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ECONOMIC CONDITIONS AND MORTALITY:
EVIDENCE FROM 200 YEARS OF DATA

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ABSTRACT

Using data covering over 100 birth-cohorts in 32 countries, we examine the short- and long-term effects of economic conditions on mortality. We find that small, but not large, booms increase contemporary mortality. Yet booms from birth to age 25, particularly those during adolescence, lower adult mortality. A simple model can rationalize these findings if economic conditions differentially affect the level and trajectory of both good and bad inputs into health. Indeed, air pollution and alcohol consumption increase in booms. In contrast, booms in adolescence raise adult incomes and improve social relations and mental health, suggesting these mechanisms dominate in the long run.

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The relationship between economic conditions and mortality is a subject of much debate. On the one hand, many historical studies conclude that economic growth has been the dominant factor in improved health over time (Fogel, 1994; Costa, 2015).[1] Recent studies using micro data also find that economic conditions in utero and early in life are associated with lower mortality later in life (Currie et al., 2009; Currie, 2011; Almond and Currie, 2011; Hoynes et al., 2016; Aizer et al., 2016). On the other hand, a significant body of evidence has found that improved economic conditions raise mortality in developed countries (Ruhm, 2000, 2003, 2005, 2007; Adda, 2016).[2] In fact studies show that recessions decrease mortality in the short term, but increase it in later years, for instance among the elderly (Coile et al., 2014).

The dichotomy between studies showing favorable and unfavorable effects of economic booms raises several issues. First, how are these two facts related – how do economic conditions influence health in the short and long run? Second, at what ages are economic conditions particularly salient for health and why? Third, to what extent can policy mediate the impact of the economy on health?

In this paper we examine these questions by studying how unexpected changes in GDP affect the lifetime mortality of cohorts who experience shocks at different points in life. We first show theoretically the ambiguity of the link between economic conditions and mortality. The model treats health as a stock, the level of which determines mortality. Economic conditions affect mortality in several ways by changing the level and the trajectory of inputs that determine the stock of health. These inputs include basic resources such as food and medical care, health behaviors

[1]This is not without controversy. For instance, mortality did not in fall in England during the industrial revolution (See Cutler et al., 2006).

[2]There are some exceptions to this. For instance, mortality appears to be less procyclical in recent time periods in the United States (Ruhm, 2015), and there is some debate about whether mortality rises or falls in big recessions (Brenner, 1979; Granados and Roux, 2009).

like smoking and exercise; and environmental factors such as pollution. Economic fluctuations also have long-term effects on mortality by influencing the composition of people who survive to older ages (selection).

To investigate these relationships empirically we match cohort life tables from 32 countries, compiled in the Human Mortality Database, to GDP data from various official sources. The data cover more than 100 birth cohorts and track their actual mortality over time. We identify unexpected shocks as deviations of GDP from its long term trend. We then examine how contemporary shocks, and shocks from birth to age 30, affect adult mortality.

We reach four principal findings. First, booms and busts have a non-linear contemporaneous effect on health. Small booms increase mortality (as in the Ruhm analysis); however, large recessions increase mortality and large booms decrease it, consistent with studies of the Great Depression (Brenner, 1979).

Second, adverse economic conditions at any point early in life significantly increase later adult mortality. Our results support the fetal origin hypothesis that economic conditions in utero are associated with mortality, but the magnitude is smaller than the effects of economic conditions around adolescence. The micro-level data explains why: earnings and other important lifetime inputs into health are more affected by shocks in adolescence than by shocks at birth.

Third, both pollution and alcohol consumption rise substantially in booms and seem to explain the harmful effects of expansions. Over the longer run, booms and busts also affect the path of income and other health inputs. More favorable early life conditions raise lifetime incomes, particularly for youth (Oreopoulos et al., 2012). Cohorts who are adolescents in good times are also more socially integrated and have better mental health as adults. In times and places with lower emissions of polluting agents, procyclical mortality tends to disappear.

Fourth, government spending appears to mitigate the effect of economic conditions on health, at least outside of major booms and busts. In countries with high levels of government spending as a share of GDP, both early life and contemporaneous economic conditions have smaller impacts on middle and late life mortality. But large shocks are more difficult to insure, explaining why there is no difference in the effects of large shocks for countries with high and low government expenditures.

Overall, the findings on the link between contemporaneous economic conditions and mortality is a balance between the positive impact of greater consumption and the negative impact of pollution resulting from more output. And the difference between short term and long term effects of recessions appears to be driven by how economic shocks affect the profile of these health inputs over time. These 'direct effects' on inputs are much stronger than any 'selection effects' from marginal survivors.

The closest analog to our paper is van den Berg et al. (2006), who examine the effects of economic conditions at birth on later life mortality in the Netherlands. By making use of newly available data covering a much larger set of countries and time periods, we show that their findings generalize to 32 countries, and we extend them to show that conditions up to age 25 matter, with the greatest effects in adolescence. We also investigate mechanisms and how policy influences the link between economic outcomes and mortality. Finally, we offer a theoretical framework and a set of empirical results which explain contradictory and heterogeneous findings in the prior literature.

II. Data

II.1 Human Mortality Database (HMD)

Mortality data are taken from the Human Mortality Database (HMD). The HMD contains detailed cohort life tables by age and gender in different years.[3] To understand the effects of economic conditions over the lifetime, we need populations with significant time series representation. Appendix Table A1 lists the 32 countries we study, all of which have with mortality data available prior to 1970.[4] The average number of years observed is 97.

Figure 1 shows mortality rates by age for four cohorts: those born in 1850, 1875, 1900, and 1925. In each case, we report the logarithm of the average mortality rate for men and women across countries. To approximate a 'world' population, we weight each observation by the country's population in the relevant years.

Log mortality is J-shaped in age: it is high at very young ages, falls rapidly and remains low from around age 10 to around age 40, and increases thereafter. In addition to being non-monotonic in age, mortality exhibits great variability during ages 10 to 40. For example, there is a spike in mortality for the 1875 and 1900 cohorts at the time of the Great Flu epidemic (1918) and a spike for the 1925 cohort at the time of World War II. Because mortality rates are low and variable, relationships between economic conditions and mortality are sensitive to time periods and exact ages examined in this age range. But past approximately age 40, the logarithm of mortality is linear with age, as noted by Gompertz (1825) nearly two centuries ago.

[3] A typical observation in the HMD is the number of deaths per 100,000, for men (women) born in a particular year in a particular country at some later age, along with the relevant population estimate.

[4] These countries are mostly European countries, and a few other developed countries. Six of the countries are Eastern European (Belarus, Estonia, Latvia, Lithuania, Russia, and Ukraine) and others are formerly Soviet Union (Bulgaria, Czech Republic, Hungary, Poland, and the Slovak Republic); our results are not sensitive to including or excluding these countries. We exclude Chile (1992-), Germany (1990-), Israel (1983-), Slovenia (1983-), and Taiwan (1970-) because the data covers very few years.

We thus model log mortality as a function of economic conditions starting at age 45. We also limit our analysis to the population aged 90 and below, because mortality above these ages is imputed in the HMD. Our final sample includes 245,512 country-gender-cohort-year observations.

Figures 2a and 2b show the evolution of mortality rates for men and women ages 60-69 in 7 countries. The mortality rates of women started falling earlier and fell substantially more than those of men. And although on average mortality has fallen, mortality changes have not been uniform across countries. For example Japan experienced very rapid mortality declines. Other countries such as Denmark had less rapid declines, and mortality increased in the case of Russia. Overall, the standard deviation of male mortality in 1880, 1930, 1960 and 2000 is 1.4, 1.0, 0.8 and 1.4 percent, which correspond to about 32, 27, 26 and 58 percent of the mean, respectively.[5] Figures 2c and 2d repeat these analyses for people aged 50-59 to illustrate that the trends also differ by age within countries. For example, the mortality rate of those aged 60-69 in United States has declined by 1.2 percent per year since 1933 but for those aged 50-59 it declined by 1.4 percent. Russia also shows a large deviation between younger and older people.

To account for these differential patterns, we model the log of the mortality rate for each country, gender, and age as a quadratic function of time. This specification allows for the observed non-linearities in Figure 2 and provides an equally good fit as one with higher order terms.[6]

[5]The increase in the variance of mortality in the late 20th century has also been noted before, for instance Becker et al. (2005).

[6]The adjusted R-square is 0.988 if we control for country-gender-age dummies and country-gender-age specific linear time trends, 0.994 if we include a quadratic time trend, 0.995 if we include up to fourth order terms, and 0.996 if we control up to sixth order terms.

II.2 Historical GDP data

The literature on the contemporary effects of recessions has focused attention on the relationship between mortality rates and unemployment. However, high quality unemployment rate data is not available for most countries prior to 1950. Instead we follow van den Berg et al. (2006) and use the deviation of GDP per capita from its long-term trend as our measure of interest. Real per capita GDP data are taken from a variety of data sources, including Angus Maddison, IMF and World Bank, and start from 1800 for most of the countries we study.[7]

To measure good and bad economic conditions, we compute deviations of ln(GDP per capita) from its long run trend. For each country, the long run trend in GDP is estimated using a Hodrick and Prescott (1997) filter with a smoothing parameter of 500. We then define good (bad) economic times as periods when actual GDP is above (below) its predicted long run trend. In a slight abuse of language, we refer to a positive residual of GDP above trend as a 'boom' and a negative residual as a 'bust'. We use a smoothing parameter of 500 because it makes the residuals most predictive of unemployment rates (see Appendix C). But we extensively investigate the robustness of the results to alternative parameters and de-trending methods in Appendix C. Because GDP is measured with error, especially as we go back in time, our results are likely underestimates of the true effects of economic conditions.

As shown in Appendix Figure C1, the biggest divergence between GDP and its long-run trend in the United States occurred during the Great Depression and the immediate post-World War II era. Other significant divergences occur in the severe recession of the 1890s and the Great Recession of 2008-09. Appendix Figures C3a

[7]The data are compiled on the Gapminder website: http://www.gapminder.org/data/documentation. Amounts are expressed in fixed 2011 dollars using Purchasing Power Parities.

and C3b show all periods/countries in the data where GDP diverges from its long term trend by 10 percent or more.

By construction, the average GDP fluctuation over all time periods is zero. However, the mean is not zero in a given time period. Appendix Figures C3c and C3d show the mean and standard deviation of GDP fluctuations by year. The mean is close to zero in 1800-1880, 1950-1970, and particularly negative in 1910-1940 as well as in the 1990s.[8] In the average year, the standard deviation of GDP fluctuations is 8 percent, but it is greater than 10 percent in the late 1940s and late 1990s, and lower than 2 percent around 1860 and 1960.

