Economic Conditions and Mortality: Evidence from 200 Years of Data

David M. Cutler, Wei Huang and Adriana Lleras-Muney*

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. (JEL Codes: H51, I10, I38, N10).

Keywords: Mortality, Economic Conditions, Short-term and long-term.

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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 $I_Y = \frac{\partial I}{\partial Y} > 0$. In contrast B captures smoking, drinking, stress, pollution and all others factors that lower health $I_B = \frac{\partial I}{\partial B} < 0$. 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,

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:

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

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.

References

Adda, Jérôme, "Economic Activity and the Spread of Viral Diseases: Evidence from High Frequency Data," *The Quarterly Journal of Economics*, 2016.

Aizer, Anna, Shari Eli, Joseph Ferrie, and Adriana Lleras-Muney, "The Long-Run Impact of Cash Transfers to Poor Families," *American Economic Review*, April 2016, *106* (4), 935–71.

Almond, Douglas and Janet Currie, "Killing Me Softly: The Fetal Origins Hypothesis," *Journal of Economic Perspectives*, 2011, *25* (3), 153–72.

Bank, World, "World development indicators," *World Bank*, 2015.

Barker, David J, "Fetal origins of coronary heart disease.," *BMJ: British Medical Journal*, 1995, *311* (6998), 171.

Baxter, Marianne and Robert G. King, "Measuring Business Cycles: Approximate Band-Pass Filters For Economic Time Series," *The Review of Economics and Statistics*, November 1999, *81* (4), 575–593.

Becker, Gary S and Kevin M Murphy, "A Theory of Rational Addiction," *Journal of Political Economy*, 1988, *96* (4), 675–700.

_ , Tomas J Philipson, and Rodrigo R Soares, "The Quantity and Quality of Life and the Evolution of World Inequality," *American Economic Review*, 2005, pp. 277–291.

Bhalotra, Sonia, "Fatal fluctuations? Cyclicality in infant mortality in India," *Journal of Development Economics*, 2010, *93* (1), 7–19.

Brenner, M Harvey, "Mortality and the national economy: A review, and the experience of England and Wales, 1936-76," *The Lancet*, 1979, *314* (8142), 568–573.

Cawley, John and Christopher J Ruhm, "The Economics of Risky Health Behaviors," *Handbook of Health Economics*, 2012, *2*, 95.

Chaloupka, Frank J and Kenneth E Warner, "The economics of smoking," *Handbook of health economics*, 2000, *1*, 1539–1627.

Coile, Courtney C, Phillip B Levine, and Robin McKnight, "Recessions, older workers, and longevity: How long are recessions good for your health?," *American Economic Journal: Economic Policy*, 2014, *6* (3), 92–119.

Costa, Dora L., "Health and the Economy in the United States from 1750 to the Present," *Journal of Economic Literature*, 2015, *53* (3), 503–70.

Cullen, Mark R, Michael Baiocchi, Karen Eggleston, Pooja Loftus, and Victor Fuchs, "The Weaker Sex? Vulnerable Men, Resilient Women, and Variations in Sex Differences in Mortality since 1900," Technical Report, National Bureau of Economic Research 2015.

Cunha, Flavio and James Heckman, "The Technology of Skill Formation," *American Economic Review*, 2007, *97* (2), 31–47.

Currie, J et al., "Healthy, wealthy, and wise: socioeconomic status, poor health in childhood, and human capital development.," *Journal of Economic Literature*, 2009, *47* (1), 87–117.

Currie, Janet, "Inequality at Birth: Some Causes and Consequences," *American Economic Review*, 2011, *101* (3), 1–22.

—, "Pollution and Infant Health," *Child development perspectives*, 2013, *7* (4), 237–242.

Cutler, David M, Angus Deaton, and Adriana Lleras-Muney, "The Determinants of Mortality," *Journal of Economic Perspectives*, 2006, *20* (3).

Dehejia, Rajeev and Adriana Lleras-Muney, "Booms, Busts, and Babies' Health," *The Quarterly Journal of Economics*, 2004, *119* (3), 1091–1130.

Deschenes, Olivier and Enrico Moretti, "Extreme weather events, mortality, and migration," *The Review of Economics and Statistics*, 2009, *91* (4), 659–681.

Fogel, Robert W, "Economic Growth, Population Theory, and Physiology: The Bearing of Long-Term Processes on the Making of Economic Policy," *The American Economic Review*, 1994, pp. 369–395.

Frankel, Jeffrey A, Carlos A Vegh, and Guillermo Vuletin, "On graduation from fiscal procyclicality," *Journal of Development Economics*, 2013, *100* (1), 32–47.

Gompertz, Benjamin, "On the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contingencies," *Philosophical transactions of the Royal Society of London*, 1825, pp. 513–583.

Gonzalez, Fidel and Troy Quast, "Mortality and business cycles by level of development: Evidence from Mexico," *Social Science & Medicine*, 2010, *71* (12), 2066–2073.

Granados, José A Tapia and Ana V Diez Roux, "Life and death during the Great Depression," *Proceedings of the National Academy of Sciences*, 2009, *106* (41), 17290–17295.

_ **and Edward L Ionides**, "The reversal of the relation between economic growth and health progress: Sweden in the 19th and 20th centuries," *Journal of Health Economics*, 2008, *27* (3), 544–563.

Hanlon, W Walker, "Pollution and Mortality in the 19th Century," Technical Report, National Bureau of Economic Research 2015.

Hodrick, Robert J and Edward C Prescott, "Postwar US business cycles: an empirical investigation," *Journal of Money, credit, and Banking*, 1997, pp. 1–16.

Hoynes, Hilary, Diane Whitmore Schanzenbach, and Douglas Almond, "Long-Run Impacts of Childhood Access to the Safety Net," *American Economic Review*, April 2016, *106* (4), 903–34.

Idler, Ellen L and Yael Benyamini, "Self-rated health and mortality: a review of twenty-seven community studies," *Journal of health and social behavior*, 1997, pp. 21–37.

Jensen, Robert, "Agricultural volatility and investments in children," *The American Economic Review*, 2000, *90* (2), 399–404.

Kueng, Lorenz and Evgeny Yakovlev, "Long-Run Effects of Public Policies: Endogenous Alcohol Preferences and Life Expectancy in Russia," *Available at SSRN 2776422*, 2016.

Lindo, Jason M, "Aggregation and the estimated effects of economic conditions on health," *Journal of Health Economics*, 2015, *40* (C), 83–96.

Lleras-Muney, Adriana and Flavien Moreau, "The Shape of Mortality: Implications for Economic Analysis," *Working Paper*, 2016.

Oreopoulos, Philip, Till von Wachter, and Andrew Heisz, "The short-and long-term career effects of graduating in a recession," *American Economic Journal: Applied Economics*, 2012, *4* (1), 1–29.

Paxson, Christina and Norbert Schady, "Child health and economic crisis in Peru," *The World Bank Economic Review*, 2005, *19* (2), 203–223.

Rao, Neel, "The Impact of Macroeconomic Conditions in Childhood on Adult Labor Market Outcomes," *Economic Inquiry*, 2016.

Ruhm, Christopher J, "Are Recessions Good for Your Health?," *The Quarterly Journal of Economics*, 2000, *115* (2), 617–650.

_, "Good times make you sick," *Journal of Health Economics*, 2003, *22* (4), 637–658.

_, "Healthy living in hard times," *Journal of Health Economics*, 2005, *24* (2), 341–363.

_, "A healthy economy can break your heart," *Demography*, 2007, *44* (4), 829–848.

_, "Recessions, healthy no more?," *Journal of Health Economics*, 2015, *42*, 17–28.

Stevens, Ann H, Douglas L Miller, Marianne E Page, and Mateusz Filipski, "The Best of Times, the Worst of Times: Understanding Pro-cyclical Mortality," *American Economic Journal: Economic Policy*, 2015, *7* (4), 279–311.

Sullivan, Daniel and Till Von Wachter, "Job displacement and mortality: An analysis using administrative data," *The Quarterly Journal of Economics*, 2009, pp. 1265–1306.

Townsend, Joy, Paul Roderick, and Jacqueline Cooper, "Cigarette smoking by socioeconomic group, sex, and age: effects of price, income, and health publicity," *Bmj*, 1994, *309* (6959), 923–927.

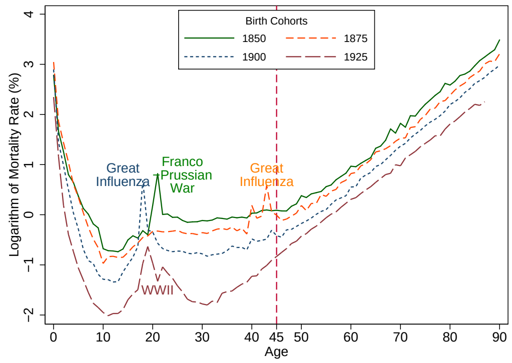
van den Berg, Gerard J, Maarten Lindeboom, and France Portrait, "Economic conditions early in life and individual mortality," *The American Economic Review*, 2006, pp. 290–302.

Vaupel, James W, Kenneth G Manton, and Eric Stallard, "The impact of heterogeneity in individual frailty on the dynamics of mortality," *Demography*, 1979, *16* (3), 439–454.

Vegh, Carlos A and Guillermo Vuletin, "How Is Tax Policy Conducted Over the Business Cycle?," *American Economic Journal: Economic Policy*, 2015, *7* (3), 327–370.

Wilcox, AJ, "On the importance–and the unimportance–of birthweight.," *International Journal of Epidemiology*, 2001, *30* (6), 1233.

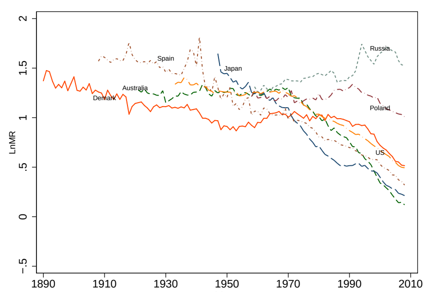
Figure 1: Logarithm of Mortality Rates by Age. 1850, 1875, 1900 and 1925 Birth Cohorts



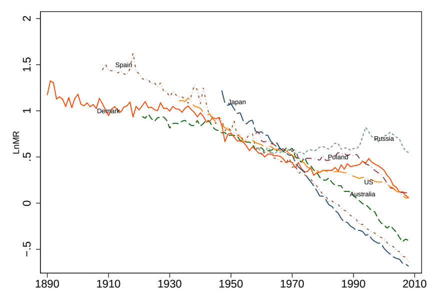
Notes: Authors' calculations from Human Mortality Database (HMD). Logarithm of the population-weighted mean mortality rates are plotted. We average mortality across all countries with data for each cohort. Thus, there are more countries represented for more recent cohorts.

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

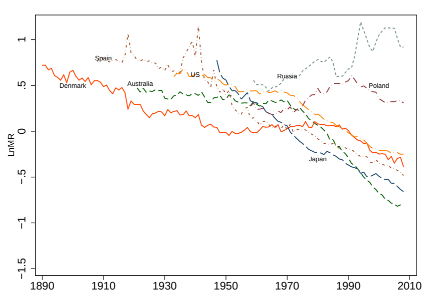
(a) Men, 60-69



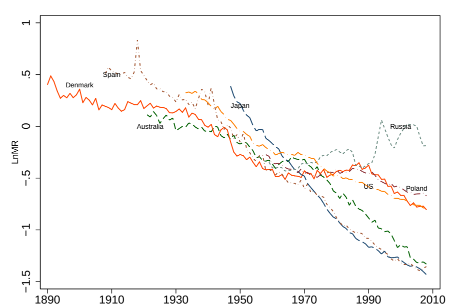
(b) Women, 60-69



(c) Men, 50-59



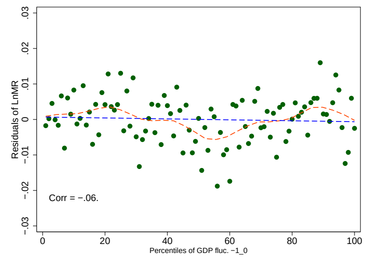
(d) Women, 50-59



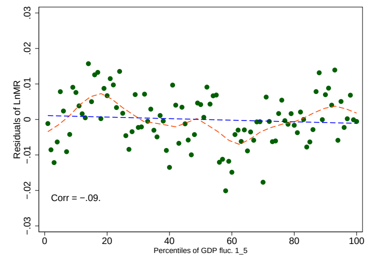
Notes: Authors' calculations from Human Mortality Database (HMD).

Figure 3: GDP fluctuations during the lifetime and residual mortality

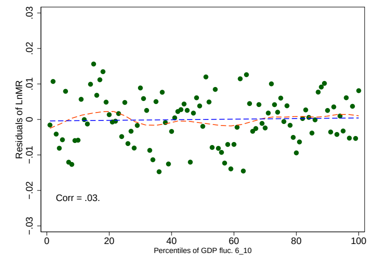
(a) GDP fluc. at ages -1-0



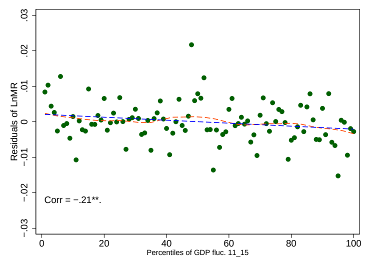
(b) GDP fluc. at age 1-5



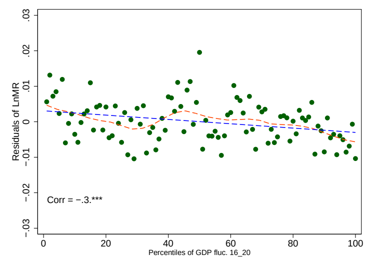
(c) GDP fluc. at age 6-10



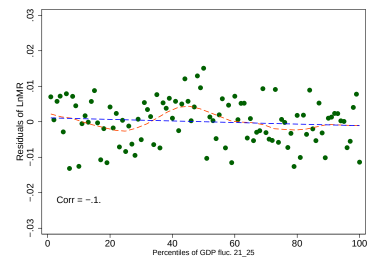
(d) GDP fluc. at ages 11-15



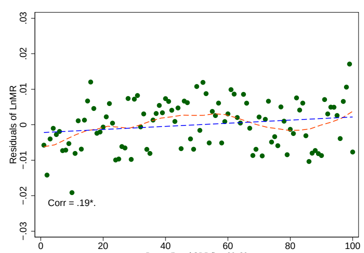
(e) GDP fluc. at age 16-20



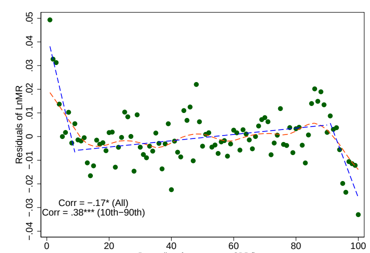
(f) GDP fluc. at ages 21-25



(g) GDP fluc. at age 26-30



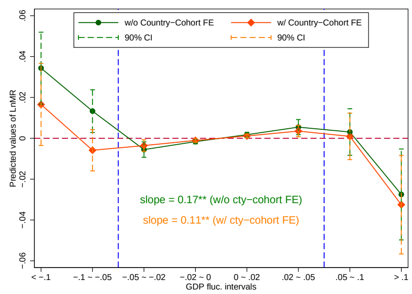
(h) Contemporary GDP fluc.



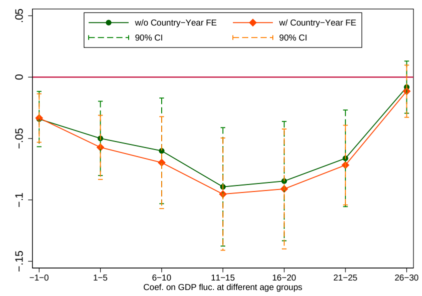
Notes: Mortality is detrended by regressing the logarithm of the mortality rate on country-age-gender fixed effects, those fixed effects interacted with a linear and quadratic term in time, gender-year of birth fixed effects, and gender-year fixed effects. GDP is detrended using a HP filter with smoothing 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

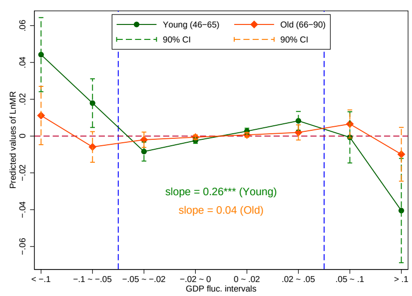
(a) Contemporary effects, full sample



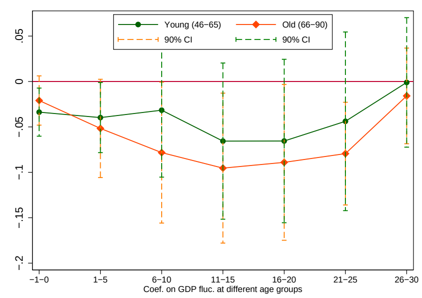
(b) Long-term effects, full sample



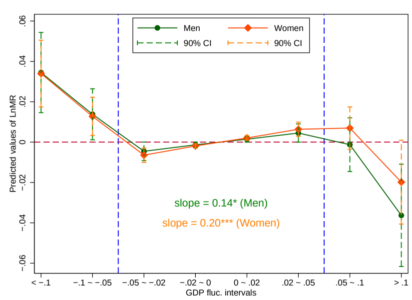
(c) Contemporary effects, by Age



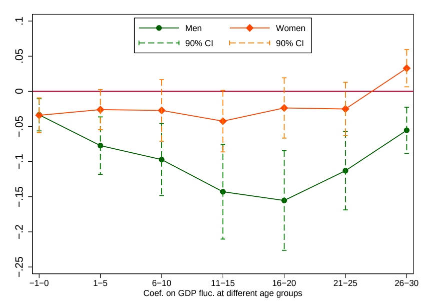
(d) Long-term effects, by Age



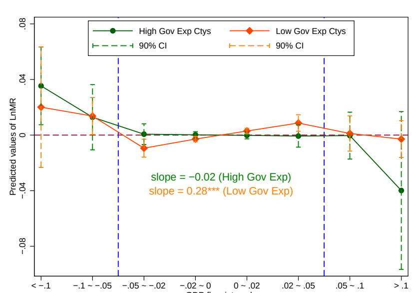
(e) Contemporary Effects, by Gender



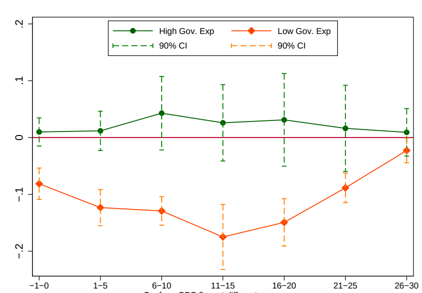
(f) Long-term Effects, by Gender



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



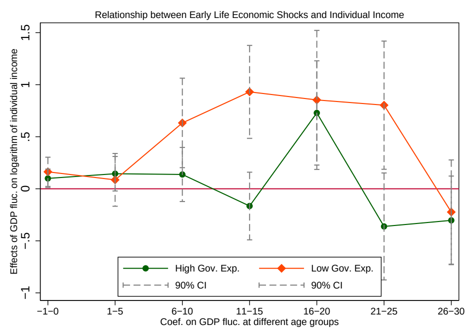
(h) Long-term effects, by gov. exp. lvl



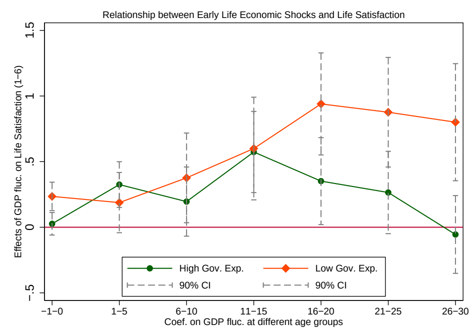
Notes: Each point in the left column figures is the predicted log(mortality) from a regression in a particular interval defined on the X-axis. Each point in the right column figures is the coefficient on the early life GDP fluctuation in the ages indicated on the X-axis. Regressions in column 1 of 1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

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

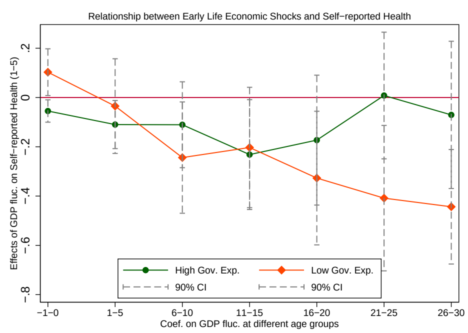
(a) Income, ECHP



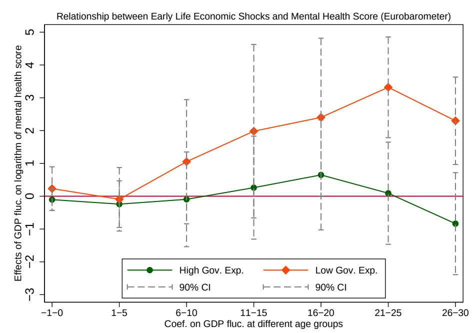
(b) Life Satisfaction, ECHP



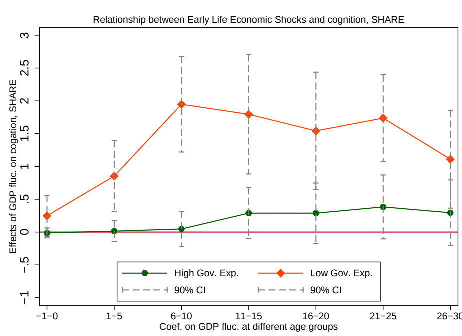
(c) Self-reported health, ECHP



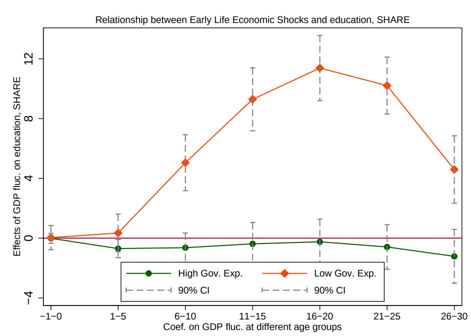
(d) Mental health, Eurobarometer



(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 $\leqslant$ 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

Appendix

For Online Publication

This appendix contains 4 parts. Section A presents the comparative statics and the Figures resulting from simulating the model which are referred to in Section III in the paper. Section B introduces the data and provides summary statistics. Section C shows how different filters work, and why we choose the setting in the paper. Section D presents various empirical analyses described in the paper.

