON$_{pc}$	15.932***			21.584***			7.002***		
	(5.756)			(7.774)			(2.716)		
INV/GDP	11.872***	-4.577*	-0.728***	13.225*	-8.216***	-0.722**			
	(4.312)	(2.701)	(0.228)	(6.800)	(2.801)	(0.315)			
EXPORT/GDP	-3.654*	0.550*	0.282***	-5.072	0.283	0.253*			
	(2.039)	(0.332)	(0.098)	(3.247)	(0.465)	(0.131)			
rSTIR	0.008*	-0.000	-0.000*	0.008*	0.001	-0.000			
	(0.005)	(0.001)	(0.000)	(0.004)	(0.003)	(0.000)			
DEBS/GDP	-1.275**	-0.038	0.049	-1.615	-0.036	0.050			
	(0.612)	(0.414)	(0.039)	(1.050)	(0.710)	(0.044)			
EXPEND/GDP	14.441**	7.926***	-0.229*	18.146**	14.208***	-0.169			
	(6.804)	(2.894)	(0.136)	(8.188)	(4.026)	(0.153)			
Pandemic <1946		1.468***	0.113***		1.892***	0.080***		1.930***	0.096***
		(0.349)	(0.019)		(0.719)	(0.012)		(0.412)	(0.017)
Pandemic ≥1946		0.080	-0.037***		0.078	-0.029***		0.013	-0.065***
		(0.065)	(0.007)		(0.102)	(0.009)		(0.094)	(0.007)
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Quad. Trend	YES	YES	YES	YES	YES	YES	YES	YES	YES
War dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	1,599	1,599	1,599	1,039	1,039	1,039	1,881	1,881	1,881
	KP rk Stats	**SW stats**		**KP rk Stats**	**SW stats**				
F UnderID	8.966***	21.87***	22.25***	5.268**	16.18***	14.08***	10.42***	43.94***	66.19***
F Weak IV	9.906	20.37	20.73	6.215	14.24	12.40	14.33	41.08	61.88
(p-value): t-test size>10%	0.594	0.043	0.038	0.880	0.255	0.383	0.249	0.000	0.000
(p-value): t-test size>15%	0.101	0.001	0.001	0.370	0.015	0.035	0.014	0.000	0.000
(p-value): t-test size>20%	0.028	0.000	0.000	0.166	0.002	0.007	0.002	0.000	0.000
(p-value): t-test size>25%	0.011	0.000	0.000	0.088	0.001	0.002	0.001	0.000	0.000

Data Sources: Jordà et al. (2017) and Human Mortality Database (2020). 2SLS estimates of equations (6−8). Clustered standard errors in parentheses are robust to arbitrary serial correlation by country. Adjusted 1918 death rates remove WW1-related deaths by adjusting HMD data for the ratio of ww1 to pandemic deaths reported by Barro et al. (2020). 9 Nations with data $<$ 1908 restricts the sample to CH, DK, ES, FI, FR, IT, NL, NO and SE. $DRWAM$ is the annual death rate per 1,000 population among males age 16-65. $rCONpc$ is an index of real consumption per capital, normalized to 100 in the year 2006. $rSTIR$ is the short-term real interest rate, coefficient scaled $\times$100. F-statistics for Underidenfitication and Weak Instruments in second-stage columns are Kleibergen and Paap (2006) robust rk statistics for the full model. F-statistics for Underidenfitication and Weak Instruments in first-stage columns are Sanderson and Windmeijer (2016) multivariate statistics for individual regressors. Underidentification test statistics are distributed χ^2. For these and for coefficient t-tests, $p < 0.01^{***}; p < 0.05^{**}; p < 0.1^{*}$. p-Values for weak instrument tests with non-i.i.d. errors are the subject of ongoing research and are presently unavailable to the research community. We follow Bazzi and Clemens (2013) and compute p-values for maximal test sizes based on Stock et al. (2005) critical values, acknowledging the limits of the conclusions drawn from these.

consumption decreases and pandemic-induced mortality rates on year-over-year changes in real GDP.

6 Discussion and Conclusion

Our results suggest that influenza pandemics have indeed had non-trivial effects on GDP fluctuations over the last 150 years. These effects have occurred via supply-side mortality effects reducing labour supply of working age males as well as demand-side effects on consumption expenditure as consumer activity contracts. However, these two effects differ in their intensity based on time. In the late nineteenth century and early twentieth century, given the absence of influenza vaccines, it would appear that the mortality effects were predominant. Coming forward into the twentieth century and into the post-world War II era, the increasing importance of consumption activity as well as the presence of influenza vaccines appears to have reduced the supply-side impact of pandemics but amplified the demand-side effects via consumption.