All told, we have 6,816 country-years with GDP for the 32 countries. By comparison, there are only 1,366 country-years with unemployment rates. GDP fluctuations are highly correlated with unemployment rates, consistent with Okun's Law ($\rho = -0.25$ taking out countery and year fixed effects). Figure C2b and Table C1 show the strong negative correlation in all the countries, consistent with Okun's Law. Controlling for country and year fixed effects, a negative 1 percent GDP fluctuation is associated with a 0.11-0.21 percentage point increase in unemployment rates (Table C1).[9] We use this relationship to compare the magnitude of our results to previous estimates.

III. A Model of Economic Conditions and Mortality

In this section we provide a characterization of mortality based on frailty, in the spirit of Vaupel et al. (1979), and use it to describe implications for the short and

[8]This is largely driven by the eastern European countries.

[9]Without country or year fixed effects, a negative 1 percent GDP fluctuation increases unemployment by 0.14 percentage points. With country and year fixed effects, the increase is 0.11 percentage points. If we add country-specific quadratic trends, the increase is of 0.21 percentage points.

long term effect of economic fluctuations. This section is based on Lleras-Muney and Moreau (2016) which fully characterizes the model.

Assume individuals are born with an initial health level H_0. This initial health endowment differs across individuals in the population and has a unknown distribution, which is likely to be normal.[10] In the absence of investments in health, the health stock falls with age at an increasing rate: $\delta * t^{\alpha}$. It is also affected by random shocks (diseases, wars, etc) given by ε_t, which are i.i.d. over time with distribution $F(.)$. But the health stock can be affected through technology $I = I(Y,B)$, the health production function which is affected by two sets of inputs Y and B. Y denotes the vector of all inputs that increase health (food, shelter, health care, etc), so $I_Y = \dfrac{\partial I}{\partial Y} > 0$. In contrast B captures smoking, drinking, stress, pollution and all others factors that lower health $I_B = \dfrac{\partial I}{\partial B} < 0$. The health stock evolves according to

$$H_t = H_{t-1} + I(Y_t, B_t) - \delta * t^{\alpha} + \varepsilon_t \tag{1}$$

People die when their stock of health first crosses a lower threshold $\underline{H}$. We assume that all individuals have a stock greater than this minimum at birth. Let
$D_t = I(H_t \leq \underline{H})$ denote the random variable equal to one if the individual dies in period t, and define the mortality rate at time t as
$MR_t = E(D_t|G_t) = P(D_t = 1|D_{t-s} = 0 \forall s < t, G_t)$, where $G_t = \{g_1, g_2, ..., g_t\}$ denotes the history of economic conditions up to time t.

III.1 Effect of economic conditions

We assume that $Y_t = Y(G_t)$ and $B_t = B(G_t)$ are functions of $G(.)$, specifically: (1)

[10] Birth weights and other traits measured at birth follow a normal distribution Wilcox (2001).

$\frac{\partial Y_t}{\partial g_t} > 0, \frac{\partial B_t}{\partial g_t} > 0$: good current economic conditions lead to increases in both types of inputs; (2) $\frac{\partial Y_t}{\partial g_s} > 0, \frac{\partial B_t}{\partial g_s} > 0$ for any $s < t$: past economic conditions can have effects on current inputs. For instance large recessions lower incomes of graduating cohorts for many years thereafter (Oreopoulos et al., 2012). Similarly, individuals facing large negative shocks can be more likely to smoke or drink many years later, consistent with models of habit formation or addiction (Becker and Murphy, 1988); and (3) $\frac{\partial Y_t}{\partial g_s} = \frac{\partial B_t}{\partial g_s} \equiv 0$ for any $s > t$: changes in economic conditions are not anticipated and do not influence current inputs.[11]

Short-term effects. Appendix A derives expression for the ambiguous impact of an unexpected improvement in current economic conditions on mortality. There are two effects, one through Y ($\frac{\partial Y_t}{\partial g_t}$) and the other through B ($\frac{\partial B_t}{\partial g_t}$). Because the two inputs have opposite effects on health, the overall sign of the short-term effect of improved conditions is determined by the relative magnitudes of the two effects, which input changes more when GDP changes and which input matters more for health. These effects could well differ across individuals. For example retired individuals will not necessarily see their incomes increase during booms, but they will be exposed to increased pollution. In countries with high levels of (countercyclical) expenditures, the government provides some insurance so that $\frac{\partial Y_s}{\partial g_s}$ is smaller, at least for small shocks. Lastly the responsiveness of health to a given input (I_Y, I_B) could vary across individuals, and by age.

Long term effects. Consider now the effect of economic conditions earlier in life,

[11] If inputs are like food, more of which are purchased with greater incomes, then we are assuming that there is no full insurance at a population level over time. If inputs are like pollution, a by-product of production, then we are assuming that in the short run technology is fixed: when a good shock leads to more production, the technology is not available to increase output without increasing pollution as well.

specifically the effect of economic conditions one period earlier. This comparative static (in Appendix A) also has an ambiguous sign and might differ from the sign of the short term effect.

Intuitively several effects operate. First, economic conditions in the past affect prior investments $\left[\frac{\partial Y_{t-1}}{\partial g_{t-1}}, \frac{\partial B_{t-1}}{\partial g_{t-1}}\right]$ and this also affects health in period t. Second, past conditions affect the level of current investment $\left[\frac{\partial Y_t}{\partial g_{t-1}}, \frac{\partial B_t}{\partial g_{t-1}}\right]$, with ambiguous effects on health. For many inputs Y and B, one might suspect that the effects on Y are longer lasting than the effects on B. For example, one might hypothesize that pollution generated in prior times does not remain in the air for long, $\frac{\partial B_t}{\partial g_{t-1}} = 0$, but the effect on income and thus food consumption persists, $\frac{\partial Y_t}{\partial g_{t-1}} > 0$. In this case the positive effect of increased income could potentially offset the negative short-term pollution effect, generating a positive effect of economic conditions over time, despite a negative impact in the short term. These effects on inputs and health may vary by age if there are "critical periods" during which individuals are particularly sensitive to shocks. For instance adolescent smoking responds more to income and price than adult smoking (Chaloupka and Warner, 2000). Cognition appears more sensitive to inputs early in life, while social traits appear more sensitive to events in adolescence (Cunha and Heckman, 2007).

Lastly mortality in previous periods gives rise to selection effects, which are also of ambiguous sign. A negative investment results in fewer individuals right at the threshold surviving, which lowers mortality the next period. But a negative investment decreases the health stock of the entire population, thus potentially increasing the number of individuals at the threshold the next period.[12]

[12] The Appendix and Lleras-Muney and Moreau (2016) also consider temporary shocks to mortality that do not affect the stock of health, such as idiosyncratic shocks to the dying threshold. In this case

III.2 Model properties from simulated data

The expression for mortality rates at age t is a non-linear function of the history of shocks and investments from birth up to period t. To understand the behavior of mortality in this model, we simulate the evolution of mortality and of the average health stock. Appendix Figure A1a shows that the model reproduces the shape of the mortality rates well: the log of mortality starts high and falls to very low levels by adolescence. It remains low and highly variable until around age 40, and then it rises linearly with age.

Appendix Figure A1c illustrates the effect of a negative shock lasting two periods but occurring at different ages. It shows that mortality after age 40 is more affected by shocks at age 15 than by shocks at birth and age 1, because at age 1 mortality is high even in the absence of a shock. It also shows that the effects of a shock on mortality are dominated by the sign of the shock (the curves do not cross): good shocks lower subsequent mortality and bad shocks increase it. Appendix Figure A1d illustrates the effect of a shock at age 15 that increases both bad and good inputs, but differentially over time. During the first two years the overall effect of pollution is larger than the effect of increased consumption. After two years pollution effects fall to zero (by assumption) but the affected cohorts have higher incomes until age 30. This "lucky" cohort experiences high mortality until age 19, but lower mortality thereafter, resulting from higher incomes.

Empirical implications. We do not observe a measure of the health stock throughout the lifetime. Nor do we observe all health inputs or how they evolve in response to changes in economic conditions. Also the data that we have on mortality, GDP,

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the long term effects of shocks are standard: when more survive in one period more will die the following period.

and various health inputs begin in different time periods and have different missing data patterns. Thus, there is not enough data to estimate a fully structural version of the model.

Instead, we first look to study the “reduced form” implications of the model, namely how unexpected economic shocks affect mortality and health inputs, by estimating the sign of economic shocks in the short- and long-term. We then look at how a few inputs respond to economic conditions, and discuss the implications of the results in light of the model’s predictions. By taking the model in stages – first relating GDP to mortality, and then seeing how various investments mediate that relationship – we can draw relatively firm inferences about the underlying hypotheses.

IV. A Comparison of Cohorts

We start by investigating the relationship between GDP fluctuations and adult mortality non-parametrically. Since GDP data begin in 1800, and we wish to analyze the relationship between early life GDP and mortality after age 45, we work with mortality starting in 1860. This includes a total of 245,512 observations.

To compare cohorts, we need to take out trends in mortality - as noted above, by age, gender, and country. We regress the logarithm of the mortality rate for each country-age-gender-year cell on a full set of age-gender-country interaction dummies (2880 terms), along with their interactions with a time trend and that trend squared (2880 terms*2). We also include gender-specific year dummy variables (149*2 variables) and year of birth dummy variables (161*2 terms). Effectively, we are estimating a different mortality regression for each age, gender and country, modeling the time series as a quadratic function of time. In addition, we allow for common cohort effects and year effects.

After de-trending mortality, we relate mortality residuals to GDP fluctuations at different ages. We present these results graphically by dividing the sample into percentile bins based on GDP fluctuations. For each bin, we calculate the average GDP fluctuation, along with the average residual mortality.

Figure 3 shows the results. The first figures look at GDP fluctuations when young: at birth and in utero (age -1 to 0), ages 1-5, 6-10, 11-15, 16-20, 21-25, and 26-30. There is no obvious relationship between mortality after age 45 and economic conditions at birth and up to age 10. A negative relationship emerges between GDP fluctuations during adolescence and young adulthood (ages 11-25) and middle/late life mortality. While noisy, the relationship appears linear. After age 25 a positive relationship emerges, though it is not large. Overall good economic conditions in the teenage years are associated with lower mortality in adulthood.

The last panel in the figure shows the relationship between mortality residuals and contemporary GDP fluctuations. To allow effects to play out over a short period of time, we take the average fluctuation in the year we are considering mortality and the two previous years. We do this throughout our analysis. Very large booms (fluctuations greater than the 90th percentile, larger than 0.05) lower mortality; and very large busts (below the 10th percentile, or lower than -0.05) increase it. But between the 20th and the 80th percentile (i.e., relatively small fluctuations) there is a positive slope: small positive fluctuations increase mortality.