A. Theory appendix

A1. mortality rates and economic conditions: comparative statics

Using the expressions in Section III, we can compute the mortality rate at any given age. To illustrate the effects of economic conditions we consider the mortality rate age 2 and how it varies with changes in conditions at age 2 and age 1.

In the first period the (infant) mortality rate MR_1 is given by

$$
\begin{aligned}
MR_1 = P(H_1 \leq \underline{H}|g_1) &= P\left(H_0 + I(Y_1, B_1) - \delta + \varepsilon_1 \leq \underline{H}|g_1\right) \\
&= P(\varepsilon_1 \leq \varphi_1) = F(\varphi_1)
\end{aligned}
$$

where $\varphi_1 = \underline{H} - I(Y_1, B_1) + \delta - H_0$ captures the threshold for dying in period 1 in terms of the random shock. Consider now the probability of dying at age $t = 2$. This is given by the probability that the stock falls below $\underline{H}$ at age 2, conditional on having survived to age 2, which can be expressed as:

$$\begin{aligned} MR_2 &= E(D_2 = 1 | D_1 = 0) \\ &= P(H_2 < \underline{H} | H_1 > \underline{H}, g_1, g_2) \\ &= \frac{P(H_2 < \underline{H}, H_1 > \underline{H} | g_1, g_2)}{P(H_1 > \underline{H} | g_1, g_2)} \\ &= \frac{P(\varepsilon_2 < \varphi_2 - \varepsilon_1, \varepsilon_1 > \varphi_1)}{1 - F(\varphi_1)} \\ &= \frac{K(\varphi_2, \varphi_1)}{1 - F(\varphi_1)} \end{aligned} \tag{1}$$

where $\varphi_2 = \underline{H} - I(Y_1, B_1) - I(Y_2, B_2) + \delta + \delta * 2^{\alpha} - H_0$, and $K(\varphi_2, \varphi_1) = \int_{\varepsilon_1=\varphi_1}^{\infty} \int_{\varepsilon_2=-\infty}^{\varphi_2-\varepsilon_1}$ $f(\varepsilon_1) f(\varepsilon_2) d\varepsilon_1 d\varepsilon_2$.

Short-term effects. Under assumptions (1)-(3) in Section 3.1 of the text, we can now express the effect of an unexpected improvement in current economic conditions g_2 on the logarithm of mortality at age 2 as

$$\frac{\partial lnMR_2}{\partial g_2} = \frac{-1}{K(\varphi_2, \varphi_1)} \underbrace{\frac{\partial K}{\partial \varphi_2}}_{>0} \left[\underbrace{I_y \frac{\partial Y_2}{\partial g_2}}_{>0} + \underbrace{I_B \frac{\partial B_2}{\partial g_2}}_{<0} \right] \tag{2}$$

The term outside the parentheses captures the responsiveness of the probability of dying to changes in H and is negative (higher health results in lower mortality). The term inside the parentheses captures the effect of changes in economic conditions on health, and it has an ambigous sign. It depends on how conditions affect both inputs and on how inputs affect health. Because (by assumption) the two inputs have opposite effects (signs) on health, the overall sign of the short term effect of improved conditions is ambigous and determined by the relative magnitudes of the two effects. If overall investment goes up, mortality falls.

Long term effects. Consider now the effect of economic conditions earlier in life, specifically the effect of economic conditions one period earlier, $\frac{\partial lnMR_2}{\partial g_1}$. This effect is given by:

$$\begin{aligned}\frac{\partial lnMR_2}{\partial g_1} &= - \frac{1}{K(\varphi_2,\varphi_1)}\frac{\partial K}{\partial \varphi_2}\left[I_y\frac{\partial Y_2}{\partial g_1}+I_B\frac{\partial B_2}{\partial g_1}+I_y\frac{\partial Y_1}{\partial g_1}+I_B\frac{\partial B_1}{\partial g_1}\right] \\ &\quad - \left[\frac{1}{K(\varphi_2,\varphi_1)}\frac{\partial K}{\partial \varphi_1}+\frac{F'(\varphi_1)}{1-F(\varphi_1)}\right]\left[I_y\frac{\partial Y_1}{\partial g_1}+I_B\frac{\partial B_1}{\partial g_1}\right]\end{aligned}$$

The first term shows that good economic conditions in the past affect current mortality because they affect the level of current health. This is composed of two parts. First, economic conditions in the past affect prior investments $\left[I_y\frac{\partial Y_1}{\partial g_1}+I_B\frac{\partial B_1}{\partial g_1}\right]$ and this changes the initial stock in period 2, h_1. Second, past conditions affect the level of current investment $\left[I_y\frac{\partial Y_2}{\partial g_1}+I_B\frac{\partial B_2}{\partial g_1}\right]$. The overall sign of the term in parenthesis is ambiguous and depends on the relative magnitudes of the two effects over time. The second term corresponds to a selection effect and it also has an ambiguous sign because $\frac{\partial K}{\partial \varphi_1} < 0$ but $F'(\varphi_1) > 0$. Thus the overall effect of changing conditions on the long term is also ambiguous.

Culling versus scarring. Selection effects in this model are small because shocks have permanent "scarring" effects on the health stock of the population, and thus on mortality. We can also consider temporary shocks to mortality that do not affect the stock of health, which might just then by thought of as "culling". One way to characterize these shocks is to model them as idiosyncratic shocks to the dying threshold, so that $\underline{H}_t = \underline{H}(g_t) = \underline{H} + \eta(g_t)$. If we assumed no scarring effects but only temporary culling effects then we can express the effects of shock in the short term as

$$\frac{\partial lnMR_2}{\partial g_2} = \frac{1}{K(\varphi_2,\varphi_1)}\underbrace{\frac{\partial K}{\partial \varphi_2}}_{>0}\frac{\partial \eta(g_2)}{\partial g_2} \tag{3}$$

if good economic conditions raise the threshold ($\eta'(g_t) > 0$), then more people will die. The fraction dying depends on the mass close to the threshold.

The long term effect of this temporary shock to the threshold will be given by

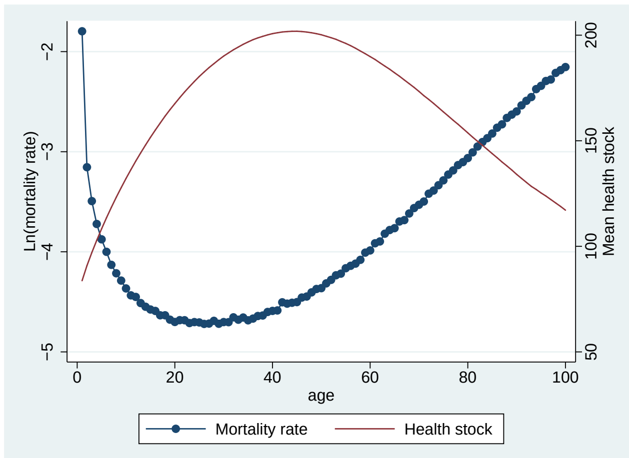
$$\frac{\partial lnMR_2}{\partial g_1} = -\left[\frac{1}{K(\varphi_2,\varphi_1)}\frac{\partial K}{\partial \varphi_1}+\frac{F'(\varphi_1)}{1-F(\varphi_1)}\right]\frac{\partial \eta(g_1)}{\partial g_1}$$

in which case the long term effects are given exclusively by selection effects.

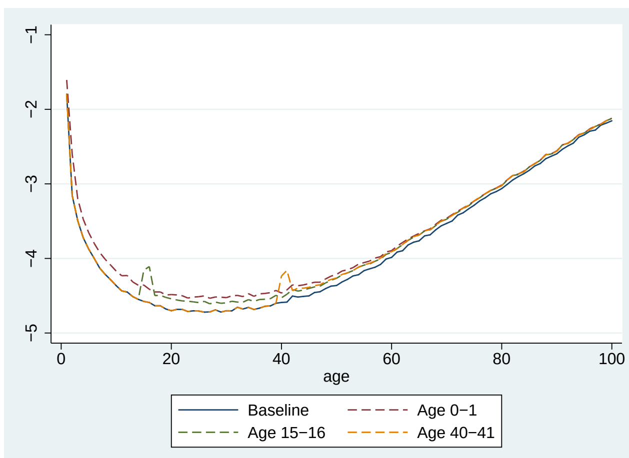
To understand the implications of the model, we simulate mortality rates under different assumptions. We assume the initial health stock H_0 is normally distributed with mean 68 and standard deviation of 34. The threshold for death H is 36. Shocks ε_t are drawn every period from a $N(0,16)$. The rate of depreciation is $\delta = 0.04$, and the aging rate is $\alpha = 1.3$. Last the level of investment is constant at 4.5. These values result in mortality rates matching the profile of males in Belgium in 1860, with an infant mortality of about 17 percent and life expectancy around 38. For details see Lleras-Muney and Moreau (2016).

Figure A1(a) shows the evolution of the health stock and mortality rates with age. Figure A1(b) shows the impact of mortality shocks at three different ages: 1, 15, and 40. We model the shock as a temporary decrease in the investment level from 4.5 to -0.5 that last for two years, and then investment reverts back to 4.5. In each case, mortality remains higher after the shock than in the no-shock baseline, throughout the range of ages.

Figure A1: Evolution of health stock with age



(a) Evolution of mortality rates and health



(b) Effect of negative shocks at different ages

Note: We assume the initial health stock H_0 is normally distributed with mean 68 and standard deviation of 34. The threshold for death H is 36. Shocks ε_t are drawn every period from a $N(0,16)$. The rate of depreciation is $\delta = 0.04$, and the aging rate is $\alpha = 1.3$. Last the level of investment is constant at 4.5. These values result in mortality rates matching the profile of males in Belgium in 1860, with an infant mortality of about 17 percent and life expectancy around 38.

B. Data appendix

B1. Macro level data

Human Mortality Database (HMD) Mortality data are taken from the Human Mortality Database (HMD).[1] To understand the effects of economic conditions over the life time, we need populations with significant time series representation. Table B1 lists the 32 countries with mortality information available prior to 1970 that we study. We exclude Chile (1992-), Germany (1990-), Israel (1983-), Slovenia (1983-), and Taiwan (1970-) because the data covers very few years. The countries in our sample are mostly European countries, and a few other developed countries (Australia, Canada, the US, New Zealand and Japan). 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, as we show below. For some countries such as Belgium, Denmark, France, and Sweden, we can follow the mortality of all ages since about 1850. But not all countries collected high quality data so early. For example, Australia, Canada, the United Kingdom, and the United States started around 1930. The last country enters the sample in 1960. The average number of years observed is 97 years.

Agriculture Shares of GDP Data on agriculture shares are compiled data from multiple national and international sources and reported by the International Historical Statistics.[2] The data only cover 23 countries in our database. We attempted

[1] See http://www.mortality.org/ for more details.
[2] http://www.eui.eu/Research/Library/ResearchGuides/Economics/Statistics/DataPortal/IHS.aspx

to examine the industrial and service share of the economy as well, but these are not measured as consistently across time or over countries. For example, the industrial sector covers construction for European countries but not for the North America countries. For another, the commerce sector excludes financial for European countries and other services, but covers finance in North America. Thus, we confine our analysis to agriculture.

Figure B1 shows the share of agriculture changing since 1800. Among the countries with available data, the average agriculture share declines from around 40 percent in 1800-1850 to 2 percent in the 2000s.

Unemployment Rate Unemployment rates are not available for all countries and all years. For example, many countries in the former Soviet Union only have unemployment data for the 1990s. The unemployment rate used in this paper are from World Development Index (WDI), Layard et al. (2005), OECD website and Mitchell (1998). Our previous paper Cutler et al. (2015) provides the details.

PM 2.5 data The PM 2.5 data are from Atmospheric Composition Analysis Group (See http://fizz.phys.dal.ca/~atmos/martin/). The researchers estimate ground-level fine particulate matter (PM2.5) by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWIFS instruments with the GEOS-Chem chemical transport model, and subsequently calibrated to global ground-based observations of PM2.5 using Geographically Weighted Regression (GWR) (Van Donkelaar et al., 2016). The data are available since 2000.

Figure B2a show the pro- cyclicality of PM 2.5. Higher GDP fluctuations are associated with higher values of PM2.5.

CO_2 emissions The CO_2 data come from the World Development Indicator (WDI). Carbon dioxide emissions result from the burning of fossil fuels and the manufacture of cement. CO2 emissions are estimated using data on consumption of solid, liquid, and gas fuels and gas flarings (Bank, 2015).

The U.S. Department of Energy's Carbon Dioxide Information Analysis Center (CDIAC) calculates annual anthropogenic emissions from data on fossil fuel consumption (from the United Nations Statistics Division's World Energy Data Set) and world cement manufacturing (from the U.S. Department of Interior's Geological Survey, USGS 2011). Although estimates of global carbon dioxide emissions are probably accurate within 10 percent (as calculated from global average fuel chemistry and use), country estimates may have larger error bounds. Trends estimated from a consistent time series tend to be more accurate than individual values.

Figure B2b show the strong correlation between CO_2 and $PM_{2.5}$ emissions. For the country-year cells with valid measures for both, we regress each on country and year fixed effects, and plot the residuals of $PM_{2.5}$ against those of CO_2. There is a strong positive correlation between the two residuals ($\rho = 0.24$; $p = 0.001$).

Figure B3a shows the trend in average per capita CO_2 emissions across the countries in the sample. Emissions rose rapidly in the 1960s and slowed in the 1970s. After 1980, CO_2 emissions are generally flat, perhaps as a result of environmental regulations (e.g., the Clean Air Act of 1970 in the United States), which would have affected both CO_2 and $PM_{2.5}$. Similar to PM2.5, CO_2 is also strongly procyclical, consistent with Khan et al. (2016). This is shown visually in the top left panel of Figure B4a for CO_2. To form residual CO2 emissions, we regress per capita emissions on country and year dummy variables, and a quadratic time trend for each country.

Other mediators Other mediators in this study including working hours, labor force participation, and transportation. The data are all from OECD website. The alcohol consumption and smoking consumption data are from WHO website.

Figure B3b shows that labor force participation (LFP) of women is increasing over time, while that for men is decreasing. An analogous analysis for women's LFP finds a strong pro-cyclicality, as shown in Figure B3b. Figure B3c shows that hours worked per worker are generally fairly constant over time, fluctuating in a range of about 4 percent. We use the same methodology to detrend work hours and do not find a significant correlation between working hours and GDP fluctuations. Figure B3d transportation miles have increased over time, and the vehicle kilometers present a strong pro-cyclicality in Figure B4d.

We also examine the patterns for health behaviors, including alcohol and tobacco consumption. Panel e in Figure B3 does not show a obvious time trend in alcohol consumption (i.e., the alcohol consumption is measured in liters of pure alcohol per capita), but panel f shows that the tobacco consumption (grammes per capita) has been declining since the 1980s. Panels e and f in Figure B4 shows that both alcohol and tobacco consumption significantly pro-cyclical.

Figure B5 shows the pro-cyclicality of the mediators by government expenditure level. For mediators like CO_2, labor force participation, vehicles miles driven, and tobacco, we find the pro-cyclicality is very similar between high and low government expenditure countries. However, for working hours and alcohol consumption, we find a stronger pro-cyclicality in low-government expenditure countries. The difference is significant (P-value = 0.05) for alcohol consumption but not statistically significant for working hours. We also find that the counter-cyclicality for alcohol is mostly driven by the eastern European countries such as Russia, the pro-cyclicality is similar when we drop Russia, which is classified as a high expenditure country according to our definition.

Consumption Consumption data are from Barro-Ursua Macroeconomic Data (See Barro's website: http://scholar.harvard.edu/barro/publications/barro-ursua-macroeconomic-data for details). It is measured in country-year level. Panels a and b in Figure B6 show the show the pro-cyclicality of consumption in high and low government expenditure countries. The slope is larger in lower expenditure countries. The difference in pro-cyclicality between high and low government expenditure countries is significant (coef = .057 in .032 in high and low government expenditure countries respectively; p-value for difference = 0.04).

B2. Micro level data

European Community Household Panel (ECHP) The ECHP is a panel survey started in 1994, which follows households until 2001. Households are interviewed annually over the seven year span. The ECHP samples people in 14 countries for which we have mortality data. Most of the countries are high government spending countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, and Italy), but there are some low spending countries as well (Ireland, Luxembourg, the Netherlands, Portugal, Spain, and the UK). To focus on early life conditions, we consider people aged 30 and older who live in the country they were born (95.8 percent of the total sample). In total, there are about 750,000 observations for about 150,000 unique individuals, corresponding to 31 countries and covering cohorts born

1911 to 1972. Panel A of Table B2 report the summary statistics for the ECHP sample.

The primary measure of health we employ is self-reported health status, scored on a basis from very good (1) to very bad (5).[3] The average person rates their health a 2.4 on the 1-5 scale. The next outcome is the log of total personal income. We also include variables for satisfaction with work and main activity; financial situation; and leisure time. In each case, the scale is from 1 to 6, with higher levels corresponding to greater satisfaction. The averages are 3.7 for financial satisfaction and 4.6 for leisure time satisfaction.

Our fourth set of variables is for health behaviors. We measure current smoking status and a dummy for obesity (BMI$\geq$30). All of these variables are based on self-reports. Across the cohorts and years, 33 percent of people are current smokers and 13 percent are obese.

Finally, we include measures for social integration: the frequency with which people talk with others and meet with friends. Each of these variables is expressed on a 1 to 5 scale, from never (=1) to on most days (=5). The median person reports talking with others and meeting with friends once or twice a week.

Eurobarometer (EB) The EB is the longest running regular cross-national and cross-temporal opinion poll program in Europe. Starting in 1997 and up to 2012, 31 countries in Europe conducted biannual face-to-face interviews. We use the EB data because we have no mental health or alcohol in the ECHP. But the EB contains

[3]Since the survey is a panel, we can also measure mortality, but the samples are not large enough for accurate estimates at the country-cohort level. Nevertheless, though noisy, our qualitative results are very similar to those we report for self reported health, and for those presented earlier using the HMD.

a smaller number of observations so for other outcomes we present results from the ECHP. We restrict analyses to individuals aged over 30.

As part of the SF-36 Health Survey-instrument the EB asks the occurrence of current mental health problems, and the answers vary from 1 for "Never" to 5 "Almost everyday". These nine questions are about the frequency of feeling full of life, feeling tense, felling down in dumps, feeling calm, having a lot of energy, felling downhearted, feeling worn out, feeling happy, and feeling tired. We use the principle component factor (PCF) model of the answers to the nine questions to construct an overall mental health index. Higher score means being mentally healthier. The EB also contains questions on alcohol–we construct a consistent measure across surveys and look at an indicator for whether the individual drinks every day.

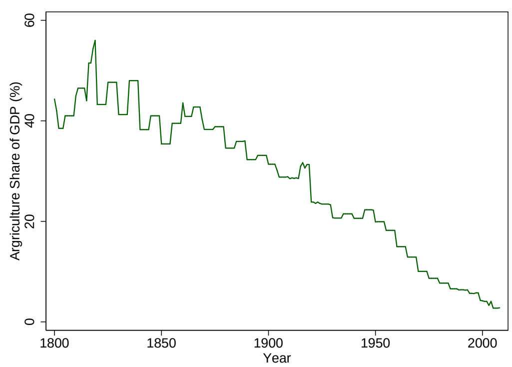
Panel B of Table B2 report the summary statistics for the EB sample. The mental health is standardized with mean value of zero. The standard deviation for the mental health score is 2.16. There are 11 percent of individuals who drink every day.