Stronger impacts in more recent history are worth further consideration. One might argue that information travels faster in the post-World War II period resulting in more drastic changes in expectations regarding both investment and consumption. However, the speed of communication in the 19th century approaches that of the twentieth century after the laying of a reliable transatlantic cable in 1865. By 1900 there was instantaneous communication via submarine cables around the world. It is more likely that virus transmission during a pandemic was more rapid after 1945 given increasing population density as well as the age of jet travel. Since these changes coincide roughly with the advent of broad-based vaccine programs, our pre- and post- vaccine era is best interpreted in light of broader technological change that includes medical innovation. In any case, the data suggest this period as an important break in consumer behaviour.

One may also argue that part of the stronger impact may be partly due to the fact that with economic growth, later twentieth and early 21st century societies and economies are much wealthier and more complicated and more prone to economic disruption. Modern economies have relatively larger service sectors, which certainly appear to have taken a major blow during the COVID-19 pandemic. As well, Bloom et al. (2021) notes that pandemic shocks induce saving in lieu of consumption and savings effects may simply be more significant in wealthier modern societies.

The results presented here may help explain three factors behind the growing severity of the COVID-19 pandemic. First, at the time of writing there was no vaccine widely available, making this pandemic somewhat more similar to those of the mid twentieth century. As of February 1st, 2021, the pandemic has resulted in nearly 105 million infections worldwide and about 2.3 million deaths Worldometer (2021). Second, government-imposed lockdowns have led to major supply-side disruptions including shocks to the integrated global production chain. Third, consumption patterns characterizing modern economies are dominated by services that have been particularly prone to disruption, including food, accommodation, retail and travel. The corresponding macroeconomic decline has been considerable. In the United States, second quarter GDP fell by 9.1 percent with an annualized second quarter contraction equivalent to 32.9 percent (Casselman, 2020). The Eurozone saw a second quarter drop of 12.1 percent. These six-month contractions are record drops not seen since the Great Depression, where similar sized contractions of real occurred over a three to four-year period. Placing global economies back on track will require countering each of these three disruptive forces and the linchpin will have likely be an effective vaccine or treatment.

The effects we measure represent those manifesting through two channels that the literature has found most relevant to macroeconomic cycles. Yet, other forms of manifestation are possible. Measuring the medium and long-term impacts, including the public health responses to these pandemics, likely require the estimation of structural macro-epidemiological models using microdata not currently at-hand. This remains an important avenue for future research, as does the ongoing analysis of the COVID-19 pandemic that is gathering steam in the literature.

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A Appendix

Table A1: Available Data by Country

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	
US	1870-2016			1933-2016	

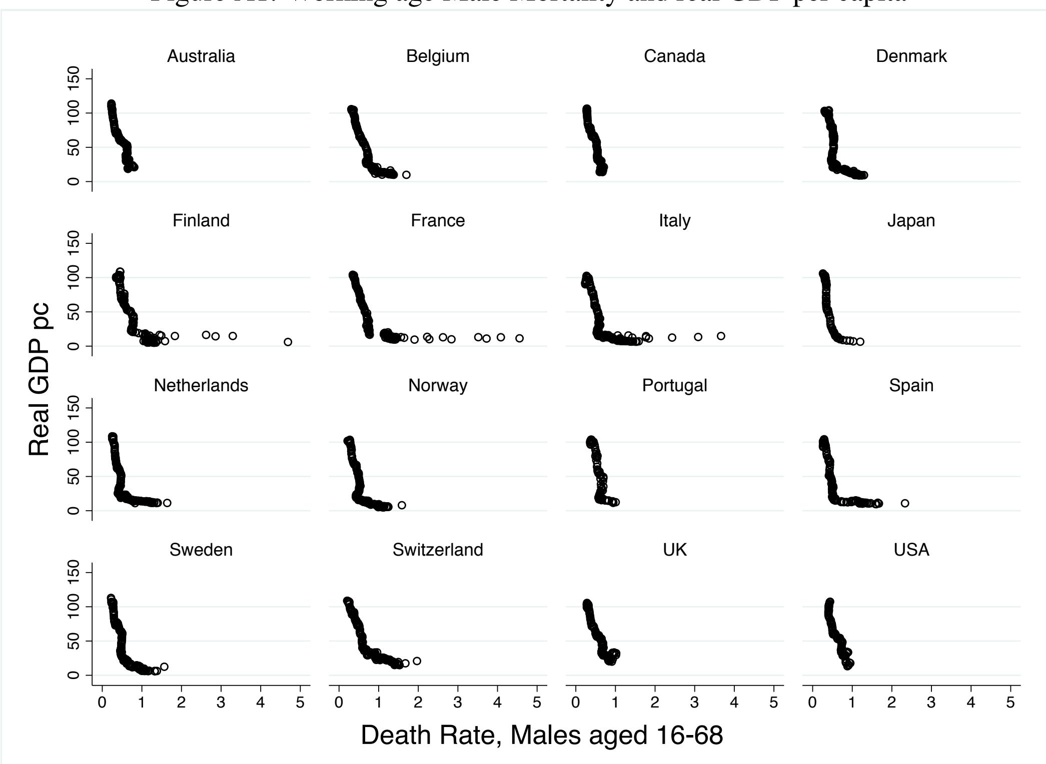
Data Sources: Jordà et al. (2017) and Human Mortality Database (2020).

