Economic Conditions and Mortality:

Evidence from 200 Years of Data

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Abstract

Using historical mortality data covering over 100 birth cohorts in 32 countries, this paper examines the short- and long- term effects of economic conditions on mortality. We confirm two seemingly contradictory patterns documented before. Poor economic conditions while growing up (from birth to age 25) significantly raise adult mortality. Yet contemporary downturns appear to decrease mortality. In addition we document some new findings. Poor economic conditions in adolescence have the largest adverse effect on adult mortality. Moreover this is not due to selective survival of the fittest. We also find that although small expansions raise mortality, large expansions lower it. We rationalize these findings with a model of health investments that affect the stock of health, which in turn determines mortality. This simple model suggests that selection cannot explain the difference between the short- and long-term effects of good economic conditions. Instead economic conditions differentially affect the level and trajectory of both good and bad inputs into health. We investigate these implications by examining how several health (income, pollution, behaviors and social relations) inputs are affected by economic conditions. In line with previous work, shocks in adolescence have a large and lasting effect on adult incomes. Moreover higher government expenditures offset some of the negative effects of early-life economic fluctuations on health and incomes, consistent with the idea that these programs provide some form of insurance. Air pollution is strongly procyclical and helps explain the contemporaneous impact of economic conditions on mortality. Finally, data from the European Community Household Panel suggests that in addition to income, social integration improves with good economic conditions earlier in life, but does not support the idea that health behaviors do. (JEL Codes: H51, I10, I38, N10)

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I. Introduction

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). For example, Fogel argues that improved nutrition led to the vast bulk of the remarkable decline in mortality experienced in developed countries in the past three centuries.[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, 2001, 2011; Currie et al., 2009; Almond and Currie, 2011). On the other hand, a significant body of evidence has found that improved economic conditions immediately raise mortality in developed countries (Ruhm, 2000, 2003, 2005, 2007). Although there are some notable exceptions to these patterns,[2] these results appear difficult to reconcile.

The dichotomy between studies showing favorable and unfavorable effects of economic booms raises several issues. First, how are these two facts related – that is, how does the impact of short-term economic conditions interact with the impact of earlier economic conditions in influencing health? 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 this shock 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, and the level of this stock determines mortality. Economic conditions may affect mortality in several ways. First they affect the level and the trajectory of inputs that in turn affect the stock of health: by increasing or decreasing access to resources such as food and medical care; by affecting health behaviors such as smoking and exercise; and by changing environmental factors such as pollution. Economic fluctuations may also have long-term effects on mortality by

[1] This is not without controversy. See Cutler et al. (2006).

[2] For instance, mortality did not in fall in England during the industrial revolution Cutler et al. (2006). Also 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).

changing the composition of people who survive to older ages, but simulations suggests that this mechanism is unlikely to explain the effects of shocks we observe, except among the very old or the very young (before age one).

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 covers more than 100 birth cohorts and tracks their actual mortality. We identify unexpected shocks as deviations of GDP from its long term trend. We then examine how contemporary shocks, and shocks and birth and during the teenage years affect adult mortality.

We reach four principal findings. First, we show that 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. The largest impact is from economic conditions between ages 11 to 20; cohorts with better economic environments during that time period have significantly reduced mortality after age 45. Our results also support the fetal origin hypothesis that economic conditions in utero are associated with mortality, but the magnitude is much smaller relative to the effects of economic conditions around adolescence. This is partly mechanical–our model shows equally sized shocks will have larger effects in adolescence than at birth, because mortality in adolescence is at its lowest. But the micro-level data also shows that earnings and other important inputs into health are more affected by shocks in adolescence than at birth.

Third, 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. This is consistent with government expenditures providing insurance and thus mitigating fluctuations in income. But large shocks are more difficult to insure (XXX), particularly explaining why there is no difference between high and low spending countries for large shocks.

Fourth, we tentatively explore the mechanisms through which economic conditions affect health. More favorable early life conditions raise incomes, particularly for youth–consistent with Oreopoulos et al. (2012)'s findings on the effects of graduating in recessions. Also cohorts who leave school in better times are more socially integrated when older; they have more friends and social contacts. But better conditions are not associated with improved health behaviors; in fact smoking is higher for cohorts with better childhood economic environments, and adolescent smoking is very sensitive to income (Chaloupka and Warner, 2000). Short term effects of booms and recessions appear to be closely related to pollution, which is strongly procyclical.

Overall, the mixed findings on the link between contemporaneous economic conditions and mortality appears to be a mix between the positive impact of greater income and the negative impact of pollution that accompanies 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 inputs, rather than by selection effects.