V. Regression analysis

We now estimate the formal relationship between mortality rates and unanticipated economic conditions throughout the lifetime. The model is quite similar to the non-parametric analysis presented above:

$$ln(MR)_{bgct} = \beta_0 + \beta_c fluc_{ct} + \beta_{-1-0} fluc_{bc}^{-1-0} + \beta_{1-5} fluc_{bc}^{1-5} + ... + \beta_{26-30} fluc_{bc}^{26-30} + \theta_{agc} + \theta_{agc} * t + \theta_{agc} * t^2 + \theta_{gt} + \theta_{gb} + \varepsilon_{bct} \quad (2)$$

The dependent variable, $ln(MR)_{bgct}$, is the (natural logarithm of the) mortality rate in year t for birth cohort b, gender g, born in country c. We include a full set of age-gender-country interaction dummies (θ_{agc}), along with their interactions with a time trend and its square ($\theta_{agc} * t$ and $\theta_{agc} * t^2$), gender-specific year dummy variables (θ_{gt}), and gender-specific year of birth dummy variables (θ_{gb}).

The key explanatory variables are contemporaneous GDP fluctuations in country c and year t (i.e., mean value of log GDP fluctuations previous three years), denoted $fluc_{ct}$, and lagged fluctuations, using the same time periods as in figure 3. We average over five year intervals, which successfully lowers collinearity in fluctuations across periods (Appendix Table C1). The identifying assumptions are that economic shocks are not caused by mortality itself (no reverse causality), and that there are no omitted factors affecting both mortality and economic conditions.

Our non-parametric analysis suggests that contemporaneous GDP fluctuations have a non-linear effect on mortality. Therefore we model GDP fluctuations linearly within |5%| and estimate a different line in large booms and busts. To do so, we include a dummy for an economic boom or recession (defined as GDP fluctuations > 5% or < -5%) and the interaction of each of these with GDP fluctuations. Following Ruhm (2000), we weight each observation by the square root of the population. Standard errors are all clustered at the country level to allow for serial correlation in mortality within countries: residual mortality rates still exhibit serial correlation.

A few issues about this specification are noteworthy: First, we have fully accounted for cohort effects with the gender-specific year-of-birth dummy variables. Thus, any secular factor, such as improved nutrition or aggregate changes in disease patterns, will not influence our results. Second, because contemporaneous GDP fluctuations vary by country-year, country-year effects cannot be included when examining the effect of current GDP fluctuations. In examining the effect of lagged economic shocks only, we control for country-year fixed effects. Similarly, we can include country-specific cohort effects when examining the impact of contemporaneous GDP fluctuations alone. We also note that GDP and mortality are implicitly detrended in different ways. Mortality detrending is quadratic in time, whereas GDP detrending uses the Hodrick-Prescott filter (and is additionally detrended using quadratic trends in the regression). We return to this below.

Table 1 shows the results from estimating equation (2), and Figure 4 displays the results graphically. The first rows of the table, along with Figure 4(a), show the impact of contemporary economic fluctuations on mortality. When per capita GDP is within 5 percent of its trend, higher GDP is associated with higher mortality: a move from the 25th to the 75th percentile of GDP fluctuations raises GDP by about 5.4 percent, and translates into an increase in mortality of 0.92 percent. On average, mortality declines by about 0.6 percent annually, so this is about 1.5 years of progress in mortality.

But large booms lower mortality; the bigger the boom, the lower is mortality. On average, economies more than 10 percent above trend (roughly 5.2 percent of the observations) experience mortality that is 4 percent lower. Conversely a large bust is associated with an increase in mortality. On average, mortality is about 5 percent higher when GDP is 10 percent or more below trend. We cannot reject the null that the effects are symmetric (F-statistic = 1.06, p-value = 0.31).

The second half of Table 1 (and Figure 4b) shows the coefficients for economic conditions between birth and age 30. All these coefficients are negative and statistically significant with the exception of economic conditions between ages 26 and 30. Moreover these coefficients exhibit a U-shaped pattern in age: although all cohorts benefit from growing up in good times, cohorts that experience booms between ages 11 and 20 have the lowest mortality after age 45. The impact of economic deprivation at birth is consistent with the findings in Barker (1995) and the review by Almond and Currie (2011), that fetal under-nutrition and other stressors in utero are associated with later coronary heart disease. But our results are surprising–we find that effects in adolescence matter more. We explore this later in the paper.

The second and third columns examine the impact of contemporaneous GDP fluctuations and early life GDP fluctuations in more demanding specifications. In the second column we control for country-by-birth-year fixed effects, which fully absorb early-life GDP. The coefficients on contemporaneous GDP are statistically identical, as shown in Figure 4a. The third column includes country-by-year dummy variables, which fully absorbs contemporary GDP fluctuations. The coefficients on GDP fluctuations in earlier life are very similar to those in the first column, or a bit larger in magnitude, as shown in Figure 4b.

V.1 Selection and treatment

Our model showed that early life GDP fluctuations could affect later life mortality through two channels: selection and scaring. To separate these two factors, column 4 of Table 1 shows the impact of including the share of people who survive up to age

45.[13] A larger share of survivors at age 45 is associated with lower mortality after age 45. In contrast, selection effects would imply the opposite. The data suggests that shocks affect the stock of health rather than the threshold for dying. Further, the effects of contemporary economic conditions remain unchanged. The coefficients on early conditions remain negative and significant, though some are a bit smaller.

To further investigate selection effects we directly examine how early life conditions affect the share of individuals that make it to adulthood. We group the data so that there is one observation per gender-country-cohort. On average, we have approximately 120 cohorts for each gender for 32 countries, for a total of 3,680 observations.[14] For each, we construct the share of the population of a given gender, born in a given country and birth year that survived to age 45. We relate this share to the early life conditions faced by that cohort:

$$\begin{aligned} Prop_{cb} &= \beta_0 + \beta_{-1-0} fluc_{bc}^{-1-0} + \beta_{1-5} fluc_{bc}^{1-5} + \ldots + \beta_{26-30} fluc_{bc}^{26-30} \\ &\quad + \theta_{gc} + \theta_{gc} * b + \theta_{gb} + \varepsilon_{bct} \end{aligned} \tag{3}$$

To control for other factors influencing childhood survival, we include dummies for cohort, gender, and country, along with country-specific linear trends in year-of-birth ($\theta_{gc} * b$). All regressions are weighted by the square root of cohort size and standard errors are clustered at country level.

Table 2 shows the results. Positive GDP fluctuations before age 30 increase the

[13] The share of the population surviving to age 45, included in columns 4 and 7, is not known for all birth cohorts. Therefore a set of dummies is included for the beginning age for the birth cohorts. For those birth cohorts with minimum age above 45 (about 20% of the observations), we use the sample mean and include a missing indicator. The results are similar if we only use observations with valid values of the share of the population surviving to age 45.

[14] For cohorts with data since birth we compute share surviving since birth. For other cohorts we compute survival from the earliest observed age (1, 2, 3, etc). We only keep cohorts that we can observe starting at age 10 or younger, discard cohorts only observed after age 10 and include dummy variables for the youngest age at which the population is measured. The results are robust if we use other ages as thresholds.

share of those who survive to age 45. The effects are roughly similar at all ages from 6-20. Columns 2 and 3 show these selection effects are similar for men and women: the F-test marginally rejects the equality of those coefficients at 10 percent significance level (p-value = 0.10). Columns 4 and 5 divide the sample by whether the cohorts were born before or after 1910. Consistent with intuition, effects on survival are much larger for early cohorts for whom mortality early in life is large (only 58 percent make it to age 45 for the pre-1910 cohorts, compared to 87 percent of those born after 1910). The effects are statistically insignificant for cohorts born after 1910, and the coefficients for cohorts born after 1910 are statistically different from those for cohorts born in 1910 or earlier (p-value < 0.01).

V.2 Differentiation by gender and age

Previous research and our descriptive statistics show that compared to men women's life expectancy has increased substantially more (Cullen et al., 2015), and mortality has fallen much more at younger ages (Cutler et al., 2006). Next we investigate if economic factors have differential effects by age and gender.

Figure 4 (c) and (d) divide people into two age groups: younger adults (45-65) and older adults (66-90). The results show that the contemporary effects of GDP fluctuations are more muted among the older adults–in fact there is no significant effect of fluctuations for 66-90 year-olds, and the effects are very close to zero for small GDP fluctuations. One explanation might be that those over 65 are protected from income fluctuations because of social insurance programs such as Social Security. We investigate this later. But the long-term effects of fluctuations are qualitatively similar for both groups–though significantly larger for the older cohorts (p-value < 0.01).

Panels (e) and (f) show the impact of contemporaneous and early life conditions by gender. Panel (e) shows that contemporary effects are almost identical between men and women (though women appear to benefit slightly less from large booms). Because women in our cohorts participated in the labor force at much lower rates, these results suggest that work per se (and its associated stress) is unlikely to explain our short run effects. On the other hand Panel f shows that the long term effects of economic conditions are economically and statistically significantly smaller for women than men. The impact of economic deprivation at birth is relatively similar for men and women. But there is no significant impact of economic fluctuations after age 6 on women's mortality. In contrast we observe a pronounced U-shape for men, with larger effects in adolescence than in utero. These findings are consistent with two explanations. One is that women are "sturdier" (have a larger initial health stock), consistent with higher mortality of men than women at almost every age in now-developed countries (Cullen et al., 2015). Another is that economic conditions in adolescence are larger predictors of male lifetime incomes, because that is when they enter the labor market, whereas women's lifetime resources are more tied to their husbands' incomes. We return to this issue in Section 6.