Survey of Health, Ageing and Retirement in Europe (SHARE) The Survey of Health, Ageing and Retirement in Europe (SHARE) is a multidisciplinary and cross-national panel database of micro data on health, socio-economic status and social and family networks of approximately 123,000 individuals (more than 293,000 interviews) from 20 European countries (+Israel) aged 50 or older (See http://www.share-project.org/ for details)

We use the SHARE data because it contains measures of cognition. The cognition measures we use include verbal fluency, numeracy, and delayed word recall. For verbal fluency tests, the respondents were asked to name members of animals within a limited time span of one minute. The score is the sum of acceptable animals that range from 0 to 100. The numeracy test asks the individual to subtract 7 from the prior number, beginning with 100 for five trials. Correct subtractions are based on the prior number given, so that even if one subtraction is incorrect subsequent trials are evaluated on the given (perhaps wrong) answer. Valid scores are 0-5. Delayed word recall tests memorization ability. It is the count of the number of words from the 10 word immediate recall list that were recalled correctly after a delay spent answering other survey questions. The measure ranges from 0 to 20.

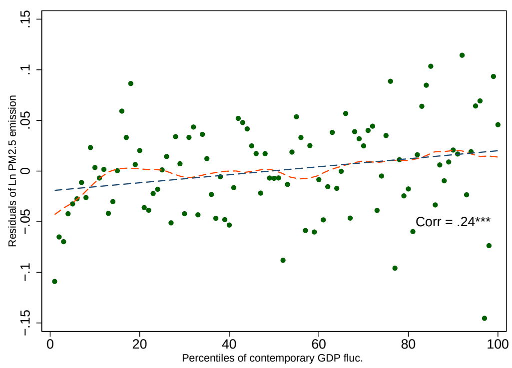
Panel C of Table B2 report the summary statistics for the SHARE. The mean score for verbal fluency, numeracy, and word recall are 20, 3.3 and 8.8, respectively.

Figure B1: Agriculture share over time

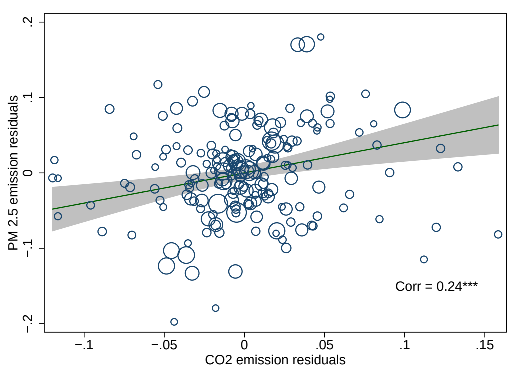


Note: We collect the data from International Historical Statistics (IHS). IHS provides the shares of GDP in about every 5-10 years for each country. The mean value of agriculture share of the 23 countries is plotted.

Figure B2: Pro-cyclicality and correlation with CO_2 of $PM_{2.5}$



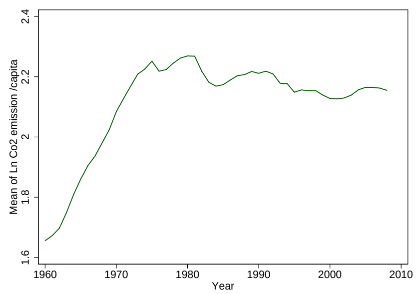
(a) Pro-cyclicality of PM 2.5



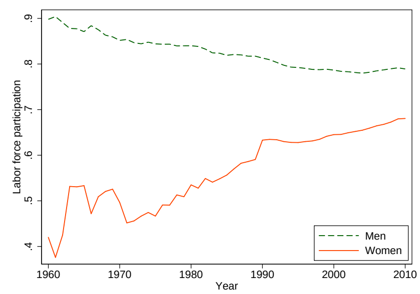
(b) Correlation of PM 2.5 with CO_2

Note: The PM 2.5 data are from Atmospheric Composition Analysis Group. To form residual $PM_{2.5}$ and CO_2 emissions, we use the data from the 23 countries in 2000-2008 and regress per capita emissions in logarithm on country and year dummy variables.

Figure B3: Time Trends for Mediators

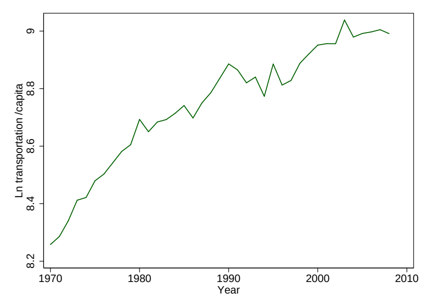


(a) CO_2

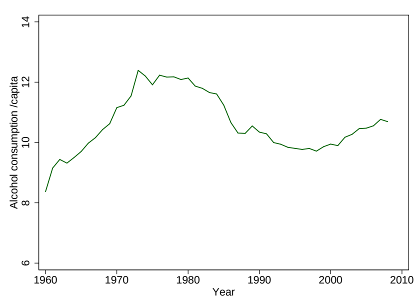


(b) Women and Men LFP

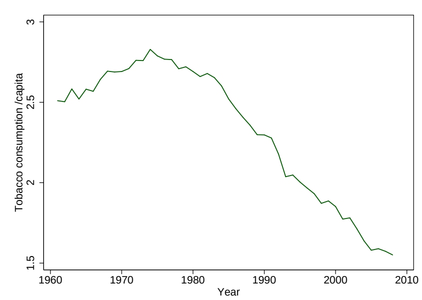
(c) Working Hours



(d) Vehicle Miles Driven



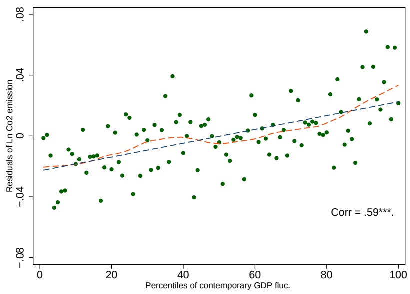
(e) Alcohol consumption



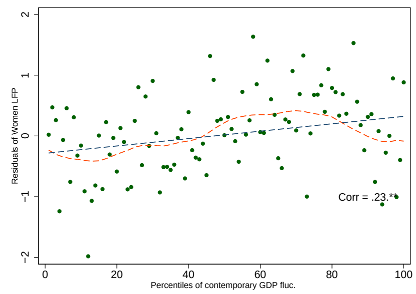
(f) Tobacco consumption

Note: Data source of CO2 emission is World Development Indicators. Working hours and vehicle miles driven are from OECD website. Alcohol and tobacco consumption are from the WHO website. The mean values of all available countries are plotted against the years.

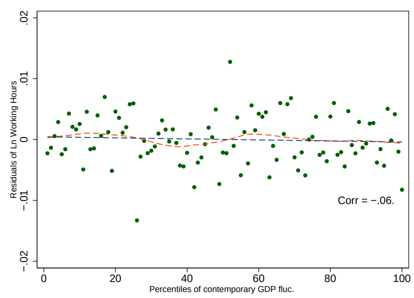
Figure B4: Pro-cyclicality of Pollution, Work Hours, Motor Vehicle, and Health Behaviors



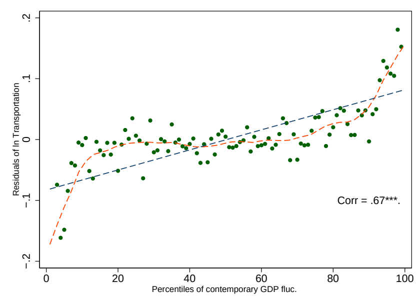
(a) CO_2



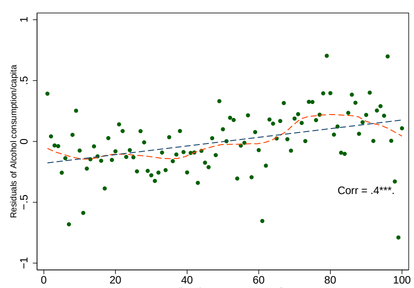
(b) Women LFP



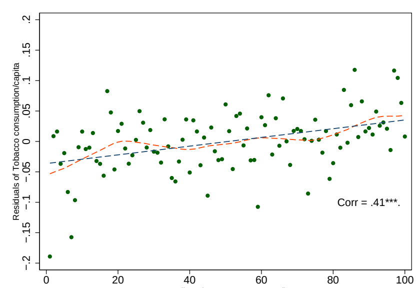
(c) Working Hours



(d) Vehicle Miles Driven



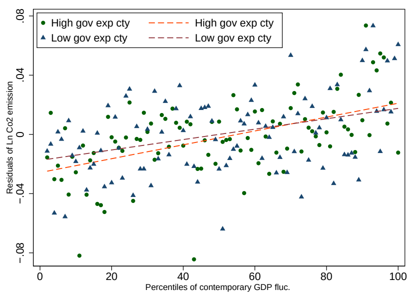
(e) Alcohol consumption



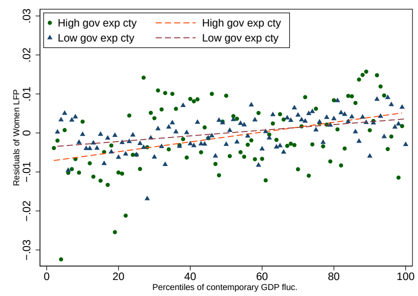
(f) Tobacco consumption

Note: Data source of CO2 emission is World Development Indicators. Working hours and vehicle miles driven are from OECD website. Alcohol and tobacco consumption data are from WHO. To obtain the residuals of the mediators, we use the data from all the available countries in all the years, and then regress each mediator on country and year dummy variables, as well as country specific linear and quadratic trends in time. Then we plot the mean value of the residuals over the bins of the GDP residuals.

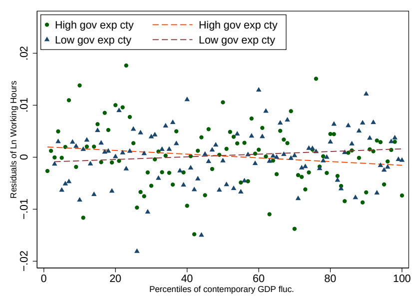
Figure B5: Pro-cyclicality of Mediators, in High and Low government expenditure countries



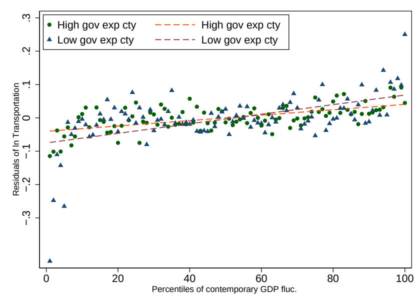
(a) CO_2



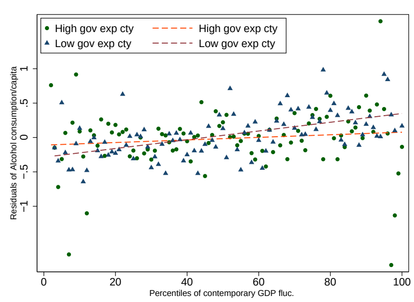
(b) Women LFP



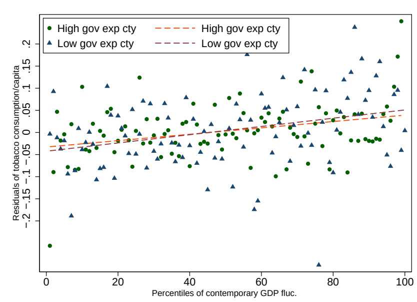
(c) Working Hours



(d) Vehicle Miles Driven



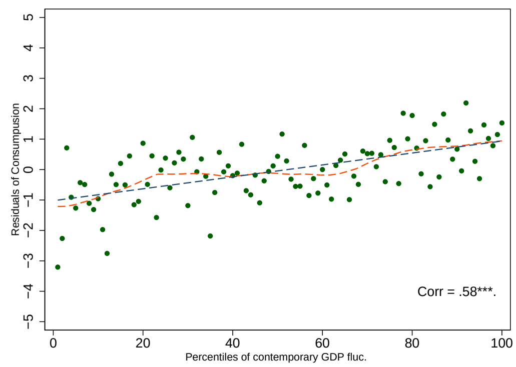
(e) Alcohol consumption



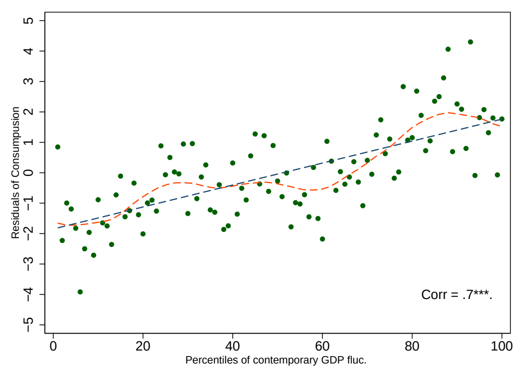
(f) Tobacco consumption

Note: Data source of CO2 emission is World Development Indicators. Working hours and vehicle miles driven are from OECD website. Alcohol and tobacco consumption are from the WHO website. The methodology is the same as that in Figure B4.

Figure B6: Consumption and GDP fluc. in high gov expenditure and low gov expenditure countries



(a) Consumption - GDP (High G countries)



(b) Consumption - GDP (Low G countries)

Note: Consumption data are from Barro-Ursua Macroeconomic data. It is measured in country-year level. The methodology is the same as that in Figure B4. Panels a and b show the pro-cyclicality for consumption in high government expenditure (high G) countries and low government expenditure (low G) countries, respectively.

Table B1: Countries in Human Mortality Database

Country	Earliest Year	Latest year	Gov. exp as share of GDP in 2000	Birth cohorts in sample
Sweden	1800	2011	**55.1%**	1800-1962
France	1816	2012	**51.6%**	1800-1962
Denmark	1835	2011	**53.7%**	1800-1962
Iceland	1838	2010	41.9%	1800-1962
Belgium	1841	2012	**49.1%**	1800-1962
Norway	1846	2009	**42.3%**	1800-1962
Netherlands	1850	2009	**44.2%**	1800-1962
Italy	1872	2009	**46.2%**	1800-1962
Switzerland	1876	2011	35.1%	1800-1962
Finland	1878	2009	**48.3%**	1800-1962
Spain	1908	2009	39.1%	1818-1962
Australia	1921	2009	35.5%	1831-1962
Canada	1921	2009	41.1%	1831-1962
United Kingdom	1922	2011	39.1%	1832-1962
United States	1933	2010	33.9%	1843-1962
Portugal	1940	2012	41.1%	1850-1962
Austria	1947	2010	**52.1%**	1857-1962
Bulgaria	1947	2010	---	1857-1962
Japan	1947	2012	39.1%	1857-1962
New Zealand	1948	2008	38.3%	1858-1962
Czech Rep.	1950	2011	41.8%	1860-1962
Hungary	1950	2009	**46.8%**	1860-1962
Ireland	1950	2009	31.3%	1860-1962
Slovak Republic	1950	2009	**52.1%**	1860-1962
Poland	1958	2009	41.1%	1868-1962
Belarus	1959	2012	---	1869-1962
Estonia	1959	2011	36.1%	1869-1962
Latvia	1959	2011	---	1869-1962
Lithuania	1959	2011	---	1869-1962
Russia	1959	2010	**42.3%**	1869-1962
Ukraine	1959	2009	---	1869-1962
Luxembourg	1960	2009	37.6%	1870-1962

Note: Data are from the HMD. The values in **bold** in the last column denote countries with government spending as a share of GDP that is above the median. Government spending data is not available or less relevant for Eastern European countries.

Table B2: Summary Statistics for ECHP, EB and SHARE Data

Variable	Observations	Mean	Std.
Panel A: ECHP data (Age 30+)			
ln(Total Individual Income)	529,376	11.37	2.17
Health			
Self-reported health status	746,712	2.41	0.97
(1= very good; 5 = very bad)			
Satisfaction (1= not satisfied; 6=very satisfied)			
Life satisfaction	637,846	4.18	1.34
Financial satisfaction	670,227	3.62	1.36
Leisure time satisfaction	637,386	4.19	1.40
Health behaviors			
Current smoker (yes = 1)	241,128	0.33	0.46
Obese (yes = 1)	212,102	0.13	0.33
Social relationships			
Freq. of the activity (1=Never; 5=On most days)			
Talking with others	658,761	4.18	1.01
Meeting friends	729,166	4.01	0.93
Panel B: Eurobarometer data (Age 30+)			
Mental health (PCA score)	45,650	0.00	2.16
Current drinker (yes = 1)	17,831	0.11	0.31
Panel C: SHARE data (Age 50+)			
Self-reported health status	185,236	3.14	1.09
(1= very good; 5 = very bad)			
Cognition			
PCA score	117,670	0.00	1.38
Verbal fluency (0-100)	180,560	19.7	7.63
Numeracy (1-5)	120,316	3.34	1.14
Words recall (0-20)	181,080	8.82	3.71

Note: The data in Panel A are from the European Community Household Panel, 1994-2001. The sample is people aged over 30 with the exception of individual income, which is for people aged 30-64. Birth cohorts 1910 and earlier ones are dropped because of top coding. The data in Panel B are from Eurobarometer. The data in Panel C are from SHARE.

C. Filters for GDP and Mortality

A central issue in our analysis is measuring trend GDP. The most common method to form trend GDP is using a Hodrick and Prescott (1997) filter. This method locally smooths GDP to form trend. A parameter can be adjusted to determine how much smoothing occurs. We use various filters to smooth the ln(GDP /capita).

Panels a and b in Figure C1 shows how they work for the United States. The left column shows the actual ln(GDP /capita) and the smoothed value derived from different smoothing filters over time; the right column shows the corresponding residuals. As the smoothing parameter increases, the filtered GDP line become more smoothed (Panel a), leaving larger variation in the residuals (Panel b). Panels c and d show the results if we use polynomial smoothing. Panels e and f show results for Hamilton (2016) filter and the Baxter-King (BK) filter (Baxter and King, 1999). Panels g and h show the results of moving average (MA) filters. As expected, the larger the bandwidth used to calculate the mean value is, the more smoothed the filtered GDP line is, and the larger variation there is in the residuals.

C1. Characteristics of GDP residuals

C1.1 Correlation of GDP residuals with Unemployment and Autocorrelation

The first column in Table C1 reports the standard deviations for the GDP residuals from the various filters used for all the 32 countries from 1800 to 2008 (N=6,688). Consistently, more smoothed GDP line yields larger variation in the residuals. For example, the standard deviation of residuals from HP 500 filter is 0.088 but that for HP 10 is only 0.038. The largest variation in the residuals are those from polynomial time trend filters. The standard deviation is about 2-3 times of that for others.

Given all these different filters and the corresponding residuals, a natural question is which method is more accurate. We take two approaches to answer this question. The first way to judge is to see which is more correlated with other macroeconomic indicators; the second way is to examine whether our results are sensitive to the smoothing methods used.

Columns 2 through 7 of Table C1 present the relationship of the residuals with unemployment rates in 1,438 country-year cells. Columns 2 and 3 present the OLS regressions without any controls. The next two columns control for country and year fixed effects, and columns 6 and 7 further control for country specific linear and quadratic year trends.

In almost all cases, the residuals are negatively correlated with the unemployment rates. However, the performance for the filters differs. For example, the residuals from the polynomial filters and Hamilton (2016) filter are not so strongly correlated with unemployment rates when country and year fixed effects are included. Another fit index is the R^2. The R^2 for the HP 500 residuals are always higher than those for all the other HP filters, most MA filters, and BK filter. These results suggest that HP 500 filter is a good candidate.

The last column reports the coefficients for AR(1) model of the residuals, which vary from 0.25 for BK filter residuals to 0.96 for the polynomial residuals. Since we use the three-year average to measure contemporary economic conditions and five-year average for the economic conditions in early life, we also investigate the autocorrelations among three-year and five-year averages. We find that the HP 500 and HP 1000 are almost not serially correlated after five-year average.

For these reasons, we use HP filter with smoothing parameter 500 as the main filter used in this study.

C1.2 A Summary of GDP HP 500 residuals

Panel a in Figure C2 presents the relationship between GDP residuals from HP 500 filter and unemployment rates in the United States, The correlation coefficient is -0.56. Panel b shows the data points for all observations.[4]

The upper two panels in Figure C3 show the country-year combinations with GDP fluctuations over |10%|. One can see the Great Depression clearly. Many countries suffered large recessions after World War II. Countries in the former Soviet Union saw adverse shocks in the late 1990s. There are also a number of booms in the first half of the 20th Century. The bottom two panels show the time series mean and standard deviation of GDP fluctuations measured using the HP 500 filter. These mirror the results in panels a and b.

C1.3 Autocorrelation in Mortality Residuals

We also use the different filters on log(mortality) and show the AR(1) results in Table C2. After the linear and quadratic time trend filter, the AR(1) coefficient for the residuals is 0.38. Using HP 10, HP 100, and some moving average filters makes the residuals negatively autocorrelated, which suggest that HP 10 filter may keep too little information in the residuals.[5] Therefore, the main setting in our paper uses the 2nd order polynomial trend smoothing. However, we show below that our short-run

[4]The covariates include country dummies, year dummies, and country specific linear and square trends in years.

[5]The results for BK filter are not shown because BK is a frequency Band-pass filter which may not be applied on mortality.

results are robust to many different filters but the long-run effects will be present when we do not detrend the mortality "too" much.

C2. Results of different filters on GDP and Mortality

C2.1 Results from different GDP residuals

In this section, we show the robustness of our results when detrending GDP in different ways. The first three columns in Table C3 are almost the same as those in Table 1.[6] Columns 4-6 show the results using the BK filter, and the next three columns show the results using MA (+/-3 years) filter. The residuals from these filters are significantly correlated with unemployment and relatively weakly or negatively autocorrelated after 5 years.