The closest analog to our paper is van den Berg et al. (2006), who examine early life economic conditions and later life mortality in the Netherlands. They also report that the greatest effects of economic conditions on lifetime mortality occurs for adolescents. We show that their findings generalize to 32 countries. We then investigate mechanisms and how policy influences the link between economic outcomes and mortality. We also provide a theoretical framework to understand these findings.

This paper is organized as follows. Section II introduces the data we used in this paper, and describes the basic patterns of mortality. Section II provides a theoretical framework to guide our analysis. Section IV provides basic results and discusses potential issues. Section V further investigates the short- and long- term effects by looking into different subsamples and adding more controls. Section VI provides some evidence on possible mechanisms and Section VII concludes.

II. Data

II.A Human Mortality Database (HMD)

Mortality data are taken from the Human Mortality Database (HMD). The HMD contains detailed cohort life tables by year of birth and gender. 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 this is the relevant population estimate. These cohort tables, which track the actual mortality rates of given cohorts as they age, constitute the most comprehensive, high-quality, population data available. As such, only countries with high quality registration systems are included.

To understand the effects of economic conditions over the life time, we need populations with significant time series representation. Table 1 lists the 32 countries with mortality information available prior to 1970 that we study.[3] These countries 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 length of years observed is 97 years.

Figure 2 shows mortality 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.[4]

[3]We exclude Chile (1992-), Germany (1990-), Israel (1983-), Slovenia (1983-), and Taiwan (1970-) because the data covers very few years.

[4]Although the sample of countries used in this figure is not consistent across cohorts, the patterns are the same if we only include countries with data for all cohorts.

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 with age thereafter. It reaches the same level as in infancy only very late in life, after age 80 or so. In addition to being non-monotonic in age, the mortality rate 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.

Mortality rates are sufficiently low past early childhood up to middle age that relationships between economic conditions and mortality at those ages are very unstable.[5] Past approximately age 40, the logarithm of mortality is roughly linear with age, as noted by Gompertz (1825) nearly two centuries ago. We thus model log mortality as a function of economic conditions.

Mortality rates of the oldest old are measured with substantial error. Further, the samples of older individuals is small. As a result, the HMD imputes mortality rates after age 90. To avoid such imputation, we limit our analysis to the population aged 90 and below. Our final sample includes 504,666 country-gender-cohort-year observations between ages 45 and 90.

To understand time trends in mortality in more detail, Figure 3 shows the logarithm of the mortality rate for men and women aged 60-69 by year. Averaged across all countries, the mortality rate for men fell 44 percent for men and 70 percent for women between 1880 and 2000. These declines were substantially larger after 1930 than before.

Although on average mortality has fallen, mortality changes have not been uniform across countries. Figures 4a and b show the evolution of mortality rates for ages 60-69 in 7 countries. Countries such as Japan experienced very rapid mortality declines during the period; the mortality declined by 2.5 percent (0.046 percentage points) per year. Other countries such as Russia and Denmark had less rapid declines, or even increases in some cases. The mortality of those aged 60-69 in Russia increased by 0.68 percent (0.018 percentage points) on average. 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 percent, 27 percent, 26 and 58 percent of the mean, respectively.

[5] When we estimate our models for mortality below, the estimates depend greatly on the time period chosen and the ages examined.

The increase in the variance of mortality in the late 20th century has also been noted before – for instance Becker et al (2005), and it would be more pronounced if we included countries with a large incidence of HIV/AIDS. Figures 4c and 4d 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 declined by 1.2 percent (0.028 percentage points) per year since 1933 but those aged 50-59 declined by 1.4 percent (0.015 percentage points) per year in the same period. Another striking example is Russia: the mortality rate of people aged 60-69 increased by 0.68 percent (0.019 percentage point) per year but that of people aged 50-59 increased by 1.2 percent (0.017 percentage points) per year in the same period.

To account for these differential patterns, in our analysis below we model the log of the mortality rate for each country, gender, and age as a quadratic function of time. This specification allows for observed non-linearities in Figure 4 and provides an equally good fit as one with higher or order terms.

II.B Historical GDP data

The literature studying 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. The historical GDP data are taken from a variety of data sources, including Angus Maddison, IMF and World Bank.[6] Real GDP per capita is available since 1800 for most of the countries we study.