V.3 Comparison with previous literature

Contemporaneous effects. Our results relating short term GDP fluctuations to mortality are not directly comparable to past literature, which typically relates unemployment rates to mortality. However, we can translate between our results and previous literature. As noted above, a 1 percent GDP fluctuation is associated with a 0.11-0.21 percentage point reduction in unemployment. In table 1, it is also associated with a 0.17 percent increase in mortality. Thus mortality increases by 0.8-1.5

percent when unemployment falls by 1 percentage point (i.e., 0.17/0.14 or 0.17/0.21). These estimates are higher than those in Ruhm (2000), which finds that a one percentage point decrease in unemployment increases mortality by 0.5 percent, or Stevens et al. (2015) which report estimates around 0.3. There are two likely reasons for this. One is that estimates at higher levels of aggregation like ours (at the country level) tend to be higher than estimates at lower levels of aggregation, such as states, from which the Ruhm and Stevens results are derived. (See Lindo (2015) for a detailed exposition.) The other reason is that we have a broader set of countries and time periods. Section 6 shows that the effects of fluctuations vary depending on the period and the composition of economic activity.[15]

Early life effects. To gauge the magnitude of the effect of early life economic conditions on late life mortality, we consider how economic shocks have affected different cohorts' life expectancy at age 45. We estimate predicted mortality at each age for each cohort, and then re-estimate predicted mortality assuming there were no economic shocks from birth to age 30. Because selection is important for early cohorts, we concentrate on cohorts born post 1910, and use estimates from 1945 on – shown in column 6 of table 1 and discussed more below. Appendix Figure D1 shows the distribution of life expectancy differences owing to different economic conditions. In general, the effects are not large:[16] the standard deviation of predicted life expectancy changes is 0.077 years. However some of the effects at the tails are larger. For example, the 1915 cohort of the United States, which experienced the Great Depression in the 1930s, lost 0.18 years of life as a result. The 1957 cohort of Japan lived 0.16 years longer because of large booms in the 1960s and early 1970s.

[15] Appendix Table D3 shows how mortality relates to unemployment rates for the sub-sample of country*years with unemployment rates.

[16] We evaluate life expectancy changes using 1997 US life table.

While these impacts are significant, they are not overwhelmingly large. Partly this is because an average cohort experiences both booms and busts in their first 30 years of life. If we estimate the effect of having the great depression for the first 30 years of life then we find a reduction of one year of life.[17] Another important reason is that our fluctuations are likely measured with substantial error. Finally our estimation methods are conservative in that we add many fixed effects.

The only other study of early life economic fluctuations and late life mortality is van den Berg et al. (2006). It reports that a boom at birth lowers lifetime mortality by 9 percent (-0.09). If we re-estimate our model using a dummy for boom around birth we find a (statistically significant) coefficient of -0.003, an order of magnitude smaller. We investigated this discrepancy by replicating van den Berg's results using their original data and the HMD (see Table D1). Although there are several material differences between their set-up and ours (e.g. they use GNP instead of GDP and look at cohorts born 1810 to 1903, whereas we include cohorts born up to 1962), the most important reason for the difference in magnitude is that they look at mortality from birth until death, while we only consider mortality of adults ages 45 and over. As we showed, for cohorts in the 19th century, survival to age 45 was low, and economic conditions early-on affected survival to 45 quite strongly. This is not true for more recent cohorts.

V.4 Specification checks and robustness

Outliers. One concern is whether our results are driven by outlier countries or time periods. We have explored the sensitivity of our findings to excluding Eastern

[17]This is an out of sample exercise. It is likely that if a cohort were to experience such a long downturn, effects would likely differ.

European countries and periods of global war, where mortality and economic conditions may both be determined by other factors. As shown in Appendix Table D2, none of our results are materially changed by this. This is not surprising given the dummy variables that capture the main differences across cohorts and time periods.

We also re-estimated our short term effects dropping one country at a time, with or without country-cohort fixed effects (64 regressions). The coefficients on GDP fluctuations range from 0.08 to 0.21 (mean: 0.14, standard deviation: 0.03). Thus there is some heterogeneity, but the results are very consistent across regressions. We reach similar conclusions for the effects of large booms and busts.[18] For long term conditions effects we estimate 64 regressions, dropping one country at a time, with or without country*year fixed effects. The coefficient for fluctuations at birth has mean -0.03 and ranges from -0.03 and -0.04. In contrast the coefficient on fluctuations at age 11-15 or 16-19 have mean -0.09 and range from -0.07 and -0.11. Finally we estimate survival to age 45, dropping one country at a time (32 regressions) with similar results (see Appendix C). We conclude that our results are not driven by outlier countries or periods.

De-trending. A second key issue is how we detrend GDP and mortality. A number of detrending methods have been proposed in the literature, including the Hodrick-Prescott (HP) filter, non-linear time trends, the Baxter-King (BK) method (Baxter and King, 1999), and the Hamilton (2016) filter. Two criteria stand out in determining the 'best' filter: the correlation with other macroeconomic indicators such as unemployment, and serial correlation. The two best filters by these criteria are the HP filter with smoothing parameter 500, and the BK filter. GDP residuals

[18]The coefficient on booms (busts) ranges from -0.62 to -0.41 (–0.37; -0.23), with mean of -0.55 (-0.3) and a standard deviation of 0.03 (0.03)

defined from these specifications have a large correlation with unemployment and small serial correlation (Appendix Table C1). Appendix Table C3 shows that we get identical qualitative results if we use the BK filter instead of the HP filter.

We systematically investigated the filtering issue by estimating 144 different regressions, with 8 filters for mortality (HP 100, 500, 1000; quadratic, cubic and quartic time trends for each country age gender group, 4- and 5-year moving average), and 9 filters for GDP (HP 10, 100, 500, 1000, BK, and 2-, 3-, 4- and 5-year moving averages), with or without country*year/cohort fixed effects. Appendix C shows the results from all these permutations. We summarize the results here.

Short term effects are very robust to how we detrend mortality and GDP. As expected the coefficients vary because the size of the residuals changes with the detrending method. But the sign of GDP fluctuations in the "small" range is positive in 100% of the regressions, and statistically significant (at the 5 percent level) in 60 percent of the cases. The robustness of the results for large booms and busts is harder to assess: if we use a BK filter there are no recessions or booms that we would categorize as large using the definitions we established for the HP filter. But if we always categorize large booms as fluctuations above the 90th percentile and large recessions as those below the 10th percentile, we find that large recessions always increase mortality. The results are not as robust for large expansions however, which are sometimes still harmful to health.

The long term results are more sensitive to our detrending choices. If we concentrate attention on the coefficient for economic conditions in adolescence, we find that 70% of the regressions give a negative coefficient, and among these 70% are statistically significant. Among the 30% with positive coefficients, none are statistically significant. There is a pattern to these results. The long term results are always positive and insignificant when we detrend mortality in a way that results in negative serial correlation (HP 10, 100 or moving average of 2, 3 or 4)–because the results are then very sensitive to the exact timing of GDP and the ages over which we average. Similarly certain detrending methods for GDP do not produce stable estimates. When residuals are small (e.g., those resulting from HP 10), averaging over years reduces the size of fluctuations immensely,[19] and the coefficients are insignificant. In this case, we might enter GDP fluctuations annually rather than with five year averages. But here, collinearity becomes a problem: even with detrending, lagged GDP remains significantly related to current GDP, unless we average over five years (Appendix Table C1).[20] We cannot entirely resolve these issues: we face a trade-off between collinearity and variation. In general, the long term results hold if a) the method for detrending GDP yields residuals that are highly correlated with unemployment, and b) both mortality and (5-year average) GDP residuals have AR(1) coefficients that are positive but far from one. We view these as fairly robust, since these are reasonable requirements for the choice of detrending.

Reverse Causality. We interpret our results as reflecting the causal effects of GDP on mortality rather than the reverse. Throughout our period, with the exception of wars and pandemics, the mortality rates of the working age population is small, making it unlikely that mortality directly impacts GDP. Further, the results are robust to excluding periods of high mortality of prime age adults. Lastly our results are

[19] For example, the cohort that was age 16 in the US in 1930 experienced a GDP fluctuation of only -3.8 percent between ages 16-20 with an HP value of 10, but a fluctuation of -17.8 percent with an HP value of 500.

[20] Appendix Figure C6 shows the coefficients by single-year of age for different filters: for fluctuations that are large and not very serially correlated we find a hump-shaped pattern of effects–for small, highly serial correlated residuals we do not.

similar when we use unemployment rates rather than GDP, in the time period where we have both (see Table D3).

Omitted variable bias. A related concern is omitted variable bias. Wars are an obvious possibility, which we discussed already–our results are not driven by war time periods. Another possibility is weather. In predominantly agricultural economies, droughts or periods of excessive rain will have a large impact on output. And very hot and very cold spells also result in higher short term mortality (Deschenes and Moretti, 2009). Therefore extreme weather can potentially increase mortality directly in addition to affecting incomes and GDP. We do not have data on temperature and rain for the last 200 years to directly examine this. But this omitted variable is likely to result in underestimating the effect of GDP. We find that mortality increases in good economic times (for deviations that are less than 5% of GDP). If good weather is driving GDP increases and lowering mortality, controlling for weather would be expected to increase the adverse effect of GDP (make it more positive). At the tails, we find that large busts increase mortality. The effects could be over-estimated if both busts and mortality are the result of exogenous events, for instance a bad weather event. But Figure C3 shows extremely good times and bad times are correlated across countries that are far apart, suggesting weather is not the cause.

Migration. Migration is a concern for long term effects since adults ages 45 and older in a given country may have lived elsewhere before age 45. All life tables suffer from this composition problem, and there is no good historical migration data to address this. We investigate migration instead using the European Community Household Panel described in Section 8. The long term effects we estimate are larger and statistically significant when we include only those born in the country where they live as adults (Appendix Table D4), suggesting our main results using the HMD are underestimated.

Weights. We typically follows Ruhm (2000) and weight regressions using the square root of the population in the cell as the weight. The results are robust to using different weights, for instance weighting by population over the entire period for each country (Appendix Table D2).

VI.Why do economic conditions worsen health in the short term?

Our analysis so far has shown that mortality is related to economic conditions. We now consider why. The literature suggests several possibilities: pollution, stress, and alcohol among others. To examine these theories, we first determine whether these potential mediators are procyclical. We then check if the coefficient on contemporary GDP fluctuations declines when these variables are included in our main specification (column 2 of Table 1). Because we cover a much smaller period of time, we cannot estimate the effects of large booms and busts with much precision–we report those in the Appendix. We also estimated models dropping one country at a time (Appendix D7) We report results for the full sample and note when the results are not robust to excluding a specific country.

VI.1 Pollution, economic activity and business cycles

A number of studies have shown that $PM_{2.5}$, a measure of small particulate matter in the air, is positively associated with mortality (Frankel et al., 2013). We do not have lengthy time series data on $PM_{2.5}$ across countries; the data we have exist from

2000.[21] We do have data from the World Development Indicator (WDI) on CO_2 emissions from 1960, which are estimated using data on consumption of solid, liquid, and gas fuels and gas flarings (Bank, 2015). Although CO_2 by itself is not harmful to health, it is highly correlated with $PM_{2.5}$ (Appendix Figure B2). Table 3 shows that pollution is procyclical: GDP fluctuations are a large and statistically significant predictor of CO_2 emissions (column 1), and of $PM_{2.5}$ (column 3).