The results are consistent across different columns. The magnitude differs mainly because of the different standard deviations in the residuals. For example, based on the estimates in columns 1, 4, and 7, one-stand deviation increase in GDP contemporary residuals leads to 1.2, 0.7, and 1.0 percent increases in mortality, respectively. Similarly, a one-standard deviation increase in GDP fluctuations at ages 6-10 would decrease mortality by 0.6, 1.0 and 0.9 percent, based on the estimates in columns 3, 6, and 9, respectively.

Table C4 shows the result using alternative HP filter parameters, and Table C5 shows the results for different moving average intervals. For the long-term effects, the results are negative but not significant for HP 10 filter residuals. The reason

[6] They are a bit different because of different definition of big boom and big recession. Negative 5 percent and positive 5 percent are around but not exactly at 10th and 90th percentile of HP 500 GDP residuals.

for this is that five-year average is too long for HP 10 residuals.[7] Therefore, we face a trade-off between collinearity and variation. The long term results hold if a-the method for detrending GDP yields residuals that are highly correlated with unemployment, 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.

Figure C4 graphically show the short-term effects. Similar to figure 1 in the paper, we plot the predicted values in each GDP residual intervals. To make the results comparable from different models, the X-axis is the percentiles of the GDP residuals rather than the absolute ln(GDP) residuals values because the magnitude of the residuals from different filters are not comparable. These figures show the effects of big booms or busts much more clearly. In general, the effects of big recessions are robust to the choice of filter. But the effects of big booms is not apparent when using BK filter, HP 10, and MA +/2 filters. In part, this is because the residuals generated by these filters have a much smaller variation. As the variation in residuals becomes larger, the effects of big booms are more apparent.

We also explored the impact of detrending mortality rates. We systematically investigated this question and estimated 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) and with or without country*year/cohort fixed effects.

[7]As shown in Appendix C1, HP 10 filter GDP residuals AR(1) coefficient is -0.6 for five-year average, and we will show later that the long-run effects are robust if we use GDP residuals at separate ages.

Table C6 shows the short-term effects (in 10th-90th GDP fluctuation region) and Table C7 shows the long-term effects of GDP fluctuations at age 11-15. Short term effects are very robust to how we detrend mortality and GDP. As expected, the coefficients vary because magnitude of the residuals varies 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) in 60 percent of the cases.

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 101 out of 144 of the regressions give a negative coefficient. Among the 101 negative coefficients, 70 are statistically significant. Among the 31 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 years over which we average. Similarly, certain de-trending methods for GDP do not yield significant results. When residuals are small (e.g., those resulting from HP 10), averaging over years reduces the size of fluctuations immensely,[8] and the coefficients are insignificant. An obvious solution is to include GDP fluctuations annually. But if we enter GDP fluctuations annually, collinearity becomes a problem: even with detrending lagged GDP remains significantly related to current GDP, unless we average over five years.

[8] 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.

C2.2 Different length of years used to measure economic conditions

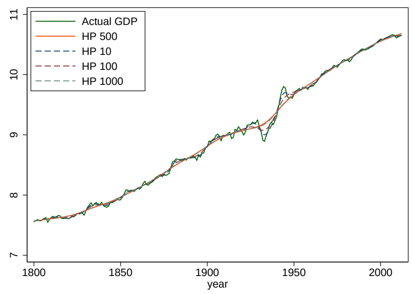
In our paper, we use three-year average HP-filtered GDP residuals to measure the contemporary economic conditions, and five-year averages to measure economic conditions in early life. This section provides results to show the robustness of these assumptions.

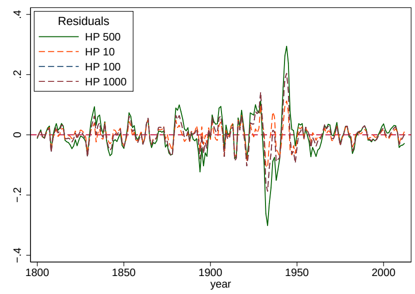
Figure C5 shows the short-term effects when using mean value of GDP fluctuations at current year and the year before (i.e., two-year average) to measure the con- temporary economic conditions. These results are comparable to Figure C4. Interestingly, the impact of big booms is larger when we only use two-year averages. Compared to those in Figure C1, the GDP 90-95th percentile residuals of the BK filter, MA (+/- 2 years) filter and HP 10 filter are more likely to be associated with a lower mortality.

Figure C6 reports the results when we use age-specific GDP residuals at ages birth to 30. Because of different standard deviations of the residuals, the coefficients are not directly comparable. Thus, figure C6 reports the effects of one standard deviation increase in the GDP residuals. Panel a presents the results for HP 10, MA (+/- 3 years), and BK filters. The three show a very consistent pattern, with similar effects of a 1 standard deviation change.

Panels b and c of Figure C6 shows the results of using different HP filters and those of using different MA filters, respectively. The patterns in the two figures echoes the AR(1) results: the results are more salient when the autocorrelation is weaker. Compared to the insignificant results of using 5-year average HP 10 filter GDP residuals, the results using the HP 10 residuals at separate ages are most salient, as shown in Panel b. Consistently, Panel c presents a similar pattern: when the bandwidth becomes larger, autocorrelation is stronger (Table C1), and the magnitude is smaller when using age-specific GDP fluctuations. Therefore, we face a trade-off between collinearity and variation. As a result, in our paper, we use five-year average for the HP 500 filtered GDP residuals.

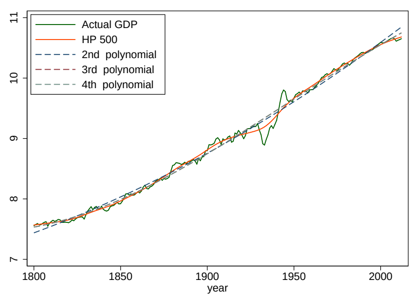
Figure C1: Actual and Smoothed GDP in the United States

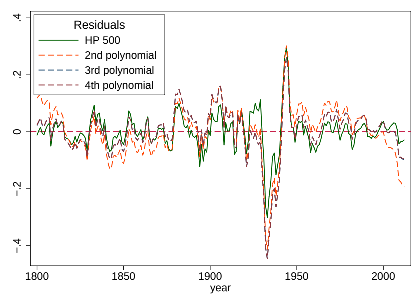




(a) HP filters

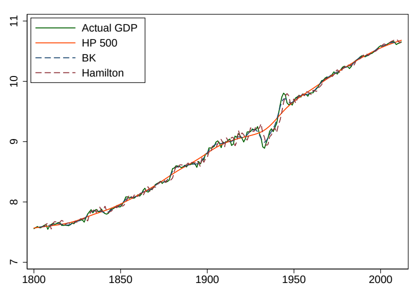
(b) Residuals from HP filters

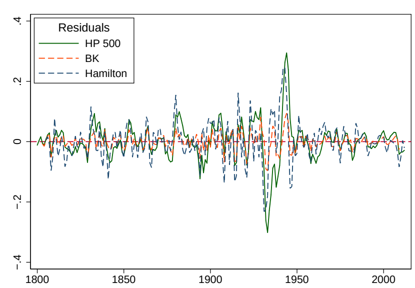




(c) Polynomial-smoothed GDP

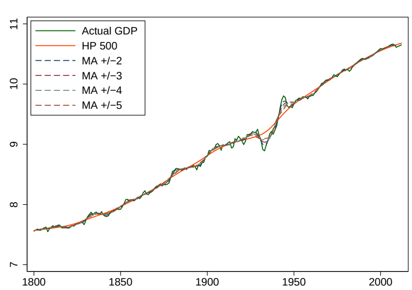
(d) Residuals from Polynomial filters

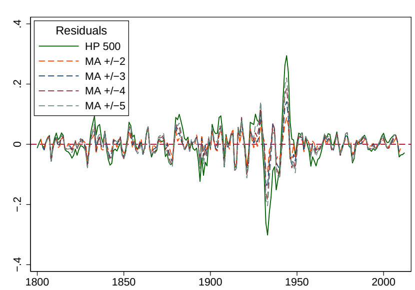




(e) BK and Hamilton Filters

(f) Residuals from BK, Hamilton filter



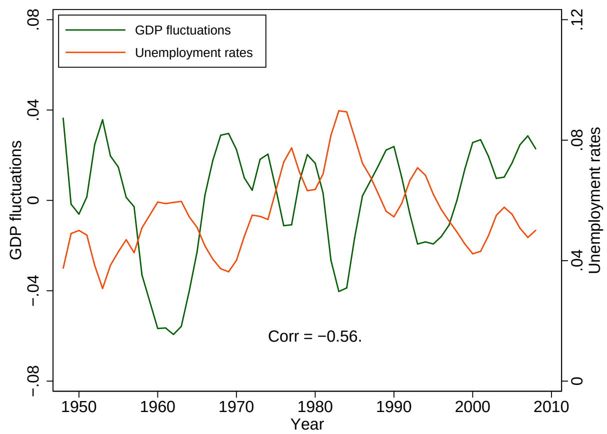


(g) Moving Average smoothed GDP

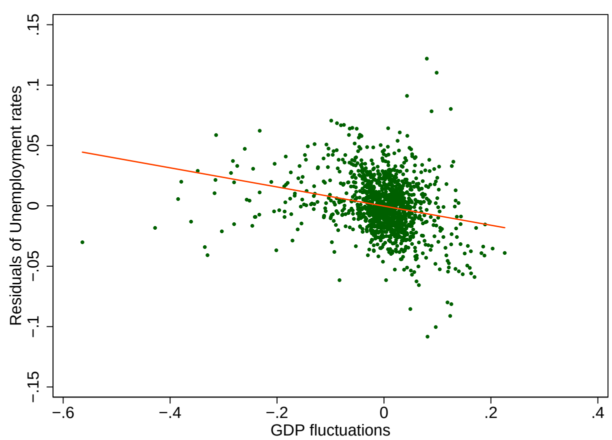
(h) Residuals from Moving Average

Note: Data of the GDP are from the Gapminder website. The actual and the smoothed values are plotted against the calendar year in the panels in left column. The GDP residuals are plotted in the panels in the right column.

Figure C2: Comparison of Unemployment Rate and GDP Residuals from HP 500



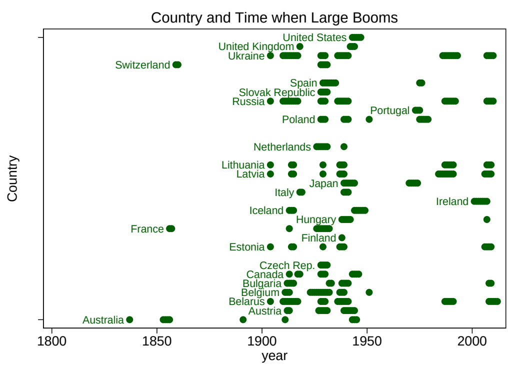
(a) Time Series in United States



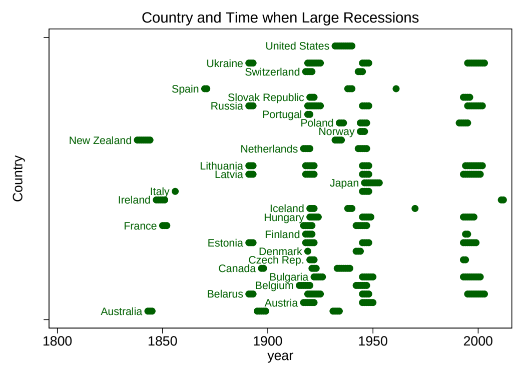
(b) GDP fluc. and unemployment rate residuals

Note: The data of unemployment rates are from World Development Index (WDI), Layard et al. (2005), OECD website and Mitchell (1998). In Panel B, to form residual unemployment rate, we regress the unemployment rate on country dummies, year dummies, and country specific linear and square trends in years.

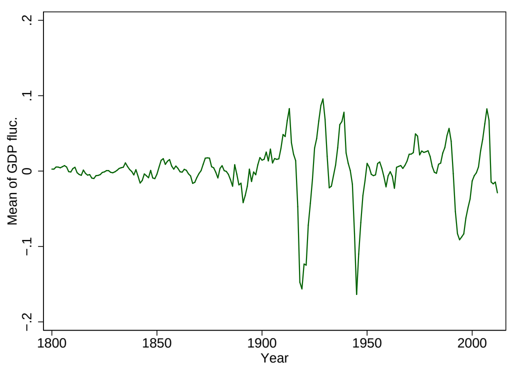
Figure C3: Country and Periods with large booms and recessions



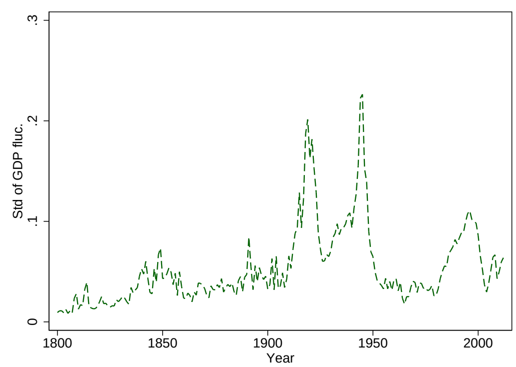
(a) Country and Periods with large booms



(b) Country and Periods with large recessions



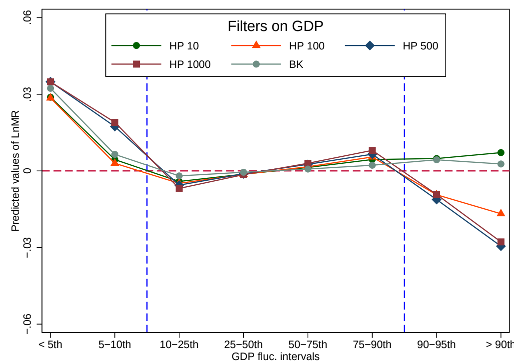
(c) Mean



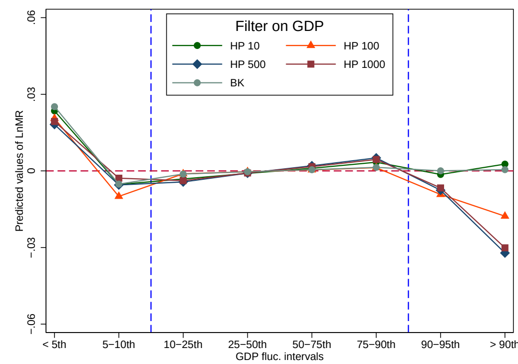
(d) Standard Deviation

Note: The left figure shows the countries and years when contemporaneous GDP fluctuations larger than 0.1 and the right one shows the countries and years when contemporaneous GDP fluctuations lower than -0.1. The bottom two figures figures show the mean and standard deviations of the 32 countries used in the study over time, respectively.

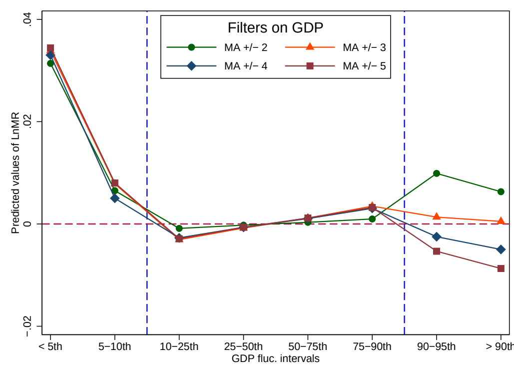
Figure C4: Contemporary effects: Different filters on GDP



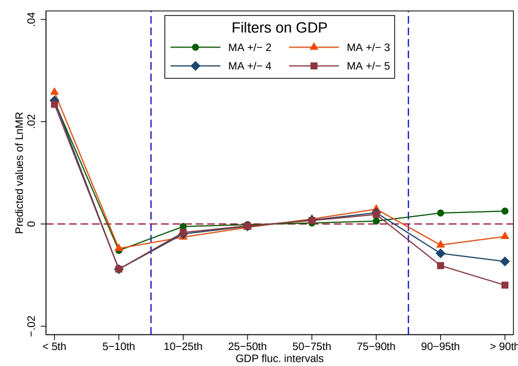
(a) HP filter and BK filter



(b) HP filter and BK filter, with Country-Cohort FE



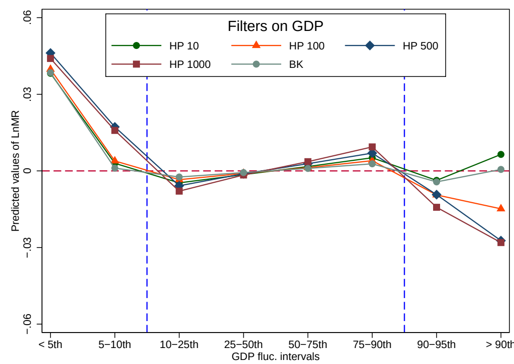
(c) MA(s) Filters



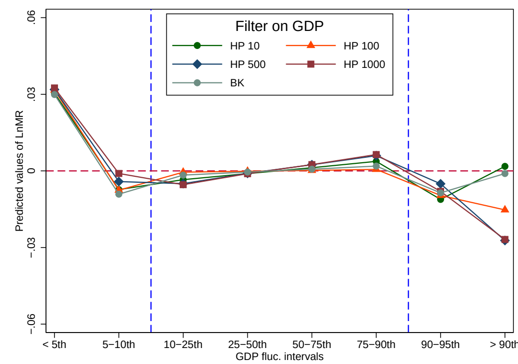
(d) MA(s) Filters, Country-Cohort FE

Note: Results of contemporary effects using different filters are shown. Contemporary GDP fluctuations are using average of GDP current year, last year and the year before last year (three-year average). Regressions used for panel a and panel c are the same as column 1 of Table 1, and those for panel b and panel d are the same as column 2 of Table 1.

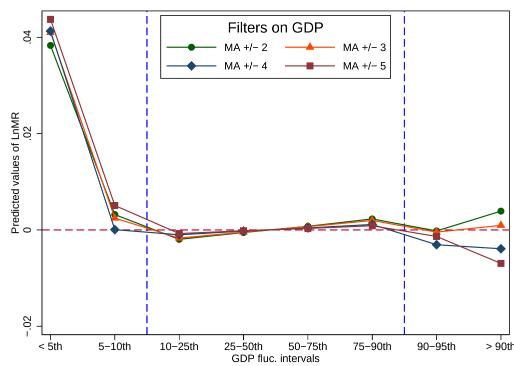
Figure C5: Using current and last year GDP residuals and different filters



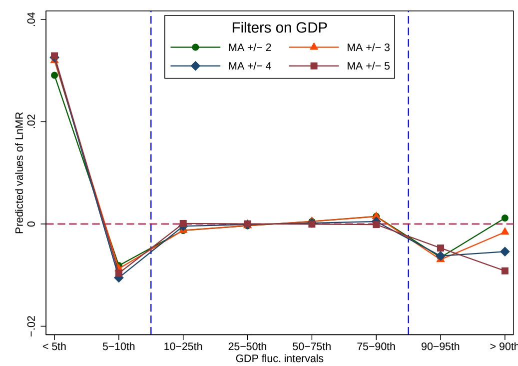
(a) HP filter and BK filter



(b) HP filter and BK filter, with Country-Cohort FE



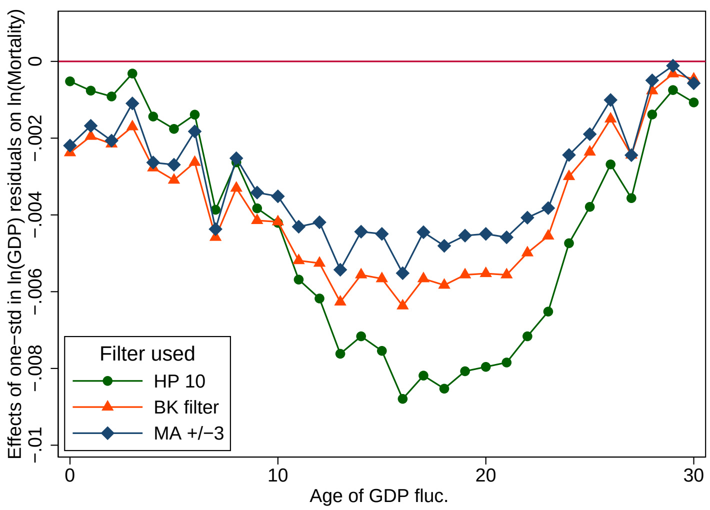
(c) MA(s) Filters



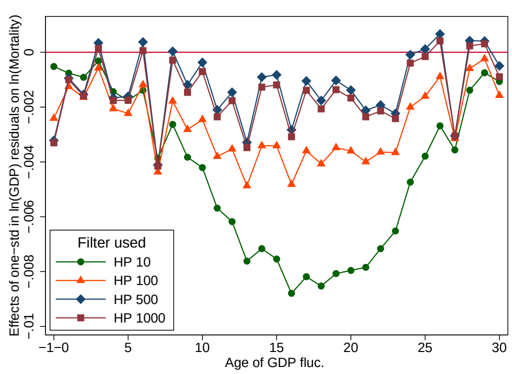
(d) MA(s) Filters, Country-Cohort FE

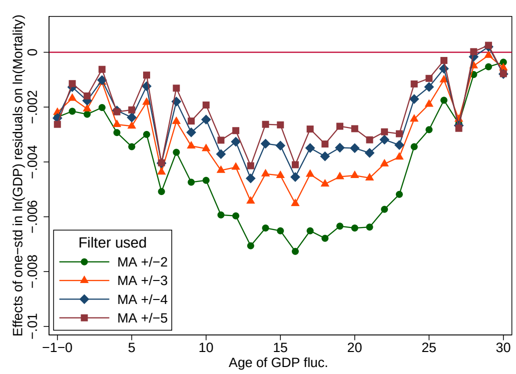
Note: Results of contemporary effects using different filters are shown. Contemporary GDP fluc. are using average of GDP current year and last year (Two-year average). Regressions used for panel a and panel c are the same as column 1 of Table 1, and those for panel b and panel d are the same as column 2 of Table 1.