To measure unanticipated 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. Commonly, GDP trend is predicted using a smoothing parameter of 500, but higher and lower values have been proposed. In

[6]We use Gross Domestic Product per capita adjusted by Purchasing Power Parities (in international dollars, fixed 2011 prices). The data are compiled on the Gapminder website: http://www.gapminder.org/data/documentation.

our primary analysis, we use the Hodrick-Prescott filter to measure trend. The Appendix explores the sensitivity of the results to using different smoothing parameters in that filter, or alternatively to using non-linear time trends.

Once trend has been estimated, the GDP fluctuation in any given year is the difference between actual ln(real GDP per capita) and its estimated level that year. Positive fluctuations correspond to "booms" and negative fluctuations capture "busts." As shown in Figure B1 in the Appendix, the biggest divergence between GDP and its long-run trend in the United States is in the Great Depression and the immediate post-World War II era. Other significant divergences occur in the 1890s, when the US suffered a severe recession,[7] and 2008, the current great recession. Appendix Figure B4 shows all periods 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. Figure B5 in the appendix shows the mean GDP fluctuation and standard deviation of GDP fluctuations by year. The magnitude of mean is particularly small in 1800-1880, 1950-1970, and particularly large in 1910-1940. In the average year, the standard deviation of GDP fluctuations is 8 percent, but it is higher 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.[8] By comparison, there are only 1,366 country-years with unemployment rates. However, GDP fluctuations are highly correlated with unemployment rates ($\rho = -0.6$ in the United States, as shown in Figure B5a). Figure B5b shows 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 0.14 percentage point increase in unemployment rates.[9] We use this relationship below in comparing the magnitude of our results to previous estimates in the literature.

[7] The US GNP contraction began in January 1893 and continued until June 1894, and a further contraction started after December 1895 until June 1897 (for the official data, one can consult D. Glasner and T. F. Cooley, Business Cycles and Depressions: An Encyclopedia, New York, 1997).

[8] For each of the 32 countries, we have 213 observations; from 1800 – 2012.

[9] Without country or year fixed effects, a negative 1 percent GDP fluctuation increases unemployment by 0.15 percentage points. With country and year fixed effects, the increase is 0.14 percentage points.

III. A Model of Economic Conditions and Mortality

III.A A model of health and death

Assume individuals are born with an initial health level H_0. This initial health endowment differs across individuals in the population and has a distribution given by $G(.)$, which is likely to be normally distributed.[10] At any time t, an individual's income (Y) and behavior (B) will affect longevity through technology $I = I(Y,B)$. Therefore we have that the health stock evolves according to

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

In the absence of investments in health, the health stock falls with age at rate δ, linearly if $f(t) = t$. It is also affected by random shocks (diseases, wars, etc), and these are given by ε_t which are iid over time with distribution $F(.)$. But the health stock can be increased through I, the health production function. We assume that income Y increases health (it is used to purchase food, shelter, health care, etc) $I_Y = \frac{\partial I}{\partial Y} > 0$, and that B lowers health $I_B = \frac{\partial I}{\partial B} < 0$ (e.g., smoking, drinking, working, pollution etc.).

Taking logs of the first equation and denoting $h_t = log(H_t)$, we get:

$$h_t = h_{t-1} + I(Y_t,B_t) - \delta f(t) + \varepsilon_t \tag{2}$$

Suppose that individuals die when their stock of health first crosses a lower threshold $\underline{H}$ and define $\underline{h} \equiv log(\underline{H})$. We assume that all individual born alive have a stock greater than this minimum, $h_0 > \underline{h}$.

Let $D_t = I(h_1 \leq \underline{h})$ denote the random variable equal to one if the individual dies in period t, and define the mortality rate at time t as $MR_t = E(D_t|G_t) = P(D_t = 1|D_{t-s} = 0 \forall s < t, G_t)$. In the

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

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

$$\begin{aligned} MR_1 = P(h_1 \quad \leq & \quad \underline{h}|g_1) = P\left(h_0 + I(Y_1, B_1) - \delta + \varepsilon_1 \leq \underline{h}|g_1\right) \\ & = P(\varepsilon_1 \leq \varphi_1) \\ & = F(\varphi_1) \end{aligned}$$

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. Investments lower this threshold (lower mortality) and depreciation increases it (increases mortality).