Table A2: Major Economic Contractions, United States Economy

Peak Month	**Trough Month**	**Months Contraction**
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
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

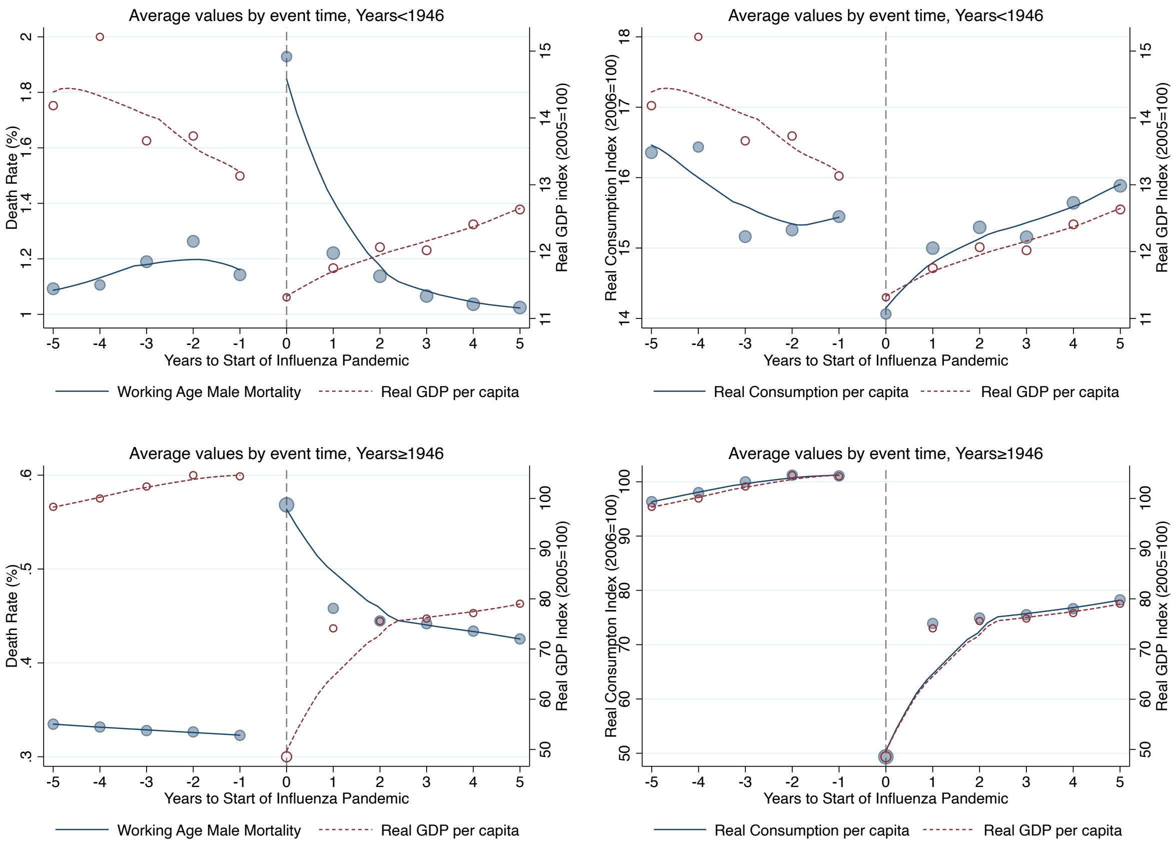
Source: NBER https://www.nber.org/cycles.html

Figure A1: Working age Male Mortality and real GDP per capita



Data Source: Jordà et al. (2017) and Human Mortality Database (2020). Real GDP per capita is an index normalized to 100 in the year 2005. Working-age male Death rate ($DRWAM$) calculated as in equation (1).

Figure A2: Discontinuities in Mortality and Consumption vs Real GDP at pandemic onset.



Sources: Author's estimates from the Jordà et al. (2017) and Human Mortality Database (2020). Data for each pandemic event are re-centred around onset of pandemic (between years -1 and 0). 11-Year time window ensures no overlap in pandemics. Averages across all countries and all available pandemics, separately for the era prior to 1946 (top panels) and the era from 1946 onward (bottom panels). Scatterplot bubble size reflects weighting by the number of observations available for each years-to-start. Lines of best fit are local linear regression predictions using a bandwidth of 1 and an Epanechnikov kernel.