Figure C6: Effects of GDP fluc. from different HP filters at separate ages



(a) Different Filters - HP, BK and MA





(b) Different HP Filters

(c) Different MA Filters

Note: The figure reports the long-term effects of one-std change in the GDP fluctuation from different HP filters at separate ages. Regressions used for all panels are the same as that in column 3 of Table 1.

Table C1: Relationship between GDP residuals and Unemployment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Std of	Relationship with Unemployment rates						AR(1)		
	shock	beta (se)	R^2	beta (se)	R^2	beta (se)	R^2	1-year	3-year	5-year
HP filter residuals										
500 filter	0.088	-14.0***	0.043	-11.4***	0.680	-21.6***	0.829	0.826***	0.409***	0.0397
		(3.31)		(3.20)		(4.84)		(0.0125)	(0.0309)	(0.0424)
10 filter	0.038	-27.8***	0.023	-11.6*	0.667	-17.0***	0.805	0.381***	-0.399***	-0.684***
		(4.39)		(5.77)		(5.05)		(0.0225)	(0.0233)	(0.0257)
100 filter	0.059	-19.3***	0.030	-12.3***	0.671	-18.3***	0.812	0.666***	-0.00473	-0.497***
		(4.21)		(3.98)		(4.73)		(0.0146)	(0.0272)	(0.0226)
1000 filter	0.083	-14.7***	0.040	-12.2***	0.679	-21.3***	0.826	0.805***	0.348***	-0.0489
		(3.53)		(3.42)		(4.82)		(0.0127)	(0.0312)	(0.0404)
BK filter	0.034	-34.2***	0.026	-16.1**	0.669	-21.3***	0.818	0.250***	-0.359***	-0.518***
		(5.33)		(6.47)		(5.03)		(0.0229)	(0.0296)	(0.0290)
Hamilton (2016)	0.085	-8.87**	0.015	3.05	0.666	-4.88*	0.802	0.512***	0.110***	-0.121**
method		(3.36)		(2.27)		(2.40)		(0.00903)	(0.0311)	(0.0516)
Moving average										
MA +/- 2	0.034	-35.4***	0.028	-17.1***	0.669	-23.3***	0.811	0.185***	-0.413***	-0.567***
		(4.98)		(5.94)		(5.08)		(0.0228)	(0.0322)	(0.0285)
MA +/- 3	0.045	-26.1***	0.029	-12.8**	0.670	-16.8***	0.818	0.442***	-0.316***	-0.520***
		(4.42)		(5.14)		(4.37)		(0.0188)	(0.0291)	(0.0296)
MA +/- 4	0.054	-21.3***	0.030	-10.9**	0.673	-12.2**	0.827	0.604***	-0.178***	-0.507***
		(4.33)		(4.82)		(4.78)		(0.0174)	(0.0300)	(0.0317)
MA +/- 5	0.064	-19.2***	0.033	-10.5**	0.676	-11.6**	0.834	0.683***	-0.0383	-0.462***
		(4.16)		(4.38)		(4.77)		(0.0146)	(0.0316)	(0.0360)
Polynomial time trends										
GDP residuals	0.19	-6.95***	0.054	-3.04	0.670	-16.87***	0.827	0.964***	0.865***	0.772***
(2nd order)		(2.07)		(2.09)		(4.890)		(0.00633)	(0.0197)	(0.0281)
GDP residuals	0.18	-9.11***	0.073	-3.62*	0.670	-16.07***	0.825	0.958***	0.839***	0.726***
(3rd order)		(1.88)		(2.01)		(4.955)		(0.00669)	(0.0214)	(0.0305)
GDP residuals	0.16	-7.72***	0.046	-1.85	0.666	-15.10***	0.823	0.948***	0.798***	0.652***
(4th order)		(1.84)		(1.60)		(4.794)		(0.00686)	(0.0227)	(0.0330)
Country, Year FE	---	No		Yes		Yes			No	
Country specific linear & quadratic trends	---	No		No		Yes			No	

Notes: The sample for each regression is country-year observations with both unemployment rates and GDP residuals (N = 1,438 for columns 2-7; N = 2,923 for column 8, N = 964 for column 9, and N = 573 for column 10). Standard errors are clustered at country level.
*** p<0.01, ** p<0.05, * p<0.1

Table C2: AR(1) model for ln(Mortality rates)

	(1)	(2)	(3)
	AR(1) Model in Residuals of Ln(Mortality)		
VARIABLES	All ages	Age <= 5	Age > 45
Polynomial time trends			
Ln(Mortality) res.	0.375***	0.229**	0.263**
(2nd polynomial)	(0.093)	(0.090)	(0.102)
Ln(Mortality) res.	0.252***	0.115*	0.178**
(3rd polynomial)	(0.079)	(0.063)	(0.080)
Ln(Mortality) res.	0.209**	0.079	0.125*
(4th polynomial)	(0.079)	(0.056)	(0.065)
HP filter residuals			
10 filter	-0.252***	-0.277***	-0.240***
	(0.020)	(0.023)	(0.019)
100 filter	-0.081**	-0.125***	-0.088***
	(0.039)	(0.032)	(0.030)
500 filter	0.014	-0.043	-0.011
	(0.052)	(0.040)	(0.041)
1000 filter	0.051	-0.011	0.020
	(0.058)	(0.044)	(0.047)
Moving Average			
MA +/- 2	-0.278***	-0.294***	-0.263***
	(0.012)	(0.014)	(0.013)
MA +/- 3	-0.146***	-0.178***	-0.137***
	(0.025)	(0.031)	(0.023)
MA +/- 4	-0.068*	-0.111***	-0.070***
	(0.035)	(0.039)	(0.026)
MA +/- 5	-0.014	-0.071	-0.028
	(0.046)	(0.046)	(0.034)
Observations	497,932	33,300	242,632

Notes: Log(Mortality) is detrended within each country-gender-age cell. Standard errors clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table C3: Alternative Filters on GDP (HP, BK and MA)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	ln(Mortality Rate)								
	HP 500 filter			BK filter			Moving Average (+/- 3 years)		
Settings	Original	Country-cohort FE	Country-year FE	Original	Country-cohort FE	Country-year FE	Original	Country-cohort FE	Country-year FE
Contemporary Economic Conditions									
Contemp.	0.144***	0.11***	—	0.202*	0.126	—	0.213**	0.178**	—
GDP fluc.	(0.0500)	(0.0398)		(0.110)	(0.111)		(0.0934)	(0.0752)	
Big Boom	0.0124	0.024**	—	0.0059	-0.0004	—	0.00216	-0.00574	—
(>90th)	(0.0111)	(0.00946)		(0.009)	(0.00961)		(0.00975)	(0.0116)	
Boom* Fluc.	-0.431***	-0.50***	—	-0.280	-0.104	—	-0.240	-0.125	—
	(0.121)	(0.125)		(0.354)	(0.345)		(0.212)	(0.233)	
Big bust	0.00561	-0.0214	—	-0.009	-0.024***	—	-0.00762	-0.0231***	—
(<10th)	(0.0148)	(0.0159)		(0.0100)	(0.008)		(0.0101)	(0.00837)	
Bust * Fluc.	-0.277***	-0.29**	—	-1.05***	-1.12***	—	-0.768***	-0.832***	—
	(0.0870)	(0.111)		(0.292)	(0.267)		(0.200)	(0.180)	
Early Economic Conditions									
GDP fluc	-0.0338**	—	-0.033***	-0.0274	—	-0.0395*	-0.0237	—	-0.0318**
Age -1-0	(0.0137)		(0.0120)	(0.0256)		(0.0217)	(0.0167)		(0.0133)
GDP fluc	-0.0495**	—	-0.057***	-0.0690	—	-0.164**	-0.0627	—	-0.130**
Age 1-5	(0.0185)		(0.0159)	(0.101)		(0.0699)	(0.0719)		(0.0494)
GDP fluc	-0.0597**	—	-0.070***	-0.104	—	-0.246**	-0.0998	—	-0.205**
Age 6-10	(0.0262)		(0.0228)	(0.173)		(0.119)	(0.126)		(0.0866)
GDP fluc	-0.0892***	—	-0.095***	-0.283	—	-0.424***	-0.224	—	-0.331***
Age 11-15	(0.0294)		(0.0279)	(0.205)		(0.149)	(0.152)		(0.112)
GDP fluc	-0.0847***	—	-0.091***	-0.304	—	-0.435**	-0.236	—	-0.336**
Age 16-20	(0.0297)		(0.0298)	(0.217)		(0.170)	(0.160)		(0.126)
GDP fluc	-0.0668***	—	-0.072***	-0.213	—	-0.316**	-0.164	—	-0.244**
Age 21-25	(0.0242)		(0.0198)	(0.186)		(0.137)	(0.135)		(0.0983)
GDP fluc	-0.00825	—	-0.0115	-0.0145	—	-0.0660	-0.0150	—	-0.0544
Age 26-30	(0.0132)		(0.0130)	(0.0752)		(0.0585)	(0.0574)		(0.0444)
N	245,512	245,404	245,512	243,880	245,404	243,880	243,880	245,404	243,880
R2	0.995	0.997	0.997	0.995	0.997	0.997	0.995	0.997	0.997

Note: Data of mortality are from HMD. Data of GDP are from Gapminder. All regressions include country-gender-age fixed effects, country-gender-age specific linear and square trends in calendar years, gender-birth year fixed effects, and gender-year fixed effects. All the regressions are weighted by the square root of the population size in the corresponding observation. For each filter, three regressions are reported. The standard errors are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table C4: Alternative Filters (HP filters)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	ln(Mortality Rate)								
	HP 10			HP 100			HP 1000		
Settings	Original	Cty-cohort FE	Cty-year FE	Original	Cty-cohort FE	Cty-year FE	Original	Cty-cohort FE	Cty-year FE
Contemporary Economic Conditions									
Contemp.	0.319**	0.243*	—	0.211***	0.0493	—	0.195***	0.109**	—
GDP fluc.	(0.136)	(0.142)		(0.0660)	(0.0829)		(0.0522)	(0.0498)	
Big Boom	0.00264	-0.00522	—	-0.00139	-0.000155	—	0.0155	0.0245**	—
(>90th)	(0.00768)	(0.00763)		(0.00980)	(0.0116)		(0.0116)	(0.0103)	
Boom* Fluc.	-0.234	-0.0961	—	-0.366***	-0.227	—	-0.509***	-0.505***	—
	(0.280)	(0.282)		(0.127)	(0.172)		(0.120)	(0.125)	
Big bust	-0.0120	-0.0248***	—	-0.0121	-0.0282***	—	0.00899	-0.0174	—
(<10th)	(0.01000)	(0.00862)		(0.00884)	(0.00813)		(0.0149)	(0.0155)	
Bust * Fluc.	-1.023***	-1.077***	—	-0.554***	-0.462***	—	-0.324***	-0.291**	—
	(0.261)	(0.235)		(0.132)	(0.146)		(0.0952)	(0.125)	
Early Economic Conditions									
GDP fluc	0.00780	—	0.00483	-0.0258**	—	-0.028***	-0.036***	—	-0.035***
Age -1-0	(0.0201)		(0.0207)	(0.0103)		(0.0095)	(0.0132)		(0.0118)
GDP fluc	0.105*	—	0.0652	-0.0700*	—	-0.093***	-0.059***	—	-0.067***
Age 1-5	(0.0608)		(0.0641)	(0.0359)		(0.0331)	(0.0204)		(0.0181)
GDP fluc	0.133	—	0.0846	-0.138**	—	-0.170***	-0.0783**	—	-0.088***
Age 6-10	(0.0836)		(0.0837)	(0.0663)		(0.0595)	(0.0299)		(0.0271)
GDP fluc	-0.0275	—	-0.0574	-0.236***	—	-0.261***	-0.113***	—	-0.118***
Age 11-15	(0.0778)		(0.0678)	(0.0842)		(0.0780)	(0.0344)		(0.0336)
GDP fluc	-0.108	—	-0.128	-0.258***	—	-0.276***	-0.109***	—	-0.114***
Age 16-20	(0.0955)		(0.0875)	(0.0880)		(0.0857)	(0.0346)		(0.0354)
GDP fluc	-0.113	—	-0.126	-0.204***	—	-0.213***	-0.086***	—	-0.089***
Age 21-25	(0.0950)		(0.0901)	(0.0695)		(0.0655)	(0.0270)		(0.0235)
GDP fluc	-0.0217	—	-0.0255	-0.0746**	—	-0.074**	-0.0220	—	-0.022
Age 26-30	(0.0398)		(0.0411)	(0.0325)		(0.0350)	(0.0141)		(0.0152)
N	245,512	245,404	245,512	245,512	245,404	245,512	245,512	245,404	245,512
R2	0.995	0.997	0.997	0.995	0.997	0.997	0.995	0.997	0.997

Note: Data of mortality are from HMD. Data of GDP are from Gapminder. All regressions include country-gender-age fixed effects, country-gender-age specific linear and square trends in calendar years, gender-birth year fixed effects, and gender-year fixed effects. All the regressions are weighted by the square root of the population size in the corresponding observation. For each filter, three regressions are reported. The standard errors are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table C5: Alternative Filters (Moving Average)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	ln(Mortality Rate)								
	Moving Average (+/- 2 years)			Moving Average (+/- 4 years)			Moving Average (+/- 5 years)		
Settings	Original	Country-cohort FE	Country-year FE	Original	Country-cohort FE	Country-year FE	Original	Country-cohort FE	Country-year FE
Contemporary Economic Conditions									
Contemp.	0.0952	0.0547	—	0.140*	0.101	—	0.120	0.0692	—
GDP fluc.	(0.134)	(0.124)		(0.0766)	(0.0646)		(0.0822)	(0.0686)	
Big Boom	0.0132	0.00178	—	0.000105	-0.00410	—	-0.00161	-0.00395	—
(>90th)	(0.00872)	(0.0094)		(0.00979)	(0.0116)		(0.0116)	(0.0112)	
Boom* Fluc.	-0.276	-0.0355	—	-0.202	-0.140	—	-0.192	-0.150	—
	(0.396)	(0.380)		(0.147)	(0.186)		(0.119)	(0.150)	
Big bust	-0.00895	-0.023***	—	-0.0113	-0.0282***	—	-0.00736	-0.028**	—
(<10th)	(0.0103)	(0.00829)		(0.0101)	(0.00879)		(0.0127)	(0.0109)	
Bust * Fluc.	-0.987***	-1.10***	—	-0.57***	-0.610***	—	-0.45***	-0.47***	—
	(0.322)	(0.283)		(0.173)	(0.150)		(0.146)	(0.125)	
Early Economic Conditions									
GDP fluc	-0.0186	—	-0.0311	-0.0237	—	-0.032**	-0.0252*	—	-0.031***
Age -1-0	(0.0281)		(0.0247)	(0.0167)		(0.0133)	(0.0124)		(0.00889)
GDP fluc	-0.0459	—	-0.140*	-0.0627	—	-0.130**	-0.0576	—	-0.099***
Age 1-5	(0.103)		(0.0724)	(0.0719)		(0.0494)	(0.0453)		(0.0310)
GDP fluc	-0.0682	—	-0.202*	-0.0998	—	-0.21**	-0.0875	—	-0.16***
Age 6-10	(0.170)		(0.119)	(0.126)		(0.0866)	(0.0791)		(0.0544)
GDP fluc	-0.250	—	-0.377**	-0.224	—	-0.33***	-0.153	—	-0.23***
Age 11-15	(0.198)		(0.145)	(0.152)		(0.112)	(0.0947)		(0.0705)
GDP fluc	-0.276	—	-0.393**	-0.236	—	-0.34**	-0.159	—	-0.23***
Age 16-20	(0.209)		(0.167)	(0.160)		(0.126)	(0.0981)		(0.0762)
GDP fluc	-0.197	—	-0.287**	-0.164	—	-0.24**	-0.109	—	-0.17***
Age 21-25	(0.181)		(0.139)	(0.135)		(0.0983)	(0.0821)		(0.0568)
GDP fluc	-0.0113	—	-0.0570	-0.0150	—	-0.054	-0.0117	—	-0.042
Age 26-30	(0.0689)		(0.0567)	(0.0574)		(0.0444)	(0.0375)		(0.0280)
N	244,444	245,404	244,444	243,880	245,404	243,880	242,692	245,404	242,692
R2	0.995	0.997	0.997	0.995	0.997	0.997	0.995	0.997	0.997

Note: Data of mortality are from HMD. Data of GDP are from Gapminder. All regressions include country-gender-age fixed effects, country-gender-age specific linear and square trends in calendar years, gender-birth year fixed effects, and gender-year fixed effects. All the regressions are weighted by the square root of the population size in the corresponding observation. For each filter, three regressions are reported. The standard errors are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table C6: Short-term effects of GDP on log(Mortality)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Filter	Filter on ln(Mortality)							
on GDP	Polynomial 2	Polynomial 3	Polynomial 4	MA +/- 5	HP 500	HP 1000	MA +/- 4	HP 100
Panel A: Without country-cohort FE								
HP 10	0.335**	0.251*	0.314**	0.276**	0.297**	0.313**	0.266**	0.263**
	(0.132)	(0.137)	(0.123)	(0.128)	(0.119)	(0.120)	(0.117)	(0.110)
Hp 100	0.208***	0.0699	0.110*	0.0486	0.0921	0.111	0.0595	0.0675
	(0.0655)	(0.0814)	(0.0620)	(0.0781)	(0.0661)	(0.0671)	(0.0625)	(0.0585)
HP 500	0.146***	0.0938*	0.113**	0.0745*	0.125***	0.139***	0.0667**	0.0853***
	(0.0497)	(0.0461)	(0.0449)	(0.0366)	(0.0353)	(0.0370)	(0.0310)	(0.0284)
HP 1000	0.201***	0.101*	0.118**	0.0838*	0.132***	0.150***	0.0759*	0.0940**
	(0.0520)	(0.0535)	(0.0504)	(0.0440)	(0.0404)	(0.0419)	(0.0389)	(0.0347)
MA +/- 2	0.0729	0.0229	0.0696	0.0942	0.0855	0.0857	0.131	0.110
	(0.137)	(0.131)	(0.130)	(0.147)	(0.145)	(0.146)	(0.142)	(0.131)
MA +/- 3	0.219**	0.180**	0.200***	0.180**	0.207***	0.222***	0.210***	0.188***
	(0.0934)	(0.0752)	(0.0695)	(0.0727)	(0.0723)	(0.0726)	(0.0668)	(0.0664)
MA +/- 4	0.122	0.0726	0.0957*	0.115*	0.125**	0.136**	0.143**	0.111*
	(0.0723)	(0.0584)	(0.0510)	(0.0639)	(0.0601)	(0.0596)	(0.0614)	(0.0567)
MA +/- 5	0.117	0.0593	0.0851	0.0659	0.0857	0.100	0.0846	0.0654
	(0.0822)	(0.0717)	(0.0619)	(0.0700)	(0.0655)	(0.0673)	(0.0597)	(0.0574)
BK	0.191*	0.116	0.155	0.192*	0.174	0.178	0.229**	0.186*
	(0.106)	(0.106)	(0.0946)	(0.110)	(0.105)	(0.105)	(0.104)	(0.0957)

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Table C6: Short-term effects of GDP on log(Mortality) (Con't)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Filter	Filter on ln(Mortality)							
on GDP	Polynomial 2	Polynomial 3	Polynomial 4	MA +/- 5	HP 500	HP 1000	MA +/- 4	HP 100
Panel B: With country-cohort FE								
HP 10	0.247	0.272*	0.323**	0.250**	0.288**	0.290**	0.238**	0.266**
	(0.146)	(0.134)	(0.127)	(0.119)	(0.125)	(0.127)	(0.104)	(0.114)
Hp 100	0.0454	0.0676	0.106	0.0343	0.0627	0.0662	0.0456	0.0580
	(0.0829)	(0.0760)	(0.0690)	(0.0839)	(0.0707)	(0.0734)	(0.0698)	(0.0609)
HP 500	0.114***	0.114***	0.129**	0.0716*	0.118***	0.127***	0.0718**	0.0840***
	(0.0390)	(0.0413)	(0.0477)	(0.0372)	(0.0348)	(0.0366)	(0.0318)	(0.0274)
HP 1000	0.109**	0.111**	0.133**	0.0791*	0.114***	0.122***	0.0793*	0.0891**
	(0.0491)	(0.0516)	(0.0560)	(0.0453)	(0.0407)	(0.0432)	(0.0396)	(0.0326)
MA +/- 2	0.0356	0.0662	0.108	0.114	0.0865	0.0794	0.135	0.117
	(0.123)	(0.120)	(0.122)	(0.150)	(0.142)	(0.143)	(0.142)	(0.130)
MA +/- 3	0.179**	0.183**	0.214***	0.184**	0.196**	0.200**	0.204***	0.190***
	(0.0751)	(0.0718)	(0.0703)	(0.0729)	(0.0726)	(0.0735)	(0.0642)	(0.0660)
MA +/- 4	0.0904	0.0899	0.115**	0.118*	0.113*	0.114*	0.143**	0.111*
	(0.0627)	(0.0590)	(0.0564)	(0.0664)	(0.0619)	(0.0627)	(0.0628)	(0.0567)
MA +/- 5	0.0659	0.0645	0.0877	0.0597	0.0738	0.0790	0.0794	0.0638
	(0.0687)	(0.0657)	(0.0635)	(0.0713)	(0.0666)	(0.0682)	(0.0604)	(0.0577)
BK	0.114	0.140	0.182*	0.213*	0.173	0.169	0.231**	0.193**
	(0.106)	(0.0975)	(0.0914)	(0.113)	(0.103)	(0.104)	(0.102)	(0.0943)