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:

$$\begin{aligned} MR_2 &= E(D_2 = 1|D_1 = 0) \\ &= P(h_2 < \underline{h}|h_1 > \underline{h}, g_1, g_2) \\ &= \frac{P(h_2 < \underline{h}, h_1 > \underline{h}|g_1, g_2)}{P(h_1 > \underline{h}|g_1, g_2)} \\ &= \frac{P(\varepsilon_2 < \varphi_2 - \varepsilon_1, \varepsilon_1 > \varphi_1)}{1 - F(\varphi_1)} \\ &= \frac{K(\varphi_2, \varphi_1)}{1 - F(\varphi_1)} \end{aligned} \tag{3}$$

where $\varphi_2 = \underline{h} - I(Y_1, B_1) - I(Y_2, B_2) + 3\delta - h_0$ captures the threshold for dying in period 2, and $K(\varphi_2, \varphi_1) = \int_{\varepsilon_1 = \varphi_1}^{\infty} \int_{\varepsilon_2 = -\infty}^{\varphi_2 - \varepsilon_1} f(\varepsilon_1) f(\varepsilon_2) d\varepsilon_1 d\varepsilon_2$. $K(\varphi_2, \varphi_1)$ is the density right above the past threshold and below the new threshold, that is the fraction of survivors who dies as a result of a new small shock. It is increasing in the current threshold $\frac{\partial K}{\partial \varphi_2} > 0$ and decreasing in the past threshold $\frac{\partial K}{\partial \varphi_1} < 0$. The denominator is the fraction of survivors, and it is a negative function of the previous thresholds (because $F'(\varphi_1) > 0$).

III.B Effect of economic conditions

Let current economic conditions at time (or age) t be given by g_t, and let $G_t = \{g_1, g_2, ..., g_t\}$ denote the history of economic conditions up to time t. We assume that $Y_t = Y(G_t)$ and $B_t = B(G_t)$ are functions of these conditions. Specifically we assume:

1. Good current economic conditions lead to increases in both inputs, $\frac{\partial Y_t}{\partial g_t} > 0$, $\frac{\partial B_t}{\partial g_t} > 0$. For example in good times individuals will work more and have higher incomes. If work causes physical or mental stress then both good and bad inputs will increase in good times. Similarly in good times, higher production will lead to higher incomes, but also generate more pollution.

2. Past economic conditions have permanent effects on current inputs $\frac{\partial Y_t}{\partial g_s} > 0$, $\frac{\partial B_t}{\partial g_s} > 0$ for any $s < t$. Empirically recent work shows that individuals exposed to large negative economic shocks, such as large recession or mass layoffs, have substantially lower incomes for many years thereafter, suggesting that $\frac{\partial Y_t}{\partial g_{t-s}} > 0$ (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 rational addiction (Becker and Murphy 1988), suggesting $\frac{\partial B_t}{\partial g_{t-s}} > 0$.

3. Changes in economic conditions are not anticipated, so that $\frac{\partial Y_t}{\partial g_s} = \frac{\partial B_t}{\partial g_s} \equiv 0$ for any $s > t$. in other words, economic conditions in the future do not influence the current income or behavior.

Short-term effects. Using the expressions in equation 3, we can now express the effect of an unexpected improvement in current economic conditions g_2 on the logarithm of mortality as

$$\frac{\partial lnMR_2}{\partial g_2} = \frac{-1}{K(\varphi_2, \varphi_1)} \underbrace{\frac{\partial K}{\partial \varphi_2}}_{>0} \left[\underbrace{I_y \frac{\partial Y_2}{\partial g_2}}_{>0} + \underbrace{I_B \frac{\partial B_2}{\partial g_2}}_{<0} \right] \tag{4}$$

The term outside the parentheses captures the responsiveness of the probability of dying to current inputs. The first term inside the parentheses corresponds to the effect of economic conditions on inputs (increasing income and increasing behavior). Because these two inputs have opposite effects (signs), the overall sign of the short term effect of improved conditions is determined by the relative magnitudes of the two effects. If overall investment goes up, mortality falls.

Moreover these short term effects on mortality will likely vary across individuals or groups for two reasons. First, the effect of economic conditions on income and behaviors ($\frac{\partial Y_s}{\partial g_s}, \frac{\partial B_s}{\partial g_s}$) is likely to differ across individuals. For instance retired individuals will not necessarily see their incomes increase during booms, but they will be exposed to increased pollution. More interestingly we expect that in countries with high levels of (countercyclical) expenditures, the government provides some insurance so that $\frac{\partial Y_s}{\partial g_s} \approx 0$, at least for small shocks. In addition, the responsiveness of health to a given input (I_Y, I_B) could vary across individuals.