To test the pollution explanation using the long time series, we examine how fluctuations are related to mortality in agricultural versus industrial economies. Until recently, prior to the use of pesticides and fertilizers, agriculture involved relatively little pollution. And prior to environmental regulation, manufacturing and transportation were extremely "dirty".[22] If large GDP fluctuations are most associated with the biggest industries, areas and times that have greater agricultural shares should see less harmful effects from GDP fluctuations. Data on agriculture shares are compiled from multiple national and international sources and reported by the International Historical Statistics.[23] Columns (2) and (4) of table 3 confirm that emissions (both CO_2 or $PM_{2.5}$) are only statistically higher during booms in countries with large non-agricultural shares.

Agricultural shares have been trending down over time (Figure B1). They averaged 40 percent around 1850 and 3 percent in the 2000s. One prediction of the pollution explanation is that the harmful effects of GDP fluctuations should be in-

[21] The PM 2.5 data are from the Atmospheric Composition Analysis Group. See the website for details: http://fizz.phys.dal.ca/~atmos/martin/?page_id=140

[22] Hanlon (2015) argues that coal use during the industrial revolution in England explains the large urban mortality penalty observed in the 19th century.

[23] The data go back to 1800 but only cover 23 countries in our database. We attempted to examine the industrial and service share of the economy as well, but these are not measured as consistently across time or over countries. Thus, we confine our analysis to agriculture.

creasing over time. Consistent with this hypothesis, Columns 5 and 6 of Table 1 show a countercyclical but insignificant relationship between economic conditions and contemporary mortality before 1945,[24] but a strong pro-cyclical relationship post-1945. If we further interact fluctuations with agriculture shares, we find that adult mortality decreases in good times in high agricultural-share economies; but increases in low agricultural-share economies (Column 6 of Table 3). Columns 7 and 8 show that the same result obtains for children under five years of age, so this is not a result of differential survival to adulthood.

We then look at the direct impact of pollution using the shorter time series. Table 4 reports the results from including CO_2 emissions (averaged over three years to allow for lagged effects). The first row shows that in this recent sample, contemporaneous GDP has a positive relationship with mortality. The next row shows that the impact of economic booms on mortality is reduced by two-thirds, and becomes statistically insignificant, when CO_2 is controlled for. Also CO_2 emissions significantly increase mortality. These estimates are robust to dropping one country at a time.

The concern with this specification is that emissions might just be another measure of economic activity, particularly since emissions are (partly) estimated based on selected production inputs and outputs. To differentiate pollution from economic activity we control for additional measures of economic activity. If pollution is picking up unmeasured economic activity, we would expect that including more measures of activity would reduce the impact of pollution. The third row of Table 4 includes labor force participation of men and women from 1960 on in the regression. Labor force participation indeed captures economic activity – when individuals work more,

[24]This result is not driven by selection; the last column shows very similar results with controls for the share of the population surviving to age 45.

adult mortality rises, and this explains much of the residual GDP fluctuation effect. But including labor force participation has little impact on the effect of CO_2. Panel B shows similar results for under-five mortality, which has been shown in previous work, using measures of particulate matter, to be very affected by pollution (Currie, 2013). Thus CO_2 appears to capture air quality separate from employment and other measures of economic activity. The results suggest that the adverse effects of booms is largely due to pollution.

VI.2 Other explanations

Adverse behaviors. Ruhm (2000, 2005) show that some adverse health-behaviors increase during booms, potentially explaining the harmful short-term effects of expansions. We use data on per capita alcohol and tobacco consumption from OECD countries since 1960 to investigate this. Figure B4 in the Appendix shows that alcohol and tobacco consumption are procylical, consistent with evidence that these are normal goods (Cawley and Ruhm, 2012).

Panel C of Table 4 then shows that only alcohol varies cyclically in a way that is correlated with mortality. Adding alcohol consumption into the regressions reduces the effects of the contemporary GDP fluctuations by 40 percent; the impact of adding tobacco is only 7 percent. The large effect of alcohol is in part driven by Russia, where binge drinking is relatively common (Kueng and Yakovlev, 2016). If we drop Russia from the analysis, then the reduction in the GDP coefficient is smaller, about 15 percent. Additional analysis shows that the alcohol effects are particularly apparent for younger (45-65) males (Appendix Table D7).

Time use and stress. People work more in expansions, which may increase stress and lower immune function. It may also reduce time available for tending to elderly parents or children, whose health could deteriorate as a result. We examine the possible role of work-induced stress using OECD data on hours worked per worker, available only from 1981 on for 28 countries. Generally, hours worked per worker vary only a little over the cycle. From trough to peak, for example, hours per worker tend to change by 0.1 percent. Further, average hours are not particularly correlated with the economy ($\rho = 0.06$). When average work hours are added to the regression, the coefficient falls by 17%. But strangely the coefficient on work hours is negative, rather than positive as the stress hypothesis suggests. In addition, if we drop Japan, then in this smaller sample the coefficient on hours is small and insignificant. Because these results are not as robust as the results for alcohol or CO_2 we do not emphasize this explanation.

Transportation and related explanations. Transportation is pro-cyclical, as are transport accidents. Next we investigate whether increased transportation explains mortality effects. Data on millions of vehicle kilometers are available from the OECD website from 1970 on for 26 countries in our sample. We normalize these by population to get annual data on kilometers per capita. Vehicle kilometers driven are positively related to GDP fluctuations, particularly in the tails (Figure B4d). But the last row of table 4 shows there is no statistically significant relationship between miles driven and mortality. Further, the regression does not attribute any of the impact of GDP fluctuations to increased automobile travel. This remains true in subsamples of countries.

There are other reasons why more economic activity could lead to more deaths, though we suspect some would be proxied by transportation. Infectious diseases spread in good times because more individuals are working, traveling and interacting with others (Adda, 2016). However, influenza mortality is uncorrelated with GDP fluctuations, and controlling for it has no effect on the coefficients of interest (Appendix Table D7). Work accidents are also likely pro-cyclical. We have no data to directly assess this, but work accidents are a small contributor to overall deaths among adults over 45 and practically non-existent in the over-65 population.

Periods of expansions could be associated with greater inequality. We explored this possibility but found it difficult to establish whether inequality is pro-cyclical or countercyclical in the short term. The results depend significantly on the measure of inequality chosen.

Overall, the strongest link between economic fluctuations and contemporaneous mortality is found through the pollution channel. As much as two-thirds of the adverse effect of booms may be the result of increased pollution. We also found that increased alcohol consumption explains a (smaller) part of pro-cyclical mortality, especially in Russia.[25]

VII. Understanding The Impact of Early Life Conditions

To understand the relationship between early life economic circumstances and later life health, we use micro level data from three sources: the European Community Household Panel (ECHP), Eurobarometer (EB), and the Survey of Health, Ageing and Retirement in Europe (SHARE). The ECHP is the largest of the surveys, with about 750,000 observations for about 150,000 unique individuals, corresponding to 31 countries and covering cohorts born 1911 to 1972. The two other surveys include additional outcomes of interest, as noted below. Summary statistics for each

[25] Although micro studies find that job losers see their mortality go up (Sullivan and Von Wachter, 2009), they only constitute a small share of the population.

survey are reported in Appendix A. We sample people aged 30 and older who live in the country where they were born (95.8 percent of the ECHP sample).

For each individual i from cohort b born in country c and of gender g, we relate early life fluctuations (*fluc*) to economic, social, and health outcomes later in life (Y):

$$\begin{aligned} Y_{ibcg} = \quad & \beta_0 + \beta_{-1-0} fluc_{bc}^{-1-0} + \beta_{1-5} fluc_{bc}^{1-5} + \ldots \quad + \beta_{26-30} fluc_{bc}^{26-30} \\ & + \delta_{cgt} + \delta_{cag} + \delta_{bg} + \varepsilon_{bct}. \end{aligned} \tag{4}$$

We control for country-gender-year fixed effects effects (δ_{cgt}), fully absorbing current economic and social conditions in the country (which we cannot study because the panels are short). We also control for country-age-gender effects (δ_{cag}) and cohort-gender fixed effects (δ_{bg}), and cluster the standard errors at the country-cohort level.

Table 5 investigates how early life fluctuations are related to various outcomes. The first column considers self-rated health on a 1 (very good) to 5 (very bad) scale. Self-rated health is a well-known predictor of mortality (Idler and Benyamini, 1997). Not surprisingly, a better economy when young leads to improved self-rated health in adulthood. Further, the effect is U-shaped: the largest coefficient is for economic conditions between the ages of 11 and 20. We find very similar results using the smaller SHARE sample (Appendix Table D9).

The next column shows that economic conditions before age 30 affect incomes after age 30. The largest effect is for economic conditions at ages 16-20, the age at which people typically leave school.[26] This is consistent with other micro data findings, like those in Oreopoulos et al. (2012) or Rao (2016). Columns 3-5 show that good economic conditions during childhood increase satisfaction with life in

[26]We also found they have longer tenures at their jobs, See Appendix Table D9.

general and with finances, though not with leisure time. These are reported on a 1 to 6 scale, with higher levels corresponding to greater satisfaction. As with income, the largest effects are associated with fluctuations during teenage years.

The next columns look at self-reported health behaviors: current smoking and obesity (BMI$\geq$30). Smoking is higher for lucky cohorts, consistent with a positive income effect for cigarettes, though the effect is only significant in one age group (16-20) (Townsend et al., 1994). Obesity is unrelated to early life economic fluctuations. Neither of these variables explain the positive impact of booms on adult mortality.

In contrast to the health behaviors, individuals who grew up during good times are much more likely to have positive social interactions measured by the frequency with which people talk with others and meet with friends, ranging from 1 "never" to 5 "on most days". These effects are relatively constant across ages of early life GDP fluctuations (columns 8 and 9).

We construct an overall mental health index using nine questions in the EB (mean zero and standard deviation of 1.09; see Appendix B). A higher score corresponds to better mental health. Column (10) shows that individuals growing up in good times report improved mental health, with effects larger for fluctuations in adolescence. The next column shows that daily alcohol consumption resembles smoking: those who grew up in good times are more likely to drink as adults. The final columns in Table 5 show that good economic conditions in early life increase years of education and cognition, computed as an index (mean zero and standard deviation of 1.38) based on numeracy, verbal fluency and word recall (see Appendix D).

Overall, better health behaviors are not the reason why growing up in a good economy improves late life health. Rather, people in their teens in a good economy have higher human capital (measured by physical, mental and cognitive ability), higher incomes when older and are more socially integrated.