Note: Only the coefficients on contemporary GDP fluctuations are reported. Each coefficient presents a separate regression. All regressions include country-gender-age fixed effects, country-gender-age specific linear and square trends in calendar years, gender-birth year fixed effects, and gender-year fixed effects. All the regressions are weighted by the square root of the population size in the corresponding observation. The standard errors in parentheses are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table C7: Long-term effects of GDP on log(Mortality), GDP fluc. at age 11-15

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Filter	Filter on ln(Mortality)							
on GDP	Polynomial 2	Polynomial 3	Polynomial 4	MA +/- 5	HP 500	HP 1000	MA +/- 4	HP 100
Panel A: Without country-year FE								
HP 10	-0.0275	-0.00177	0.0243	0.0331	0.0832	0.0706	0.0392	0.0819
	(0.0779)	(0.0723)	(0.0777)	(0.0697)	(0.0688)	(0.0689)	(0.0757)	(0.0678)
Hp 100	-0.236***	-0.170***	-0.119**	0.0234	-0.00845	-0.0407	0.0234	0.0225
	(0.0842)	(0.0505)	(0.0464)	(0.0246)	(0.0212)	(0.0270)	(0.0230)	(0.0189)
HP 500	-0.0892***	-0.0739***	-0.0549***	-0.00871**	-0.0230***	-0.0340***	-0.00539	-0.00898***
	(0.0294)	(0.0147)	(0.0111)	(0.00409)	(0.00467)	(0.00683)	(0.00359)	(0.00286)
HP 1000	-0.113***	-0.0903***	-0.0667***	-0.00774	-0.0262***	-0.0401***	-0.00422	-0.00874**
	(0.0344)	(0.0173)	(0.0136)	(0.00510)	(0.00580)	(0.00847)	(0.00430)	(0.00358)
MA +/- 2	-0.250	-0.263**	-0.184*	0.0249	0.0122	-0.0407	0.0397	0.0632
	(0.198)	(0.106)	(0.0948)	(0.0543)	(0.0537)	(0.0610)	(0.0580)	(0.0496)
MA +/- 3	-0.224	-0.238***	-0.174**	0.00934	-0.0219	-0.0641*	0.0155	0.0218
	(0.152)	(0.0791)	(0.0668)	(0.0311)	(0.0294)	(0.0368)	(0.0329)	(0.0252)
MA +/- 4	-0.190	-0.203***	-0.151***	0.00354	-0.0296	-0.0638**	0.00716	0.00712
	(0.120)	(0.0625)	(0.0508)	(0.0208)	(0.0186)	(0.0252)	(0.0211)	(0.0148)
MA +/- 5	-0.153	-0.165***	-0.124***	7.23e-05	-0.0290**	-0.0560***	0.00311	0.000557
	(0.0947)	(0.0488)	(0.0382)	(0.0146)	(0.0125)	(0.0178)	(0.0139)	(0.00940)
BK	-0.283	-0.300***	-0.215**	0.0178	-0.0102	-0.0663	0.0296	0.0462
	(0.205)	(0.109)	(0.0951)	(0.0503)	(0.0478)	(0.0563)	(0.0536)	(0.0433)

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Table C7: Long-term effects of GDP on log(Mortality), GDP fluc. at age 11-15 (Con't)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Filter	Filter on ln(Mortality)							
on GDP	Polynomial 2	Polynomial 3	Polynomial 4	MA +/- 5	HP 500	HP 1000	MA +/- 4	HP 100
Panel B: With country-year FE								
HP 10	-0.0574	-0.0145	0.0116	0.0212	0.0608	0.0462	0.0309	0.0693
	(0.0678)	(0.0711)	(0.0776)	(0.0719)	(0.0693)	(0.0687)	(0.0767)	(0.0683)
Hp 100	-0.261***	-0.172***	-0.125***	0.0111	-0.0325	-0.0665**	0.0172	0.00965
	(0.0780)	(0.0444)	(0.0439)	(0.0275)	(0.0225)	(0.0262)	(0.0251)	(0.0205)
HP 500	-0.0953***	-0.0701***	-0.0524***	-0.00896**	-0.0261***	-0.0371***	-0.00463	-0.0107***
	(0.0279)	(0.0134)	(0.00894)	(0.00403)	(0.00458)	(0.00677)	(0.00336)	(0.00295)
HP 1000	-0.118***	-0.0856***	-0.0637***	-0.00881*	-0.0306***	-0.0444***	-0.00380	-0.0113***
	(0.0336)	(0.0161)	(0.0113)	(0.00511)	(0.00568)	(0.00846)	(0.00423)	(0.00353)
MA +/- 2	-0.377**	-0.265***	-0.192*	0.00870	-0.0304	-0.0859	0.0336	0.0375
	(0.145)	(0.0933)	(0.0944)	(0.0614)	(0.0520)	(0.0550)	(0.0623)	(0.0513)
MA +/- 3	-0.331***	-0.238***	-0.180***	-0.00186	-0.0561*	-0.101***	0.0122	0.000675
	(0.112)	(0.0654)	(0.0633)	(0.0351)	(0.0284)	(0.0328)	(0.0350)	(0.0268)
MA +/- 4	-0.280***	-0.202***	-0.155***	-0.00422	-0.0562***	-0.0927***	0.00535	-0.00859
	(0.0891)	(0.0517)	(0.0466)	(0.0236)	(0.0176)	(0.0224)	(0.0225)	(0.0157)
MA +/- 5	-0.226***	-0.164***	-0.126***	-0.00444	-0.0483***	-0.0773***	0.00367	-0.0100
	(0.0705)	(0.0409)	(0.0344)	(0.0160)	(0.0118)	(0.0164)	(0.0140)	(0.00962)
BK	-0.424***	-0.302***	-0.224**	0.00107	-0.0573	-0.116**	0.0236	0.0168
	(0.149)	(0.0924)	(0.0932)	(0.0566)	(0.0468)	(0.0507)	(0.0573)	(0.0459)

Note: Only the coefficients on GDP fluctuations at ages 11-15 are reported. Each coefficient presents a separate regression. All regressions include country-gender-age fixed effects, country-gender-age specific linear and square trends in calendar years, gender-birth year fixed effects, and gender-year fixed effects. All the regressions are weighted by the square root of the population size in the corresponding observation. The standard errors in parentheses are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

D. Additional Results

There are several comments that we note in the paper and explain more here.

D1. Relationship to van den Berg et al. (2006)

Table D1 shows the original results in van den Berg et al. (2006) and our replication. Panel A shows the coefficient on "Boom at birth" in Table 3 from van den Berg et al. (2006).

The first row of Panel B shows our replication using the Historical Sample of the Netherlands (HSN) data. The sample used by van den Berg et al. (2006) covers the birth cohorts 1812-1903. Although the sample has been updated in 2010 and the birth cohorts now range from 1850 to 1903, we get very similar results. In the next row, we use the HSN data and the same methodology as van den Berg et al. (2006) but trim the sample to those aged over 45. The coefficient is actually positive in this case, but not statistically significant. This suggests that survival to age 45 is crucial for these cohorts.

Next, we use the HMD data for the Netherlands, again with ages over 45, and using the van den Berg methodology (Step 2). We get a negative but statistically insignificant effect. The effect is even smaller when we use the empirical specification in our paper (Step 3). In Step 4, we replace the boom defined by GNP fluctuations by that defined by GDP fluctuations, and get very similar estimates.

In Step 5, we keep all the other features the same but expand our analysis to birth cohorts up to 1930. The effect becomes more negative and statistically significant. This is consistent with Table 1, where the effects on mortality after age 45 are stronger among these in later cohorts. In step 6, we use the same birth cohorts and analysis framework, but expand the analysis to all 32 countries. The effect is smaller in magnitude but the estimate is more precise and is statistically significant.

In Step 7, we further include all birth cohorts in the HMD sample used in the paper, which yields a bit larger effects. The magnitude suggests that an economic boom at birth defined by GDP lead to a 0.3 percent decline in mortality after age 45. Finally, we replace the boom by the GDP fluctuations, and obtain the estimates reported in column 3 of Table 1.

D2. Robust results for Table 1

We have explored the sensitivity of our main results in Table 1 in several ways. Table D2 shows many of these specifications. For convenience, the first column of Table D2 repeats column 1 of Table 1. A first question is whether the results depend on a particular set of countries. We have a modest number of former Soviet bloc countries (Belarus, Bulgaria, Czech Republic, Estonia, Latvia, Lithuania, Russia, the Slovak Republic, and Ukraine), and these countries have experienced unusual mortality increases in recent times. Since mortality data for these countries all start in 1959, we first divide the sample into pre and post-1959. Consistent with Table 1, we find both short- and long- term effects are more salient in recent years.

The next column shows that our results are not sensitive to the exclusion of Eastern European countries. Among non-Eastern European countries, the coefficient on contemporary GDP fluctuations is 0.29, which is very close to that in the third column. The fifth column shows the results for Eastern European countries. Among Eastern European countries, higher GDP lowers mortality, perhaps picking up the impacts of transition. Long-run effects of GDP fluctuations are also much smaller.

The possibility of third factors that may influence both mortality and GDP is a potential issue in our findings. It could be that particular events such as wars or social unrest both increase mortality and lead to reductions in GDP. To test this, we consider whether the results are driven by unusual relationships during war years. Specifically, we re-estimate the model without observations in 1914-1918 and 1939-1945. To consider similar relationships for the cohorts that fought in the world wars, we drop cohorts born between 1891 and 1899 and those born between 1915 and 1924 (these cohorts were 15-24 at some point during World War I and World War II). Column 6 in Table D2 shows that the results are qualitatively similar and remain statistically significant.

Our primary analysis weights observations by the square root of population in the cell, consistent with Ruhm's analysis. Columns 7 and 8 report the results with two other weighting methods: equal weights for all countries, and population weights. The results are very similar to those in column 1, in both sign and magnitude.

Finally, we have experimented with alternative age groups for the estimation. Column 9 shows one such differential sample: restricting analysis to people aged 55-85. This change has very little impact on the results.

D3. Robustness to using unemployment rates

Table D3 shows the results for how mortality relates to unemployment for the sub-sample of 31 countries with unemployment rates series, which are mostly available since 1950.[9] The first column uses the GDP fluctuations from HP 500 filter but restricts the sample to the observations with valid contemporary unemployment rates.

[9]For non-OECD and eastern European countries, the unemployment rates are only available in later years.

We find very consistent results as shown in the paper.

Starting from column 2, we use unemployment rate as the measure of economic conditions. Column 2 investigates the effects of contemporary unemployment rates. The negative coefficient suggests that a one percentage point increase in unemployment rate decreases mortality by 0.14 percent. It is a consistent estimate with Ruhm (2000), who finds that a one percentage point increase in unemployment rate decreases mortality by 0.5 percent.

Column 3 reports both the contemporary effects and the effects at ages 16-20. The sample size is smaller than one-third of that in column 2 because unemployment rate is not available at ages 16-20 for many birth cohorts in the data. Still, we find qualitatively consistent results. Columns 4 and 5 report the effects of unemployment rate at ages 21-25 and 26-30, respectively. In general, we find robust results using unemployment rates as with GDP fluctuations.

D4. ECHP results with migrants

The ECHP provide information on where the individuals were born. In our primary results, we only keep individuals with the same birth and current living country. Table D4 shows the results with migrants. These results are comparable to those in Table 5 in our paper.

As migrants are more likely to move to countries with better outcomes, it is expected that the results with migrants may underestimate the actual effects. Consistently, Table D4 shows some evidence for this. For self-reported health, income, and satisfaction, we find that the results with migrants have smaller coefficients than their counterpart in Table 5.

D5. Life Expectancy Estimation

To estimate how life expectancy at age 45 would change if there had been no economic fluctuations in early life (i.e., ages 0-30), we use column 3 in Table 1, and predict the mortality. Then we assume all the coefficients on the GDP fluctuations in early life equal to zero and re-predict mortality. The difference between the two mortality estimates are fed into the US 1997 life table to calculate the change in life expectancy. Figure D1 shows the results.

D6. Agriculture share and effects for agriculture and non-agriculture economy

To investigate the contemporary effects for agriculture and non-agriculture economy, we interact both the agriculture share and its interactions with the contemporary GDP fluctuation terms (i.e., the contemporary GDP fluctuations, big boom, big recession, boom* GDP fluctuation, and recession*GDP fluctuation). Then we use the coefficients in the regression with all other covariates to predict the contemporary effects when agriculture share equals to actual value, 5 percent (25th percentile in the data) and 22 percent (75th percentile in the data), respectively. Figure D2a shows the results. The adverse effects of economic growth are more significant in the case of lower agriculture share. In contrast to this, the positive correlation is weak (and even reverses) in situations of high agriculture share.

To investigate the long-term impacts for agriculture and industrial economies, we control for the main effects of agriculture share and interact both the agriculture share and non-agriculture share (i.e., which equals to one minus agriculture share) with the GDP fluctuations in early life (i.e., the GDP fluctuations at birth, at ages 1-5, ... , at ages 26-30). Then we report the coefficients and corresponding confidential intervals in Figure D2b and Figure D2c.

Panel b follows the methodology in Table 2 of the paper and reports the results when the dependent variable is the proportion of people living to age 45. Panel c follows the methodology of column 3 in Table 1 and reports the results for mortality rates at ages 45 and older. We find that the effects on survival up to age 45 larger when the agriculture share is higher. But the effect does not differ much for the post-45 mortality.

D7. Mediators and Short-term effects

D7.1 How Mediators explain the short-term effects

Figure D3 graphically shows how the short-term effect changes when adding mediators in the regressions. The patterns here are consistent with what is shown in the paper. Furthermore, for each mediator, we also present the graphics and regression results (See Table D5) for high and low government expenditure countries.

D7.2 Dropping one country at a time

Tables D6a-D6c present the results when dropping one country at one time. The top two rows report the results when no country is dropped. Because we cover a much smaller period of time (i.e., the longest period is 1960-2008), we cannot estimate the effects of large booms and busts with much precision. Therefore, only the coefficients on GDP fluctuations are reported. The CO_2 results in the first few columns are very consistent across all rows. But the alcohol results are sensitive to whether Russia is included or not. Specifically, controlling for alcohol explains a much smaller share of the GDP fluctuation effect when Russia is omitted from the model than when it is included. Note also that the results of working time are are sensitive to whether Japan is included or not.

D7.3 Other results for mediators

Table D7 presents additional results for the mediators mentioned in the paper. For alcohol consumption, we drop Russia, and conduct the regression in men, women, younger and older sample, respectively. The results are shown in columns 1 throughout column 10. Columns 11-12 report the results for the flu.

D8. Additional results in EB and SHARE

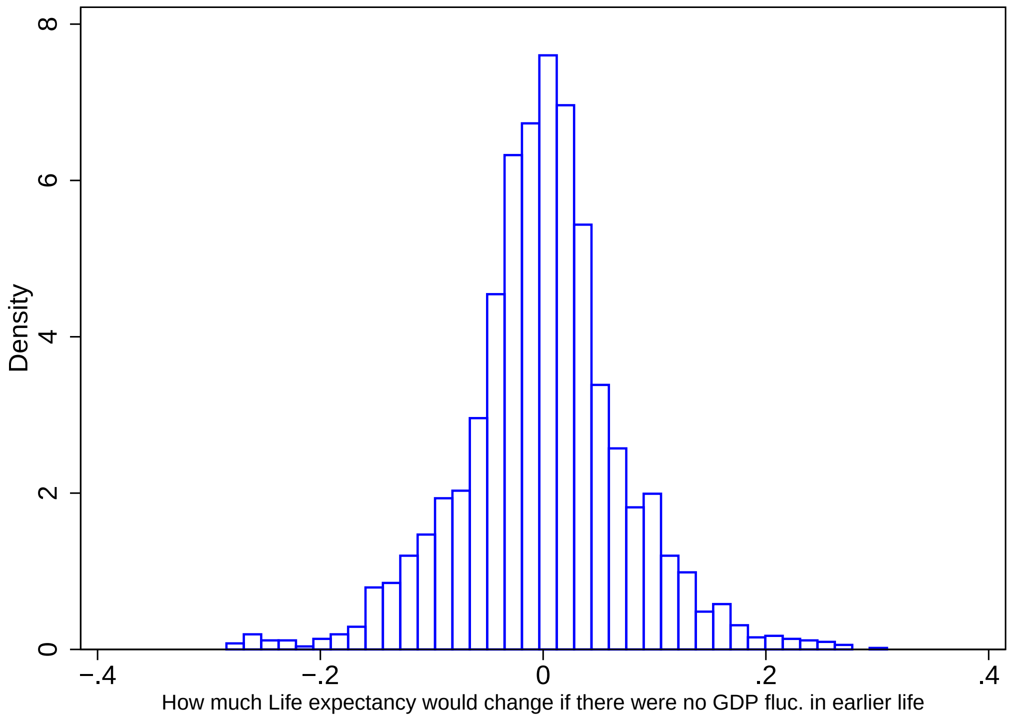
Table D8 reports the results for mental health. The mental health score is the principal component of the answers to the nine questions. For each of them, we conduct a separate regression. For the questions about feeling full of life (column 1), calm (column 4), having a lot of energy (column 5), and happy (column 8), the larger number the answer is, the better mental health is. To the contrary, for the questions about feeling particularly tense (column 2), down in dumps (column 3), downhearted (column 6), worn out (column 7), and tired (column 9), the worse mental health is if the answer is a larger number. Across all the columns, there is a consistent pattern that better economic conditions in early life are associated with better mental health, especially for booms at ages 11-25.

Columns 1-4 in Table D9 report the results for individual outcomes in SHARE. The first column echoes the results in ECHP: better economic conditions in adolescence are associated with improved self-reported health later in life. The next three columns show the results for three dimensions of cognition. In general, the results are consistent across different measures, although some coefficients for verbal fluency and word recall are not as significant as those for numeracy.

Then the next two columns in Table D9 report the results for working status and years of tenure in ECHP. We do not find significant evidence that economic conditions impact the working behavior in later life. But those who experience booms in early life are more likely to have longer tenure.

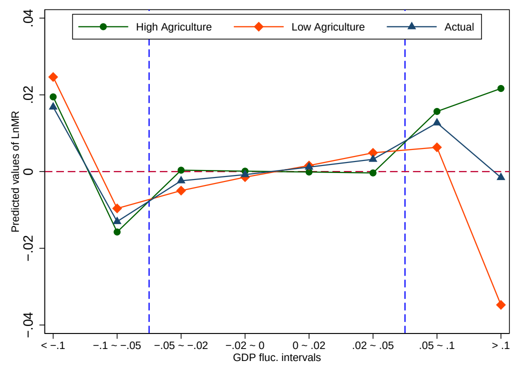
Figure D4 divides the countries in SHARE into high and low government spending. For each dimension of cognition, we present the effects of economic conditions in early life. Again, the impact of economic conditions in early life is larger among the countries with lower government expenditure, for all the three cognition measures.

Figure D1: Life expectancy change if there were no Economic fluctuations in early life

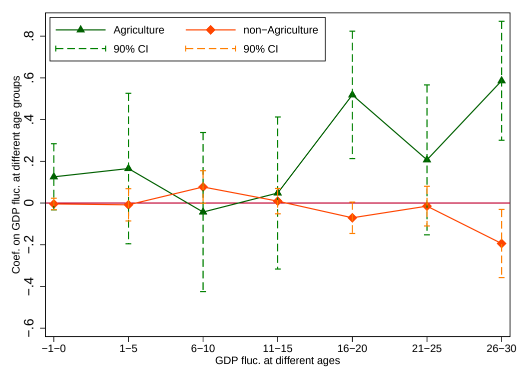


Note: Results of column 6 in Table 1 are used. For each cohort in the data, we use the estimated coefficients to predict the log(mortality) with and without early life GDP fluctuations. Then we calculate the differences in mortality and differences in life expectancy based on the 1997 US life table. The distribution for all the birth cohorts are plotted.

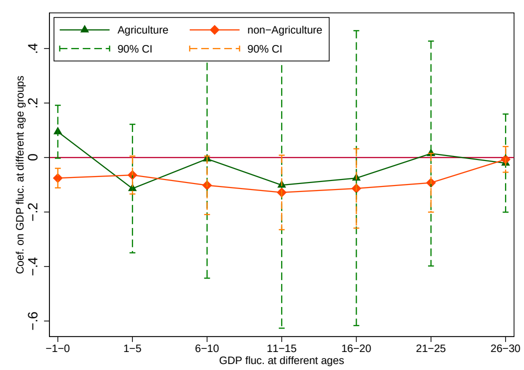
Figure D2: Contemporary and Long-term Effects of agriculture and non-agriculture share in GDP



(a) GDP shares and contemporary effects



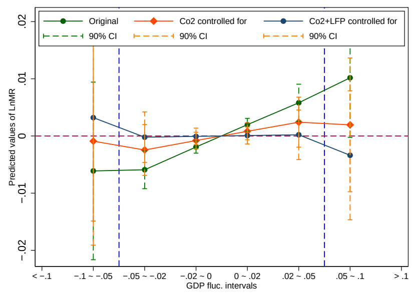
(b) Survival up to age 45



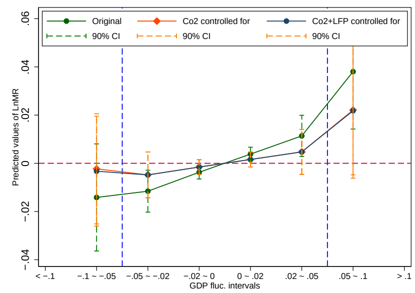
(c) Mortality after age 45

Note: The data for agriculture share are from IHS. The predicted contemporary effects with low, high and average agriculture share of GDP are plotted in panel a. The long-term effects on survival to age 45 and mortality after age 45 are plotted in panel b and panel c, respectively. For each outcome, the effects in agriculture economy and non-agriculture economy are plotted.

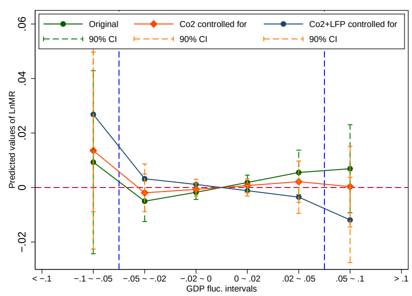
Figure D3: Effects of Contemporary Economic Conditions and Mediators (1)



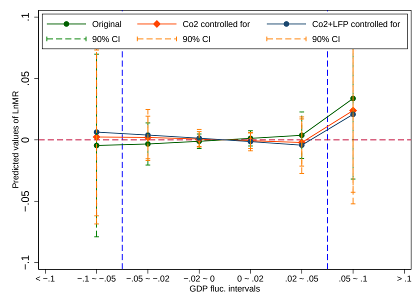
(a) Co2 and LFP



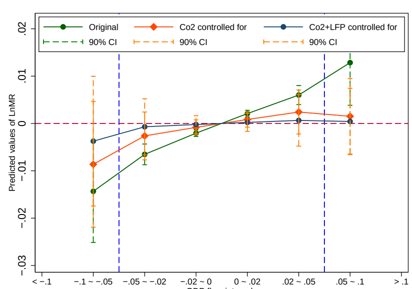
(b) Co2 and LFP, age <= 5



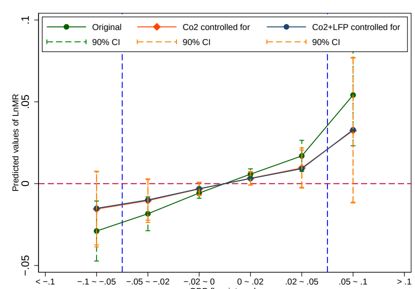
(c) Co2 and LFP (High G)



(d) Co2 and LFP (High G)

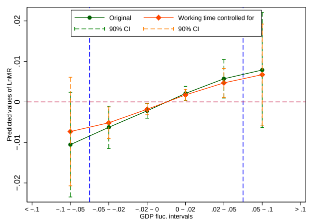


(e) Co2 and LFP (Low G)

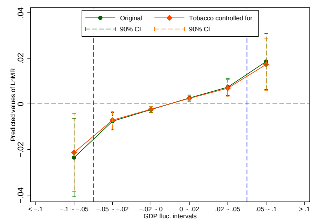


(f) Co2 and LFP (Low G)

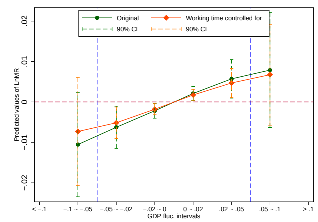
Figure D3: Effects of Contemporary Economic Conditions and Mediators (2)



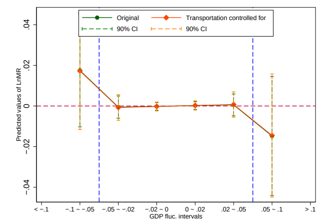
(a) Alcohol



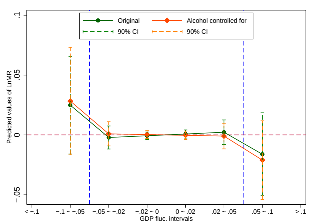
(b) Tobacco



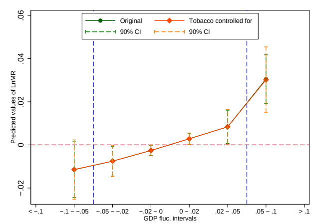
(c) Working hours



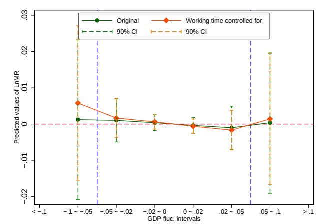
(d) Transportation



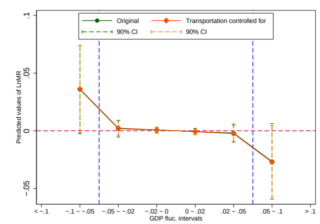
(e) Alcohol (High G)



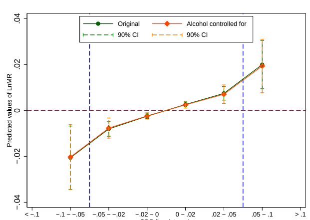
(f) Tobacco (High G)



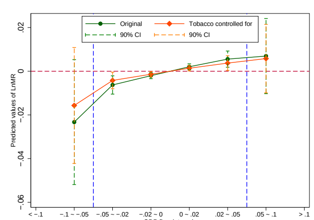
(g) Working hours (High G)



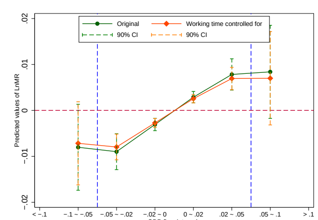
(h) Transportation (High G)



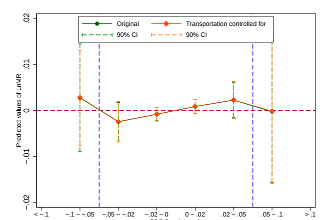
(i) Alcohol (Low G)



(j) Tobacco (Low G)



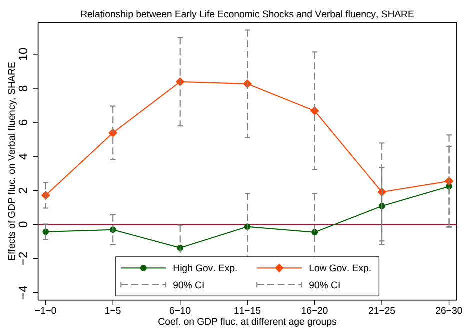
(k) Working hours (Low G)



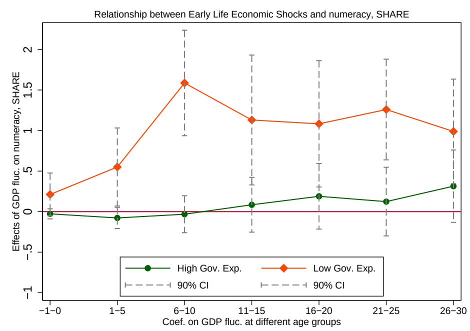
(l) Transportation (Low G)

Note: The contemporary effects are plotted for each mediator under the corresponding setting. The effects at |GDP fluctuation| > 0.1 are not plotted because there are very few observations.

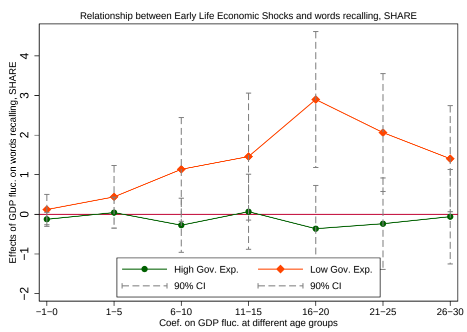
Figure D4: The Impact of Early Life GDP on Quality of Life at Older Ages, SHARE



(a) Verbal fluency, SHARE



(b) Numeracy, SHARE



(c) Words recall, SHARE

Note: Results in Panels a - c are from SHARE. The methodology follows that in Figure 5 in the paper.

Table D1: Reconciliation of magnitudes: van den Berg et al. (2006) replication

Dependent variable: ln(mortality rate)	Boom at birth (Yes = 1)
Panel A: Original results in Van der Berg et al. (2006)	
Table 3 from publication	-0.09
	T-stat: 3.5
Panel B: From Van der Berg et al. (2006) to CHLM (2016)	
Step 0: Replication	-0.10***
	(0.03)
Step 1: Restrict to age 45 and over	0.07
(Using the same data and methodology)	(0.10)
Step 2: Use HMD aggregate data for Holland	-0.015
(Age > 45 but the same methodology)	(0.029)
Step 3: Use CHLM specification	-0.005
	(0.006)
Step 4: Use GDP instead of GNP to define booms	-0.004
	(0.006)
Step 5: Include cohorts up to 1930	-0.008*
(Still Dutch HMD data)	(0.004)
Step 6: Include all 32 countries	-0.002**
(Birth cohorts 1850-1930)	(0.001)
Step 7: Include all 32 countries	-0.003*
(All birth cohorts)	(0.002)
Step 8: Use fluctuation level as explanatory variable	-0.033***
(All birth cohorts)	(0.012)

Note: Data in Panel A are from van den Berg et al. (2006). We use the HSN data to obtain the results in step 0 and step 1. The HMD data are used for the rest. The standard errors in steps 0-5 are clustered at the birth year level, and those in step 6-8 are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table D2: Results in Alternative Subgroups and under Different settings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	ln(Mortality Rate)								
Settings	Basic Regression	Earlier than 1959	1959 or later	1959 or later & no east-euro countries	East-euro countries only	Drop war years and cohorts	Equal weights for each country	Population size as weights	Ages 55-85
Mean	0.700	0.996	0.561	0.499	0.838	0.630	0.400	0.388	0.833
Contemporary Economic Conditions									
Contemp. GDP fluc.	0.170**	0.032	0.332***	0.297***	-0.429*	0.142**	0.193**	0.204**	0.142*
	(0.070)	(0.075)	(0.069)	(0.068)	(0.211)	(0.0653)	(0.0762)	(0.0780)	(0.0701)
Big Boom	0.030***	0.013	0.042***	0.032**	-0.054	0.0363***	0.0396***	0.0249**	0.0286***
	(0.007)	(0.011)	(0.011)	(0.013)	(0.027)	(0.00765)	(0.00781)	(0.00974)	(0.00780)
Boom* Fluc.	-0.559***	-0.163	-0.893***	-0.507**	0.647*	-0.630***	-0.686***	-0.657***	-0.483***
	(0.133)	(0.095)	(0.179)	(0.239)	(0.297)	(0.154)	(0.105)	(0.158)	(0.130)
Big bust	0.003	-0.028*	-0.012	-0.061***	0.049	0.0134	-0.00613	0.0172	0.00300
	(0.009)	(0.015)	(0.019)	(0.012)	(0.031)	(0.00949)	(0.0109)	(0.0131)	(0.00895)
Bust * Fluc.	-0.326***	-0.311**	-0.561***	-1.026***	0.357	-0.205**	-0.470***	-0.281***	-0.271***
	(0.090)	(0.145)	(0.149)	(0.140)	(0.238)	(0.0984)	(0.130)	(0.0924)	(0.0849)

(Continue next page)

Table D2: Results in Alternative Subgroups and under Different settings (continue)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	ln(Mortality Rate)								
Settings	Basic Regression	Earlier than 1959	1959 or later	1959 or later & no east-euro countries	East-euro countries only	Drop war years and cohorts	Equal weights for each country	Population size as weights	Ages 55-85
Mean	0.700	0.996	0.561	0.499	0.838	0.630	0.400	0.388	0.833
Early Economic Conditions									
GDP fluc Age -1-0	-0.034**	0.030	-0.035***	-0.054***	0.028*	-0.0423***	-0.0508***	-0.0469***	-0.0238
	(0.014)	(0.045)	(0.012)	(0.014)	(0.013)	(0.0146)	(0.0129)	(0.0156)	(0.0149)
GDP fluc Age 1-5	-0.050**	-0.132***	-0.043**	-0.068***	-0.023	-0.0384	-0.0634***	-0.0459**	-0.0513**
	(0.018)	(0.044)	(0.017)	(0.023)	(0.016)	(0.0248)	(0.0179)	(0.0214)	(0.0227)
GDP fluc Age 6-10	-0.060**	-0.056	-0.056**	-0.086***	0.030	-0.0332	-0.0896***	-0.0562**	-0.0453
	(0.026)	(0.053)	(0.025)	(0.027)	(0.032)	(0.0323)	(0.0317)	(0.0266)	(0.0299)
GDP fluc Age 11-15	-0.089***	-0.106*	-0.081***	-0.121***	0.006	-0.0621*	-0.119***	-0.0906**	-0.0654*
	(0.029)	(0.059)	(0.027)	(0.038)	(0.031)	(0.0364)	(0.0316)	(0.0345)	(0.0329)
GDP fluc Age 16-20	-0.085***	-0.080	-0.075***	-0.099**	0.026	-0.0563*	-0.124***	-0.0770**	-0.0701*
	(0.030)	(0.049)	(0.026)	(0.039)	(0.033)	(0.0322)	(0.0343)	(0.0306)	(0.0349)
GDP fluc Age 21-25	-0.066***	-0.062	-0.058***	-0.063***	0.003	-0.0822**	-0.0864***	-0.0566*	-0.0615**
	(0.024)	(0.051)	(0.017)	(0.022)	(0.031)	(0.0335)	(0.0315)	(0.0278)	(0.0226)
GDP fluc Age 26-30	-0.008	-0.055*	-0.008	-0.012	0.028	0.00551	-0.0274	0.00536	0.00150
	(0.013)	(0.031)	(0.010)	(0.020)	(0.026)	(0.0210)	(0.0228)	(0.0184)	(0.0149)
N	245,512	102,232	143,190	116,460	26,730	181,444	245,512	245,512	186,482
R2	0.995	0.994	0.997	0.998	0.997	0.996	0.988	0.996	0.994

Note: All regressions include country-gender-age fixed effects, country-gender-age specific linear and square trends in calendar years, gender-birth year fixed effects, and gender-year fixed effects. 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 D3: Comparison of GDP Fluctuations and Unemployment Rate

	(1)	(2)	(3)	(4)	(5)
Variable	ln(Mortality Rate)				
Economic variables	GDP fluc.	Unemployment rate			
Contemporaneous	0.0369**	-0.137***	-0.322***	-0.330***	-0.284***
economic conditions	(0.0169)	(0.0191)	(0.0470)	(0.0413)	(0.0371)
	[0.0749]	[0.0994]	[0.175]	[0.167]	[0.145]
Economic conditions in early life					
Economic conditions	-0.0376***				
at Age -1-0	(0.0114)				
	[0.0139]				
Economic conditions	-0.0281**				
at Age 1-5	(0.0132)				
	[0.0202]				
Economic conditions	-0.0215				
at Age 6-10	(0.0148)				
	[0.0288]				
Economic conditions	-0.0407***				
Age 11-15	(0.0155)				
	[0.0288]				
Economic conditions	-0.0276*		-0.00537		
Age 16-20	(0.0160)		(0.0509)		
	[0.0380]		[0.0538]		
Economic conditions	-0.0117			0.169***	
Age 21-25	(0.0140)			(0.0370)	
	[0.0370]			[0.0596]	
Economic conditions	0.0242*				0.0796**
Age 26-30	(0.0134)				(0.0402)
	[0.0207]				[0.0478]
Observations					
N	118,708	118,708	29,876	35,042	40,924
Country cohorts	2,763	2,763	655	752	871
Countries	31	31	20	21	28
R2	0.998	0.998	0.998	0.998	0.998

Note: All regressions include country-gender-age fixed effects, country-gender-age specific linear and square trends in calendar years, gender-birth year fixed effects, and gender-year fixed effects. All the regressions are weighted by the square root of the population size in the corresponding observation. Standard errors in parentheses are clustered at country-cohort level and those in brackets are clustered at country level.

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

Table D4: Early Life Economic Conditions and Middle and Late Life Outcomes, Results with Migrants

	Health	Income	Satisfaction			Health Behaviors		Social relations	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Self-rated health	Ln(Ind. income)	Life in general	Financial situation	Leisure time	Current smoker	Obese	Talking with others	Meeting friends
Mean	2.40	11.4	4.18	3.62	4.20	0.33	0.13	4.18	4.00
Economic Conditions in Earlier Life									
GDP fluc -1-0	-0.005	0.100**	0.079*	0.049	0.033	0.036*	-0.003	0.061	0.017
	(0.025)	(0.046)	(0.042)	(0.042)	(0.040)	(0.021)	(0.029)	(0.039)	(0.029)
GDP fluc 1-5	-0.066	0.176**	0.271***	0.328***	0.129	-0.006	-0.056	0.196***	0.138***
	(0.052)	(0.083)	(0.085)	(0.085)	(0.079)	(0.053)	(0.057)	(0.062)	(0.053)
GDP fluc 6-10	-0.096	0.243*	0.247**	0.189	-0.007	0.069	0.087	0.205**	0.199**
	(0.082)	(0.130)	(0.126)	(0.120)	(0.120)	(0.085)	(0.080)	(0.085)	(0.080)
GDP fluc 11-15	-0.204*	0.100	0.549***	0.462***	0.015	0.125	-0.058	0.234**	0.180*
	(0.104)	(0.164)	(0.148)	(0.143)	(0.141)	(0.107)	(0.098)	(0.104)	(0.099)
GDP fluc 16-20	-0.189	0.843***	0.521***	0.393**	0.015	0.175*	0.014	0.269**	0.205*
	(0.121)	(0.242)	(0.159)	(0.159)	(0.151)	(0.104)	(0.107)	(0.113)	(0.111)
GDP fluc 21-25	-0.061	0.112	0.392**	0.509***	0.048	0.050	0.011	0.219*	-0.004
	(0.123)	(0.229)	(0.153)	(0.150)	(0.142)	(0.094)	(0.096)	(0.112)	(0.116)
GDP fluc 26-30	-0.147	-0.210	0.253*	0.368**	0.030	0.073	-0.131	0.093	-0.187*
	(0.147)	(0.198)	(0.148)	(0.153)	(0.142)	(0.089)	(0.083)	(0.118)	(0.108)
Observations									
Total	772,314	548,048	662,462	695,596	662,640	248,382	219,274	684,455	754,932
R^2	0.255	0.794	0.139	0.168	0.191	0.186	0.034	0.174	0.198

Notes: The data in the first nine columns are from the European Household Community Panel, from 1994-2001. Standard errors clustered by country-cohort cells are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table D5: Effects of Contemporary Economic Conditions and Mediators (1)

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Mortality rate) (1960-)					
Age sample	Age > 45			Age ≤ 5		
Panel A: Higher Government Expenditure Countries						
Contemporary	0.168	0.0652	-0.108	0.113	-0.0653	-0.131
GDP fluc.	(0.152)	(0.141)	(0.111)	(0.349)	(0.354)	(0.423)
Co2 emission	---	0.0911**	0.0771*	---	0.229**	0.245**
		(0.0413)	(0.0381)		(0.0844)	(0.0843)
LFP of women	---	---	0.0883	---	---	0.0680
			(0.0605)			(0.144)
LFP of men	---	---	0.582***	---	---	0.248
			(0.187)			(0.517)
Observations	46,750	46,750	46,750	6,190	6,190	6,190
Country-year cells		520			520	
Panel B: Lower Government Expenditure Countries						
Contemporary	0.196***	0.0791	0.0212	0.552**	0.311	0.298
GDP fluc.	(0.0400)	(0.0924)	(0.108)	(0.189)	(0.243)	(0.226)
Co2 emission	---	0.124	0.0837	---	0.301	0.309
		(0.0840)	(0.0785)		(0.173)	(0.186)
LFP of women	---	---	-0.0539	---	---	0.0883
			(0.0833)			(0.143)
LFP of men	---	---	0.403***	---	---	-0.00540
			(0.132)			(0.412)
Observations	60,060	60,060	60,060	7,956	7,956	7,956
Country-year cells		668			668	