VIII. The size of government and the impact of fluctuations

Government expenditures account for nearly half of GDP in many OECD countries. This spending could moderate the link between economic conditions and health in two ways. The first is through countercyclical taxation and spending. A contemporary change in economic conditions will have a smaller effect on the consumption of normal goods and services that affect health - i.e., $\frac{\partial Y_t}{\partial g_t}$ and $\frac{\partial B_t}{\partial g_t}$ – when government taxes and transfers are countercyclical. In addition, governments have substantial social insurance programs designed to protect individuals against large lifetime shocks to permanent incomes, such as disability, poverty in childhood, and old age. If these programs succeed, the effect of economic conditions on long term outcomes will be smaller in countries with more extensive programs.

Unfortunately long annual time series of government expenditures as a share of GDP are not available. Instead we use OECD data from 2000 to categorize countries into high and low spending countries, based on whether government spending as a share of GDP is above or below the median (Appendix A). This is available only for two former communist OECD countries (Russia and Estonia), so our sample size falls a bit. Appendix Figure B6 shows that consumption is strongly procyclical, consistent with the lack of full social insurance at the population level over time, and it is more procyclical in low-spending countries compared to high spending countries, also consistent with past studies (Frankel et al., 2013; Vegh and Vuletin, 2015).[27]

[27] We use Barro's data (www.economics.harvard.edu/barroursuamacrodata.com) to construct these figures.

Figure 4 (g) and (h) show the relationship between economic conditions and mortality for high and low government spending countries. In countries where government spends above the median amount, there is no effect of contemporary economic conditions on adult mortality, nor is there a negative effect of early life conditions on late life death. But in countries with lower levels of expenditures, we observe the same pattern as in the overall sample: small booms increase mortality, but large booms decrease it. Consistent with our findings for short term mechanisms, alcohol consumption is more procyclical in low expenditure countries (Appendix Figure B5).

Figure 5 shows that the effects of early life GDP fluctuations on almost all adult outcomes is larger in countries with low levels of government spending. This is true for income, life satisfaction, self-reported overall and mental health, cognition and education**.** These results are consistent with the idea that transfers moderate the effects of fluctuations both in the short and the long term. Of course we are only studying recent cohorts–for cohorts born before 1910 living in moslty agricultural economies, other mechanisms could be at play–for instance busts could significantly worsen nutrition which is particularly important during the adolescent growth spurt.

IX. Discussion

In this paper we use cohort life tables from the Human Mortality Database matched to GDP time series to examine the short- and long-term relationship between economic conditions and mortality. We confirm that mortality of adults is procyclical, but we also show that in large recessions mortality increases, and in large booms mortality falls. The contemporaneous relationship between booms and mortality varies across cohorts and countries. In settings where pollution is low or not variable – agricultural economies, for example – mortality falls with expansions, but this reverses in industrial economies, where pollution varies with output. The harmful effects of recessions are larger in places where government spending is a smaller share of the economy.

Our overall findings are consistent with Granados and Ionides (2008), who document that the relationship in Sweden reversed from countercyclical in the 19th century to pro-cyclical in the 20th century, and with Gonzalez and Quast (2010), who find pro-cyclical mortality in developed states in Mexico, but counter-cyclical mortality in the poorest states. These results may also explain why expansions today are good in most developing countries (Bhalotra, 2010; Jensen, 2000; Paxson and Schady, 2005), but not in middle-income or rich countries (Dehejia and Lleras-Muney, 2004). And they can possibly explain why recessions appear to be less harmful to health today than in the recent past (Ruhm, 2015): The US has increasingly controlled emissions and expanded government expenditures. Finally because pollution travels, the correlation between economic activity and pollution at a given location is weak; which explains why the impacts of recessions are smaller at smaller levels of aggregation (Lindo, 2015).

We also find that economic conditions from age 0 to 30 have long lasting effects on mortality, which are also different over time and space. For earlier cohorts and more agriculture-based economies, these effects are large and they affect mostly survival to adulthood. But these beneficial effects are smaller in more industry based economies. The effects of economic conditions are substantially more muted in countries with larger government transfers.

This set of observations can be explained by considering how economic conditions affect two inputs to health: incomes and pollution. Expansions increase incomes but also industrial pollution. In the short term, pollution effects outweigh the benefits of income, particularly in places where government significantly redistributes income, resulting in larger immediate mortality. But when recessions (booms) are large, income effects dominate, explaining the non-linear patterns we observe. We provide evidence that when pollution is accounted for, mortality is much more likely to exhibit countercyclical fluctuations. We also find that alcohol consumption increases in good times, explaining some of the short term increases in mortality, particularly among men.

In the long run good economic conditions in adolescence have a particularly long lasting effect on lifetime incomes, and appear to improve health substantially by providing individuals with more satisfying lives, better social connections and improved mental health and cognitive abilities. The economic and overall health and wellbeing of individuals is better for those growing up in good times, despite the short term increases in pollution that accompany expansions, and the bad health habits that more money allows.

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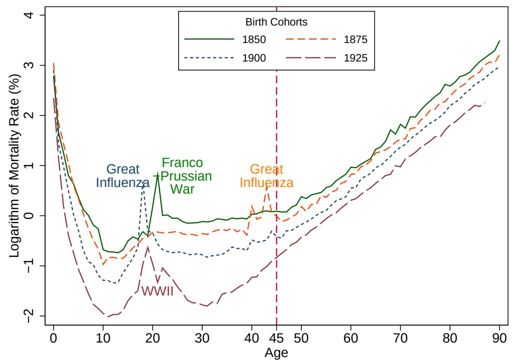
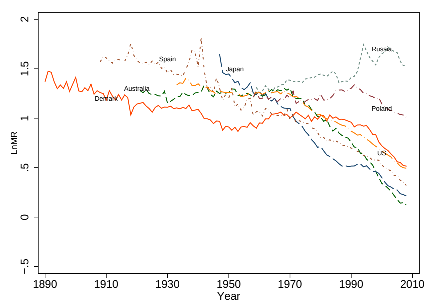
Figure 1: Logarithm of Mortality Rates by Age. 1850, 1875, 1900 and 1925 Birth Cohorts



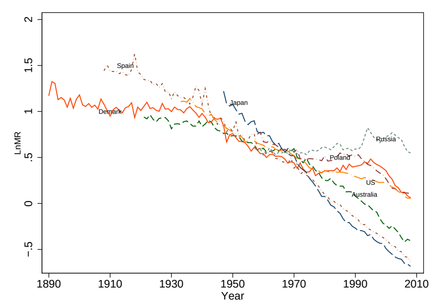
Notes: Authors' calculations from Human Mortality Database (HMD). Logarithm of the population-weighted mean mortality rates are plotted. We average mortality across all countries with data for each cohort. Thus, there are more countries represented for more recent cohorts.

Figure 2: Logarithm of Mortality Rates over Time, by Gender, Age and Country

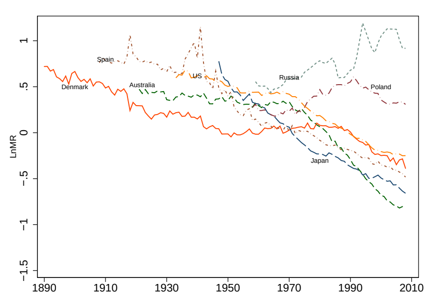
(a) Men, 60-69



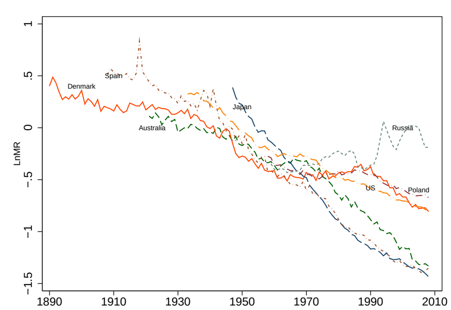
(b) Women, 60-69



(c) Men, 50-59



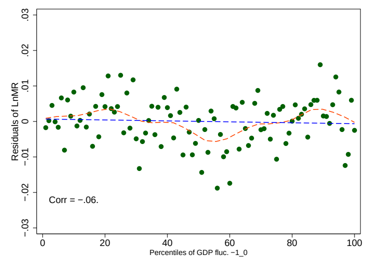
(d) Women, 50-59



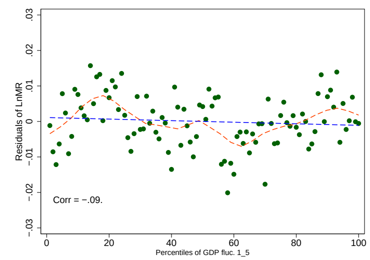
Notes: Authors' calculations from Human Mortality Database (HMD).

Figure 3: GDP fluctuations during the lifetime and residual mortality

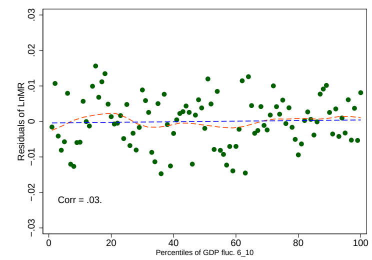
(a) GDP fluc. at ages -1-0



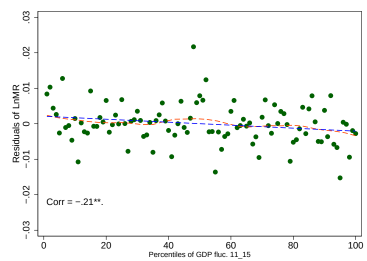
(b) GDP fluc. at age 1-5



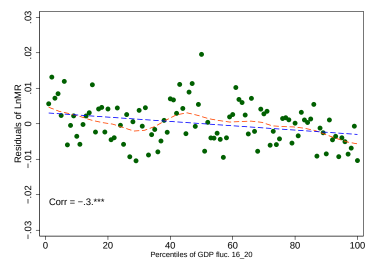
(c) GDP fluc. at age 6-10



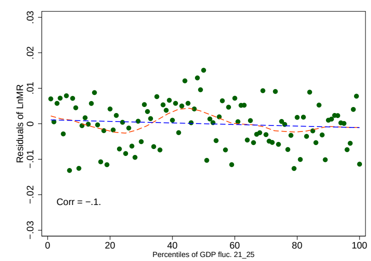
(d) GDP fluc. at ages 11-15



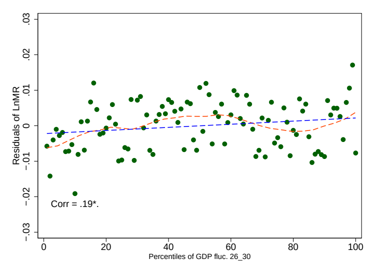
(e) GDP fluc. at age 16-20



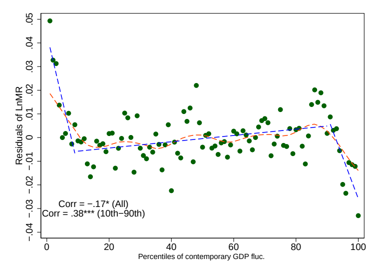
(f) GDP fluc. at ages 21-25



(g) GDP fluc. at age 26-30



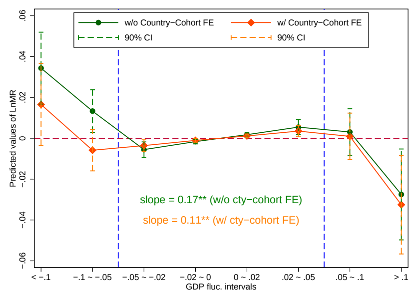
(h) Contemporary GDP fluc.