Note: All regressions include country-gender-age fixed effects, country-gender-age specific linear and square trends in calendar years, country-gender-birth year fixed effects, and gender-year fixed effects. All the regressions are weighted by the square root of the population size in the corresponding observation. The big boom, big recession and their interactions with GDP fluctuations are also included. Only the coefficients on contemporary GDP fluctuations and those on the mediators are reported. Standard errors in parentheses are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table D5: Effects of Contemporary Economic Conditions and Mediators (2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mediators	Alcohol consumption		Tobacco consumption		Working Hours		Vehicle Miles Driven	
Variables	(1960 -)		(1960 -)		(1981-)		(1970-)	
Panel A: Higher Government Expenditure Countries								
Contemp. GDP	0.0692	-0.0293	0.255	0.254	-0.0326	-0.0534	-0.0605	-0.0768
fluctuation	(0.189)	(0.198)	(0.142)	(0.147)	(0.117)	(0.106)	(0.146)	(0.128)
Mediator	---	0.0135*	---	0.00291	---	-0.393**	---	0.0482
		(0.00675)		(0.0287)		(0.156)		(0.0615)
Total	51,072	51,072	37,212	37,212	23,890	23,890	37,302	37,302
Countries	12	12	10	10	12	12	12	12
Country-year cells	567	567	414	414	266	266	415	415
Panel B: Lower Government Expenditure Countries								
Contemp. GDP	0.243***	0.231**	0.190**	0.128*	0.264***	0.234***	0.0725	0.0739
fluctuation	(0.0581)	(0.0804)	(0.0770)	(0.0700)	(0.0699)	(0.0501)	(0.0755)	(0.0794)
Mediator	---	0.00151	---	0.0273***	---	-0.326***	---	-0.00102
		(0.00356)		(0.00736)		(0.104)		(0.0257)
Total	60,330	60,330	35,812	35,812	29,190	29,190	31,804	31,804
Countries	15	15	13	13	15	15	12	12
Country-year cells	670	670	399	399	325	325	354	354

Note: All regressions include country-gender-age fixed effects, country-gender-age specific linear and square trends in calendar years, country-gender-birth year fixed effects, and gender-year fixed effects. All the regressions are weighted by the square root of the population size in the corresponding observation. The big boom, big recession and their interactions with GDP fluctuations are also included. Only the coefficients on contemporary GDP fluctuations and those on the mediators are reported. Standard errors in parentheses are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table D6: Mediator results by dropping one country in a time (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mediators	CO2 (1960-2008)			Time (1981-2008)		Transport (1970-2008)		Alcohol (1960-2008)		Tobacco (1960-2008)	
Country dropped	Basic	Control Co2	Co2+LFP	Basic	Working time	Basic	Transportation	Basic	Alcohol	Basic	Tobacco
None	0.184***	0.0763	0.00667	0.190*	0.156**	0.0169	0.0230	0.190**	0.114	0.238***	0.222***
	(0.0626)	(0.0843)	(0.0837)	(0.0959)	(0.0718)	(0.103)	(0.119)	(0.0806)	(0.0985)	(0.0726)	(0.0744)
Australia	0.185	0.0679	0.00590	0.196	0.161**	0.0250	0.0328	0.189**	0.110	0.248***	0.233***
	(0.0649)	(0.0920)	(0.0909)	(0.100)	(0.0760)	(0.106)	(0.122)	(0.0819)	(0.102)	(0.0727)	(0.0743)
Austria	0.183	0.0711	-0.000632	0.191	0.157**	0.0138	0.0204	0.194**	0.109	0.239***	0.223***
	(0.0640)	(0.0855)	(0.0842)	(0.0959)	(0.0715)	(0.103)	(0.119)	(0.0808)	(0.0997)	(0.0761)	(0.0778)
Belarus	0.184	0.0771	0.00789					0.188**	0.114		
	(0.0628)	(0.0849)	(0.0843)					(0.0801)	(0.0986)		
Belgium	0.179	0.0720	-0.000940	0.189	0.154**	0.0143	0.0205	0.192**	0.114	0.234***	0.217**
	(0.0638)	(0.0846)	(0.0839)	(0.0967)	(0.0665)	(0.101)	(0.117)	(0.0806)	(0.0986)	(0.0765)	(0.0783)
Bulgaria	0.189	0.0692	0.00210			-0.00687	-0.0177	0.186**	0.107		
	(0.0648)	(0.0839)	(0.0827)			(0.107)	(0.122)	(0.0851)	(0.102)		
Canada	0.195	0.0847	0.0159	0.212**	0.173**	0.0174	0.0236	0.197**	0.128	0.251***	0.233***
	(0.0616)	(0.0824)	(0.0804)	(0.0936)	(0.0705)	(0.103)	(0.119)	(0.0794)	(0.0938)	(0.0719)	(0.0750)
Czech Rep.	0.187	0.0782	0.00873	0.197**	0.163**	0.0250	0.0311	0.165*	0.0772	0.238***	0.223***
	(0.0624)	(0.0837)	(0.0831)	(0.0944)	(0.0704)	(0.0996)	(0.116)	(0.0824)	(0.0962)	(0.0729)	(0.0748)
Denmark	0.187	0.0772	0.0105	0.208**	0.171**	0.0165	0.0233	0.191**	0.114	0.246***	0.231***
	(0.0641)	(0.0854)	(0.0841)	(0.0960)	(0.0722)	(0.109)	(0.125)	(0.0829)	(0.101)	(0.0726)	(0.0745)
Estonia	0.181	0.0735	0.00413	0.189*	0.155**	0.0230	0.0212	0.191**	0.116		
	(0.0631)	(0.0845)	(0.0841)	(0.0962)	(0.0720)	(0.105)	(0.123)	(0.0805)	(0.0983)		
Finland	0.195	0.0775	0.0130	0.218**	0.185***	0.00603	0.0125	0.199**	0.124	0.258***	0.243***
	(0.0633)	(0.0921)	(0.0904)	(0.0911)	(0.0663)	(0.107)	(0.123)	(0.0831)	(0.101)	(0.0724)	(0.0734)
France	0.183	0.0845	0.0124	0.189*	0.160**	0.0138	0.0204	0.196**	0.119	0.234***	0.212**
	(0.0644)	(0.0855)	(0.0848)	(0.0943)	(0.0760)	(0.100)	(0.117)	(0.0807)	(0.0985)	(0.0809)	(0.0831)

Table D6: Mediator results by dropping one country in a time (2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mediators	CO2			Time		Transport		Alcohol		Tobacco	
Country dropped	Basic	Control Co2	Co2+LFP	Basic	Working time	Basic	Transportation	Basic	Alcohol	Basic	Tobacco
Hungary	0.148	0.0576	-0.00962	0.173	0.140*	-0.00900	-0.00350	0.160*	0.0953	0.183***	0.172**
	(0.0557)	(0.0832)	(0.0852)	(0.103)	(0.0778)	(0.106)	(0.122)	(0.0796)	(0.0994)	(0.0584)	(0.0632)
Iceland	0.188	0.0793	0.00808	0.186*	0.153**	0.0160	0.0222	0.193**	0.117	0.245***	0.230***
	(0.0628)	(0.0851)	(0.0853)	(0.0968)	(0.0726)	(0.103)	(0.119)	(0.0814)	(0.0993)	(0.0730)	(0.0748)
Ireland	0.178	0.0653	-0.000504	0.189*	0.156**			0.185**	0.113	0.231***	0.216***
	(0.0643)	(0.0865)	(0.0858)	(0.0960)	(0.0719)			(0.0818)	(0.0985)	(0.0729)	(0.0747)
Italy	0.206	0.0876	0.0109	0.191*	0.157**	0.0220	0.0267	0.217***	0.137	0.243***	0.228***
	(0.0617)	(0.0843)	(0.0887)	(0.0963)	(0.0718)	(0.103)	(0.122)	(0.0771)	(0.0931)	(0.0735)	(0.0753)
Japan	0.174	0.0612	-0.0170	0.0290	0.0386	-0.0190	-0.0108	0.190*	0.102	0.260**	0.251**
	(0.0840)	(0.0986)	(0.0955)	(0.0746)	(0.0716)	(0.117)	(0.128)	(0.104)	(0.123)	(0.106)	(0.107)
Latvia	0.179	0.0799	0.0113	0.189*	0.157**	0.00353	-0.00388	0.189**	0.118		
	(0.0629)	(0.0856)	(0.0853)	(0.0964)	(0.0722)	(0.109)	(0.123)	(0.0817)	(0.101)		
Lithuania	0.183	0.0776	0.00917	0.190*	0.156**	0.0185	0.0242	0.188**	0.109		
	(0.0628)	(0.0854)	(0.0850)	(0.0957)	(0.0718)	(0.103)	(0.119)	(0.0810)	(0.0998)		
Luxembourg	0.185	0.0732	0.00448	0.194*	0.160**			0.191**	0.115		
	(0.0630)	(0.0846)	(0.0839)	(0.0965)	(0.0728)			(0.0809)	(0.0990)		
Netherlands	0.158	0.0450	-0.0204	0.191*	0.154**	-0.00173	0.00323	0.170**	0.0912	0.202***	0.179**
	(0.0615)	(0.0832)	(0.0840)	(0.0951)	(0.0723)	(0.102)	(0.119)	(0.0788)	(0.0986)	(0.0709)	(0.0684)
New	0.182	0.0729	0.00300	0.181*	0.145*			0.186**	0.110	0.241***	0.225***
Zealand	(0.0644)	(0.0868)	(0.0864)	(0.0995)	(0.0744)			(0.0839)	(0.102)	(0.0757)	(0.0773)
Norway	0.191	0.0872	0.0201	0.196**	0.164**	0.0209	0.0297	0.194**	0.117	0.256***	0.239***
	(0.0637)	(0.0898)	(0.0876)	(0.0954)	(0.0727)	(0.111)	(0.129)	(0.0836)	(0.102)	(0.0730)	(0.0757)

Table D6: Mediator results by dropping one country in a time (3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Mediators	CO2			Time		Transport		Alcohol		Tobacco	
Country dropped	Basic	Control Co2	Co2+LFP	Basic	Working time	Basic	Transportation	Basic	Alcohol	Basic	Tobacco
Poland	0.201	0.150**	0.0765	0.189*	0.155**	0.0293	0.0363	0.195**	0.132	0.238***	0.222***
	(0.0623)	(0.0586)	(0.0653)	(0.0962)	(0.0722)	(0.109)	(0.124)	(0.0864)	(0.0993)	(0.0726)	(0.0744)
Portugal	0.171	0.0701	-0.00260	0.185*	0.157**	0.00550	0.0159	0.181**	0.0921	0.241***	0.225***
	(0.0648)	(0.0861)	(0.0862)	(0.103)	(0.0740)	(0.105)	(0.121)	(0.0820)	(0.101)	(0.0725)	(0.0743)
Russia	0.208	0.113	0.0452	0.223***	0.190***	0.142**	0.180***	0.254***	0.217***		
	(0.0561)	(0.0759)	(0.0741)	(0.0782)	(0.0553)	(0.0511)	(0.0559)	(0.0586)	(0.0645)		
Slovak Rep.	0.185	0.0764	0.00668	0.191*	0.155**	0.0203	0.0257	0.183**	0.105		
	(0.0625)	(0.0837)	(0.0830)	(0.0956)	(0.0705)	(0.101)	(0.118)	(0.0837)	(0.101)		
Spain	0.195	0.0725	-0.00193	0.192*	0.141*	0.0352	0.0488	0.208**	0.127		
	(0.0646)	(0.0925)	(0.0911)	(0.0981)	(0.0757)	(0.0951)	(0.106)	(0.0775)	(0.0984)		
Sweden	0.195	0.0744	0.0136	0.193*	0.164**	0.0163	0.0210	0.196**	0.117	0.252***	0.237***
	(0.0623)	(0.0855)	(0.0835)	(0.0949)	(0.0717)	(0.107)	(0.124)	(0.0822)	(0.0991)	(0.0742)	(0.0763)
Switzerland	0.187	0.0781	0.00452	0.190*	0.157**	0.0158	0.0228	0.193**	0.119	0.241***	0.226***
	(0.0641)	(0.0853)	(0.0853)	(0.0963)	(0.0721)	(0.106)	(0.122)	(0.0833)	(0.100)	(0.0738)	(0.0756)
Ukraine	0.18	0.0762	0.00726					0.189**	0.126		
	(0.0646)	(0.0876)	(0.0876)					(0.0811)	(0.101)		
United	0.188	0.0725	-0.00652	0.202*	0.159**	0.00138	0.00554	0.195**	0.122	0.245***	0.236***
Kingdom	(0.0638)	(0.0838)	(0.0811)	(0.0992)	(0.0759)	(0.110)	(0.126)	(0.0835)	(0.100)	(0.0743)	(0.0755)
United	0.161	0.0489	-0.0277	0.184**	0.147**	0.0152	0.0264	0.153*	0.0733	0.206**	0.194**
States	(0.0639)	(0.0883)	(0.0866)	(0.0892)	(0.0646)	(0.104)	(0.123)	(0.0797)	(0.101)	(0.0740)	(0.0787)

Notes: Coefficients on contemporary GDP fluctuation are reported. The standard errors are clustered at country level.

Table D7: Other results for mediators, Alcohol and Flu

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent variable: Ln(Mortality)											
Mediator	Alcohol consumption										Flu	
Sample	No Russia		No Russia & Male		No Russia & Female		No Russia & Younger (Age < 65)		No Russia & Older (Age $\geq$ 65)		All available countries	
Contempt.	0.254***	0.217***	0.242***	0.196***	0.265***	0.234***	0.250***	0.192**	0.226***	0.214**	0.214***	0.225***
GDP fluc.	(0.0586)	(0.0645)	(0.0659)	(0.0690)	(0.0579)	(0.0657)	(0.0847)	(0.0843)	(0.0776)	(0.0827)	(0.0584)	(0.0584)
Mediator		0.0045		0.0055		0.0036		0.007*		0.001		0.001***
		(0.0032)		(0.0037)		(0.0028)		(0.004)		(0.002)		(0.000)
N	121,818	121,818	60,909	60,909	60,909	60,909	51,358	51,358	67,618	67,618	105,726	105,726
R^2	0.998	0.998	0.998	0.998	0.998	0.998	0.993	0.993	0.998	0.998	0.998	0.998

Note: All regressions include country-gender-age fixed effects, country-gender-age specific linear and square trends in calendar years, country-gender-birth year fixed effects, and gender-year fixed effects. All the regressions are weighted by the square root of the population size in the corresponding observation. The big boom, big recession and their interactions with GDP fluctuations are also included. Only the coefficients on contemporary GDP fluctuations and those on the mediators are reported. Standard errors in parentheses are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table D8: Early Life Economic Conditions and Mental Health

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Mental health (1-5 for each)								
	Felt full of life	Felt partic tense	Felt down in dumps	Felt calm	Had lot of energy	Felt downhearted	Felt worn out	Felt happy	Felt tired
Mean	3.476	2.390	1.721	3.527	3.307	1.914	2.290	3.493	2.765
GDP Fluc.	-0.091	-0.005	0.011	0.025	-0.065	-0.037	-0.093	0.098	-0.047
At Birth	(0.071)	(0.072)	(0.071)	(0.067)	(0.097)	(0.082)	(0.079)	(0.081)	(0.055)
GDP Fluc.	-0.006	-0.011	0.118	0.101	-0.148	0.030	-0.113	-0.073	-0.055
Age 1-5	(0.134)	(0.124)	(0.155)	(0.107)	(0.155)	(0.177)	(0.185)	(0.125)	(0.156)
GDP Fluc.	0.019	0.008	-0.028	0.112	0.012	0.013	-0.167	0.139	-0.120
Age 6-10	(0.240)	(0.191)	(0.272)	(0.240)	(0.245)	(0.253)	(0.321)	(0.235)	(0.228)
GDP Fluc.	0.263	-0.132	-0.188	0.365	0.051	-0.177	-0.329	0.270	-0.137
Age 11-15	(0.283)	(0.240)	(0.314)	(0.272)	(0.300)	(0.276)	(0.383)	(0.265)	(0.337)
GDP Fluc.	0.597**	-0.253	-0.543**	0.582**	0.256	-0.505*	-0.595*	0.415	-0.290
Age 16-20	(0.255)	(0.287)	(0.258)	(0.262)	(0.310)	(0.289)	(0.329)	(0.294)	(0.288)
GDP Fluc.	0.320	-0.247	-0.431	0.454	0.068	-0.429	-0.415	0.471*	-0.462
Age 21-25	(0.245)	(0.278)	(0.279)	(0.269)	(0.325)	(0.266)	(0.332)	(0.253)	(0.279)
GDP Fluc.	0.147	-0.082	-0.565*	0.512**	-0.051	-0.529*	-0.333	0.194	-0.137
Age 26-30	(0.232)	(0.260)	(0.293)	(0.221)	(0.262)	(0.267)	(0.266)	(0.208)	(0.265)
Observations	55,211	55,271	55,221	55,278	55,212	55,198	55,248	55,067	55,375
R-squared	0.199	0.172	0.209	0.153	0.186	0.192	0.210	0.171	0.173

Notes: The data in the first nine columns are from the European Household Community Panel, from 1994-2001. The regressions are the same as the column 10 in Table 4 in the paper. Standard errors clustered by country-cohort cells are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table D9: Early Life Economic Conditions, Health, and Cognition, SHARE

Data source	SHARE				ECHP	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Self-rated health	Verbal fluency (0-100)	Numeracy (1-5)	Words recall (0-20)	Working now (Yes = 1)	Tenure in years (among working people)
Mean	3.14	19.7	3.34	8.82	0.56	10.0
Economic Conditions in Earlier Life						
GDP fluc -1-0	-0.0385	-0.113	0.00564	-0.0443	0.028*	0.106
	(0.0362)	(0.246)	(0.0358)	(0.0980)	(0.017)	(0.357)
GDP fluc 1-5	-0.151**	0.233	-0.0140	0.204	-0.016	2.900***
	(0.0704)	(0.473)	(0.0718)	(0.208)	(0.036)	(0.758)
GDP fluc 6-10	-0.272**	-0.248	0.146	0.233	0.009	4.770***
	(0.109)	(0.715)	(0.123)	(0.360)	(0.050)	(1.102)
GDP fluc 11-15	-0.414***	0.837	0.298*	0.675	-0.040	7.373***
	(0.152)	(0.978)	(0.172)	(0.474)	(0.062)	(1.558)
GDP fluc 16-20	-0.430**	0.621	0.460**	0.640	0.045	10.426***
	(0.174)	(1.141)	(0.205)	(0.535)	(0.086)	(2.038)
GDP fluc 21-25	-0.357**	1.356	0.380*	0.561	0.026	9.221***
	(0.168)	(1.098)	(0.208)	(0.546)	(0.094)	(1.977)
GDP fluc 26-30	-0.474***	2.015*	0.525**	0.785	-0.106	3.716**
	(0.172)	(1.123)	(0.212)	(0.536)	(0.081)	(1.849)
Observations						
Total	185,236	180,560	120,316	181,080	601,643	356,771
Individuals	104,332	102,431	100,559	102,697	120,115	84560
Country-cohort	923	931	923	932	585	584
R^2	0.186	0.257	0.200	0.263	0.276	0.256

Notes: The data in the first four columns are from the SHARE, and the sample in the rest two columns are composed of those aged between 30 and 65 in ECHP. All regressions control for country-gender-year, country-age-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

References

Bank, World, "World development indicators," *World Bank*, 2015.

Baxter, Marianne and Robert G. King, "Measuring Business Cycles: Approximate Band-Pass Filters For Economic Time Series," *The Review of Economics and Statistics*, November 1999, *81* (4), 575–593.

Cutler, David M, Wei Huang, and Adriana Lleras-Muney, "When does education matter? The protective effect of education for cohorts graduating in bad times," *Social Science & Medicine*, 2015, *127*, 63–73.

Donkelaar, Aaron Van, Randall V Martin, Michael Brauer, N Christina Hsu, Ralph A Kahn, Robert C Levy, Alexei Lyapustin, Andrew M Sayer, and David M Winker, "Global Estimates of Fine Particulate Matter using a Combined Geophysical-Statistical Method with Information from Satellites, Models, and Monitors," *Environmental science & technology*, 2016, *50* (7), 3762–3772.

Hodrick, Robert J and Edward C Prescott, "Postwar US business cycles: an empirical investigation," *Journal of Money, credit, and Banking*, 1997, pp. 1–16.

Khan, Hashmat, Christopher R. Knittel, Konstantinos Metaxoglou, and Maya Papineau, "Carbon Emissions and Business Cycles," Working Paper 22294, National Bureau of Economic Research May 2016.

Layard, P Richard G, Stephen J Nickell, and Richard Jackman, *Unemployment: macroeconomic performance and the labour market*, Oxford University Press on Demand, 2005.

Lleras-Muney, Adriana and Flavien Moreau, "The Shape of Mortality: Implications for Economic Analysis," *Working Paper*, 2016.

Mitchell, Brian, *International historical statistics: Europe 1750-1993*, Springer, 1998.

Ruhm, Christopher J, "Are Recessions Good for Your Health?," *The Quarterly Journal of Economics*, 2000, *115* (2), 617–650.

van den Berg, Gerard J, Maarten Lindeboom, and France Portrait, "Economic conditions early in life and individual mortality," *The American Economic Review*, 2006, pp. 290–302.