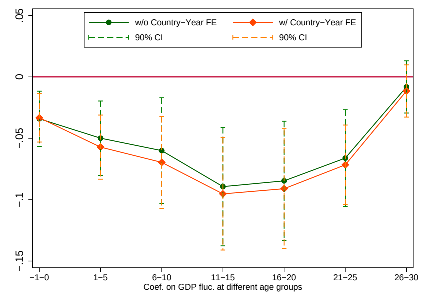
Notes: Mortality is detrended by regressing the logarithm of the mortality rate on country-age-gender fixed effects, those fixed effects interacted with a linear and quadratic term in time, gender-year of birth fixed effects, and gender-year fixed effects. GDP is detrended using a HP filter with smoothing parameter 500. Each observation is placed into a centile bin based on the GDP fluctuation at the relevant time/age group. The mortality residual is then averaged within each cell. The red line is the local smoothed regression given by the centile points. The blue line is the linear regression, with the exception of figure (h), which is piecewise linear.

Figure 4: Short and Long-term effects of GDP fluctuations on adult mortality

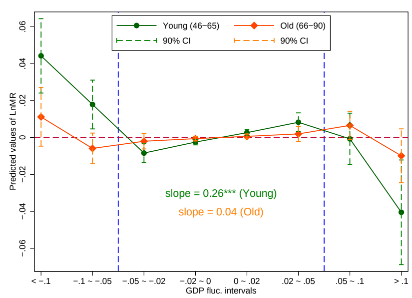
(a) Contemporary effects, full sample



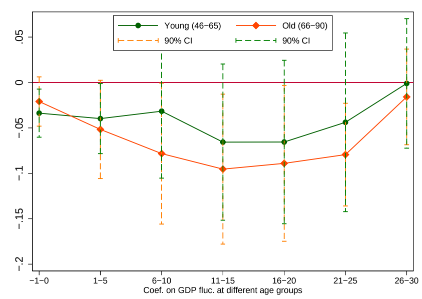
(b) Long-term effects, full sample



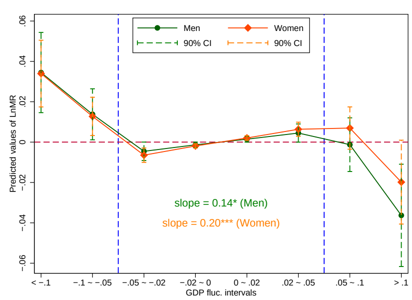
(c) Contemporary effects, by Age



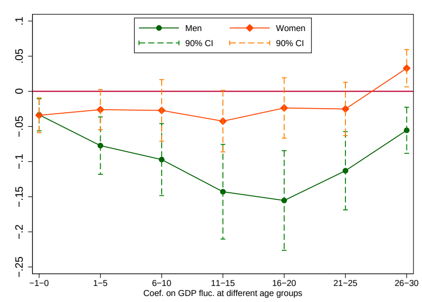
(d) Long-term effects, by Age



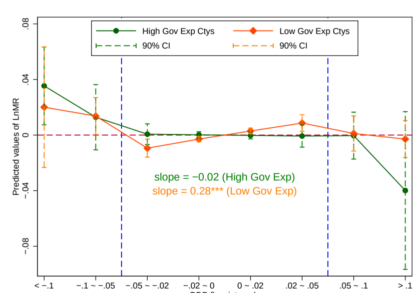
(e) Contemporary Effects, by Gender



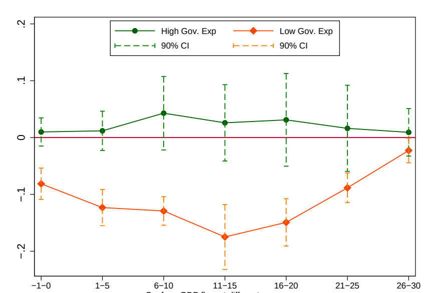
(f) Long-term Effects, by Gender



(g) Short-term effects, by gov. exp. lvl



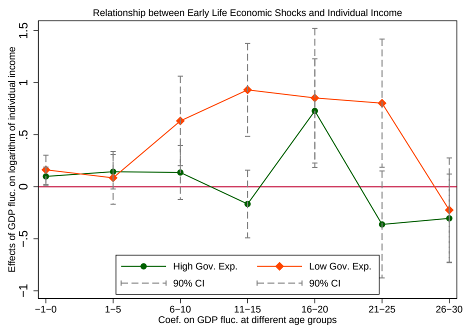
(h) Long-term effects, by gov. exp. lvl



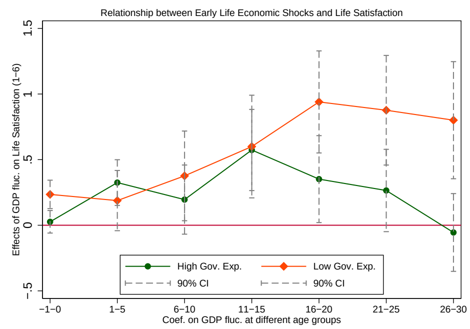
Notes: Each point in the left column figures is the predicted log(mortality) from a regression in a particular interval defined on the X-axis. Each point in the right column figures is the coefficient on the early life GDP fluctuation in the ages indicated on the X-axis. Regressions in column 1 of 1 are used for panels c-f.

Figure 5: The Impact of Early Life GDP on Quality of Life at Older Ages

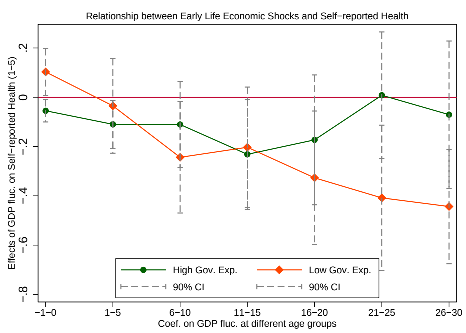
(a) Income, ECHP



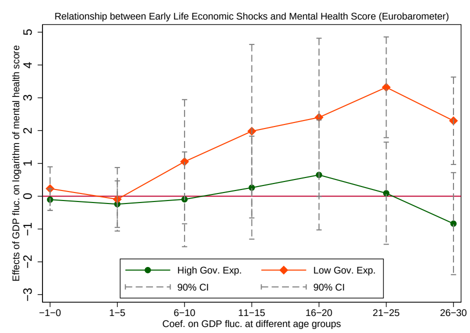
(b) Life Satisfaction, ECHP



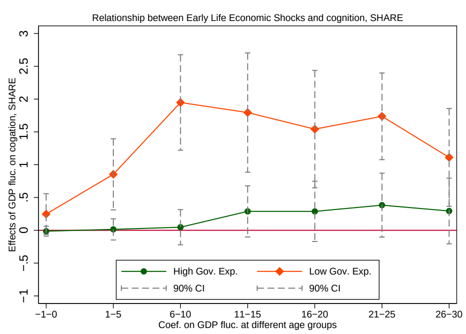
(c) Self-reported health, ECHP



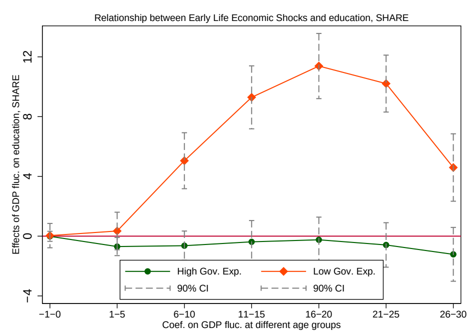
(d) Mental health, Eurobarometer



(e) Cognition, SHARE



(f) Education, SHARE



Note: Results in Panels a - c are from the European Community Household Panel. Data used in Panel d are from the Eurobarometer. Results in Panels e and f are from the SHARE. The coefficients and corresponding 90% confidential intervals are shown.

Table 1: Effects of Contemporary GDP fluctuations and GDP fluctuations in early life on Middle age and Late Life Mortality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(Mortality rate)						
Settings	Basic regression	Country -cohort FE	Country -year FE	With selection controls	Pre- 1945 Years	Post- 1945 Years	Selection & Pre- 1945
Mean	0.70	0.70	0.700	0.70	1.09	0.59	1.09
Contemporary Economic Conditions							
Contemp.	0.170**	0.109**	–	0.163**	-0.104	0.221***	-0.100
GDP fluc.	(0.070)	(0.053)		(0.071)	(0.102)	(0.070)	(0.097)
Big boom	0.030***	0.031***	–	0.030***	0.014	0.040***	0.014
	(0.007)	(0.007)		(0.007)	(0.011)	(0.009)	(0.010)
Boom*	-0.559***	-0.536***	–	-0.549***	0.048	-0.756***	0.058
fluc.	(0.133)	(0.134)		(0.133)	(0.124)	(0.140)	(0.122)
Big bust	0.003	-0.017*	–	0.003	-0.017	0.013	-0.017
	(0.009)	(0.010)		(0.009)	(0.018)	(0.011)	(0.018)
Bust*	-0.326***	-0.275***	–	-0.311***	-0.148	-0.351***	-0.141
fluc.	(0.090)	(0.100)		(0.088)	(0.156)	(0.113)	(0.155)
Economic Conditions in Earlier Life							
GDP fluc.	-0.034**	–	-0.033***	-0.031**	0.052	-0.043***	0.048
-1-0	(0.014)		(0.012)	(0.015)	(0.053)	(0.013)	(0.049)
GDP fluc.	-0.050**	–	-0.057***	-0.040**	-0.104**	-0.056***	-0.105***
1-5	(0.018)		(0.016)	(0.017)	(0.043)	(0.017)	(0.028)
GDP fluc.	-0.060**	–	-0.070***	-0.033	0.104	-0.076***	0.044
6-10	(0.026)		(0.023)	(0.025)	(0.091)	(0.028)	(0.071)
GDP fluc.	-0.089***	–	-0.095***	-0.059**	0.056	-0.100***	0.006
11-15	(0.029)		(0.028)	(0.025)	(0.070)	(0.031)	(0.049)
GDP fluc.	-0.085***	–	-0.091***	-0.054*	0.108	-0.096***	0.116
16-20	(0.030)		(0.030)	(0.027)	(0.095)	(0.031)	(0.090)
GDP fluc.	-0.066***	–	-0.072***	-0.047**	0.032	-0.071**	0.038
21-25	(0.024)		(0.020)	(0.022)	(0.060)	(0.027)	(0.061)
GDP fluc.	-0.008	–	-0.011	0.008	-0.028	-0.011	-0.011
26-30	(0.013)		(0.013)	(0.013)	(0.031)	(0.015)	(0.043)
Pr(Living	–	–	–	-0.145	–	–	-0.463***
up to 45)				(0.097)			(0.148)
N	245,512	245,512	245,512	245,512	75,052	170,460	75,052
R^2	0.995	0.996	0.996	0.995	0.993	0.997	0.993

Notes: All the regressions are weighted by the square root of the population size in the corresponding observation. Standard errors in parentheses are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Proportion Surviving to Age 45

	(1)	(2)	(3)	(4)	(5)
	Proportion Living to Age 45				
Sample	Full sample	Men	Women	Pre-1910 cohorts	Post-1910 Cohorts
Mean	0.77	0.75	0.80	0.58	0.87
Economic Conditions in Earlier Life					
GDP fluc. Age -1-0	0.024	0.024	0.024	0.039	0.021
	(0.016)	(0.018)	(0.016)	(0.032)	(0.015)
GDP fluc. Age 1-5	0.054	0.054	0.053	0.188**	-0.004
	(0.034)	(0.035)	(0.033)	(0.071)	(0.022)
GDP fluc. Age 6-10	0.150***	0.150***	0.151***	0.249*	0.028
	(0.050)	(0.053)	(0.047)	(0.118)	(0.030)
GDP fluc. Age 11-15	0.125**	0.115**	0.134***	0.242**	-0.016
	(0.046)	(0.049)	(0.044)	(0.105)	(0.030)
GDP fluc. Age 16-20	0.131**	0.117**	0.146**	0.226**	-0.021
	(0.053)	(0.053)	(0.054)	(0.087)	(0.045)
GDP fluc. Age 21-25	0.106***	0.094**	0.117***	0.123*	-0.022
	(0.032)	(0.037)	(0.031)	(0.066)	(0.032)
GDP fluc. Age 26-30	0.046	0.035	0.057	0.116**	-0.037
	(0.048)	(0.052)	(0.047)	(0.048)	(0.069)
N	3,680	1,840	1,840	1,476	2,204
R^2	0.977	0.971	0.983	0.960	0.971

Notes: The table includes all cohorts for which survival from age $\leq$ 10 to age 45 is known. Robust standard errors in parentheses are clustered at the country level. The F-test for the difference between the coefficients in columns 2 and 3 is 1.92 (p = 0.10). The F-test for the difference between columns 4 and 5 is 4.24 (p = 0.002).
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Pollution, economic activity and mortality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln(CO_2 emission per capita) (1960-2008)		Ln(Pop-weighted PM2.5) (2000-2008)		Ln(Mortality)			
Variables					Age > 45		Age ⩽ 5	
Contemporary GDP fluc.	0.856***	1.121***	0.801***	0.860**	0.078	0.200**	-0.180	0.368
	(0.162)	(0.396)	(0.138)	(0.342)	(0.070)	(0.090)	(0.230)	(0.232)
Contemporary GDP fluc. *	—	-1.825	—	-1.085	—	-0.966**	—	-3.628**
Agriculture share		(4.319)		(6.941)		(0.373)		(1.553)
Observations								
Total	1,049	1,049	194	194	175,352	175,352	23,842	23,842
Countries	23	23	23	23	23	23	23	23
Country-year cells	1,049	1,049	194	194	1,995	1,995	1,995	1,995

Notes: The CO_2 emission data are from the WDI. Agriculture share in GDP is from the IHS. The $PM_{2.5}$ data are from the Atmospheric Composition Analysis Group. For the the first two columns, covariates include country and year fixed effects as well as country specific linear and quadratic time trends. For the $PM_{2.5}$ results, we only control for the country and year fixed effects due to the short time period. For the last four columns, we use the regression in column 2 of Table 1. The standard errors are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Explaining effects of economic conditions on mortality in the short run

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: ln(mortality rate)	Contempt. GDP fluc.		Mediator		Observations	
	beta	se	beta	se	Total	Countries
Panel A: Pollution and mortality after age 45						
Baseline in sample with Co2 (1960-2008)	0.184***	(0.063)	---	---		
add Co2 emission	0.076	(0.084)	0.105*	(0.055)	117,320	32
add Co2 emission and LFP	0.007	(0.084)	0.0757	(0.052)		
Panel B: Pollution and mortality under age 5						
Baseline in sample with Co2 (1960-2008)	0.359**	(0.164)	---	---	15,530	32
add Co2 emission	0.149	(0.179)	0.263***	(0.095)		
add Co2 emission and LFP	0.149	(0.179)	0.274***	(0.097)		
Panel C: Other mediators of adult mortality after age 45						
Baseline in sample with alcohol (1960-2008)	0.190**	(0.081)	---	---	125,684	32
add alcohol	0.114	(0.099)	0.0101**	(0.004)		
Baseline in sample with tobacco (1960-2008)	0.238***	(0.073)	---	---	73,024	23
add tobacco	0.222***	(0.074)	0.0175	(0.010)		
Baseline in sample with work hours (1981-2008)	0.190*	(0.096)	---	---	54,422	29
add work hours	0.156**	(0.072)	-0.358***	(0.087)		
Baseline in sample with miles driven (1970-2008)	0.0169	(0.103)	---	---	76,654	27
add vehicle miles driven	0.0230	(0.119)	-0.006	(0.025)		

Notes: The Co2 emission data are from the WDI. Alcohol and tobacco consumption data are from WHO. Work hours and vehicle miles data are from the ECHP website. The regressions follow that in column 2 of Table 1. All the standard errors are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Early Life Economic Conditions and Middle and Late Life Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Data	ECHP sample									EB		SHARE	
	Health	Income	Satisfaction			Health behaviors		Social relations		Mental	Drinking	Cognition	Education
Variables	Self-rated health	Ln(Ind. income)	Life in general	Financial situation	Leisure time	Smoker	Obese	Talking with others	Meeting friends	Mental health	Drinker	Cognition score	Years of education
Mean	2.42	11.4	4.18	3.62	4.20	0.32	0.13	4.18	4.00	0.00	0.12	0.00	10.49
Economic Conditions in Earlier Life													
GDP fluc	-0.024	0.121***	0.093**	0.060	0.030	0.050**	-0.002	0.043	0.009	-0.007	-0.113	0.0233	0.354*
age -1-0	(0.026)	(0.046)	(0.044)	(0.043)	(0.042)	(0.023)	(0.030)	(0.039)	(0.030)	(0.193)	(0.082)	(0.0434)	(0.197)
GDP fluc	-0.087*	0.192**	0.278***	0.366***	0.148*	0.001	-0.053	0.185***	0.124**	-0.086	0.023	0.105	0.339
age 1-5	(0.052)	(0.085)	(0.087)	(0.085)	(0.080)	(0.054)	(0.059)	(0.062)	(0.054)	(0.377)	(0.156)	(0.0893)	(0.331)
GDP fluc	-0.125	0.329**	0.277**	0.244**	-0.009	0.091	0.097	0.172**	0.178**	0.357	0.557*	0.267*	1.685***
age 6-10	(0.084)	(0.134)	(0.128)	(0.120)	(0.123)	(0.087)	(0.083)	(0.087)	(0.081)	(0.784)	(0.291)	(0.145)	(0.558)
GDP fluc	-0.235**	0.188	0.591***	0.533***	0.029	0.157	-0.061	0.196*	0.154	1.009	0.319	0.572***	3.013***
age 11-15	(0.106)	(0.170)	(0.149)	(0.145)	(0.143)	(0.108)	(0.100)	(0.105)	(0.101)	(0.871)	(0.193)	(0.198)	(0.723)
GDP fluc	-0.226*	0.929***	0.542***	0.437***	0.013	0.216**	0.009	0.226**	0.188*	1.631*	0.319	0.625***	3.771***
age 16-20	(0.122)	(0.252)	(0.160)	(0.163)	(0.153)	(0.106)	(0.109)	(0.115)	(0.113)	(0.869)	(0.219)	(0.233)	(0.772)
GDP fluc	-0.077	0.196	0.415***	0.547***	0.032	0.075	-0.000	0.205*	-0.006	1.340	0.416**	0.711***	3.434***
age 21-25	(0.124)	(0.245)	(0.155)	(0.154)	(0.146)	(0.096)	(0.096)	(0.113)	(0.120)	(0.837)	(0.155)	(0.236)	(0.744)
GDP fluc	-0.157	-0.231	0.216	0.355**	-0.007	0.084	-0.133	0.074	-0.182	0.591	0.353**	0.534**	1.230
age 26-30	(0.147)	(0.203)	(0.153)	(0.159)	(0.147)	(0.092)	(0.083)	(0.116)	(0.111)	(0.771)	(0.137)	(0.240)	(0.877)
Obs.													
Total	746,706	529,375	637,841	670,223	637,381	241,123	212,098	658,755	729,160	45,650	17,831	117,651	104,082
Ind.	149,126	120,115	132,517	136,291	134,537	79,768	65,423	136,160	148,519	45,650	17,831	98,443	104,082
Cty-cohorts	849	585	831	831	830	671	549	831	847	1,401	1,107	923	936
R^2	0.257	0.796	0.143	3.623	4.190	0.190	0.035	0.173	0.199	0.176	0.127	0.323	0.215

Notes: The data in the first nine columns are from the ECHP 1994-2001. The data used in the columns 10 and 11 are from Eurobarometer. The data for the last two columns are from SHARE. The sample is people aged over 30 with the exception of individual income, which is for people aged 30-64. The regressions in the first 12 columns control for country-gender-year, country-age-gender, and gender-birth cohort fixed effects. Because education is time-invariant for a particular person, the regression in the last column keeps the particular persons in the SHARE data and only controls for country-gender and gender-birth cohort fixed effects. Standard errors clustered by country-cohort cells are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1