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:

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

The first term shows that good economic conditions in the past lower current mortality because they raise the level of current health lowering mortality. 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. For example, suppose B captures pollution or stress. We might hypothesize that $\frac{\partial B_2}{\partial g_1} = 0$, for instance suppose that pollution generated in prior times does not remain in the air for long. Suppose further that the negative short term effects of pollution are larger than the positive effects of income $I_y\frac{\partial Y_1}{\partial g_1} < I_B\frac{\partial B_1}{\partial g_1}$, and therefore the short term impact of economic conditions in $t-1$ was negative. In the next period however, the income effect will become larger and potentially offset the negative short-term pollution effect $I_y \frac{\partial Y_1}{\partial g_1} + I_y \frac{\partial Y_2}{\partial g_1} > I_B \frac{\partial B_1}{\partial g_1}$. This will generate a positive effect of economic conditions over time despite a negative impact on the short term.

However if B captures behaviors like smoking then these shocks might have a persistent effect, in which case the overall effect depends on the evolution of each input after the shock and on the relative effects of each input on health at a given age. It is well-documented that there are different "critical periods" where individuals are particularly sensitive to shocks. For instance adolescent smoking responds more to income and prices than adult smoking (Chaloupka and Warner, 2000). And around the world smoking, drinking and drug use initiation occurs in adolescence (WHO 2011). Cognition and personality traits develop at different times, cognition being more sensitive to inputs early in life while social traits appear to be more sensitive to events in adolescence (Cunha and Heckman, 2007). Heights are determined primarily by inputs up to age 3 and secondarily by inputs during the second growth spurt in adolescence (Case and Paxson, 2008; Bozzoli et al., 2009).

The second term corresponds to a selection effect and it has an ambiguous sign because $\frac{\partial K}{\partial \varphi_1} < 0$ but $F'(\varphi_1) > 0$. The first term captures the standard selection effect: a positive investment $\left[I_y \frac{\partial Y_1}{\partial g_1} + I_B \frac{\partial B_1}{\partial g_1}\right] > 0$ results in more individuals right at the threshold surviving, and this increases mortality. But a positive investment also increases the health stock of the entire population increasing the total fraction that survives. In other words a positive investment saves the least healthy individuals, potentially lowering the average health of the survivors (and thus increasing mortality), but the investment also shifts the entire distribution of the health stock right. Thus the average health of survivors need not go down.

III.C 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 implied by the model for a population of 500,000 individuals. We assume the initial health stock H_0 is normally distributed with mean 100 and standard deviation of 40. The threshold for death $\underline{H}$ is 40 generating an infant mortality rate of about 10%, close to that in the US around 1900. Shocks ε_t are drawn every period from a $N(0,1)$, the rate of depreciation is $\delta = 0.03$, $f(t) = t^{1.01}$ and the level of investment I_t is constant at 1.2.

Basic features. Figure 1a shows that the model reproduces the shape of the mortality rates well: mortality starts high and plummets to very low levels by adolescence. It remains low and highly variable until around age 40, and then it starts rising linearly with age, at a decreasing rate very late in life. The high infant mortality rate is a result of many infants born with low health endowment. After that, the number of people with low health endowment is mostly determined by the size of shocks, until individuals reach old age.

The log of health stock among survivors increases linearly with age, peaks around age 50 and then falls linearly until death. Figure 1b shows the evolution of the distribution of the health stock as cohorts age. This distribution at age 1 is truncated at the threshold, it moves right and flattens until age 40. Then it starts moving left and eventually becomes triangular at the threshold. Thus the potential for selection effects to offset the effect of shocks is greatest at birth and older ages, when the peak of the density is very close to the threshold.

Appendix Figures A1.a-d illustrate how the different parameters affect the shape of mortality. Lower initial levels of H result in markedly higher infant and child mortality but they have otherwise a very small impact on subsequent mortality rates, which are mostly determined by the relative size of the investments and the depreciation rate effects (Figure A1.a). Lowering the level of the investment also has the same effect (Figure A1.c). Increasing the depreciation rate results in a much higher level of mortality all throughout life (Figure A1.b). Thus we can think of secular improvements in mortality as reflecting either higher levels of inputs (due to higher levels of GDP), or as reflecting improvements in technology, in the form of increased knowledge/level of positive inputs or lower depreciation rates. Finally increasing the variance of the random shocks changes the shape of mortality: it becomes shallower and more linear in old-age (Figure A1.d). In the HMD we do not observe this rotation of mortality profiles across cohorts

Effect of shocks. Next we illustrate the effect of a negative shock lasting two periods but occurring at different ages. Figure 1c illustrates the results and shows that mortality after age 40 is more affected by shocks at age 15 than by shocks at birth and age 1.

Finally Figure 1d illustrates the effect of shocks that increase both bad and good inputs, but differentially over time. There is a large boom lasting two years, during which the overall effect of pollution is assumed to be large and to dominate the effect of increased incomes on investments. But then we assume that the affected cohort has higher incomes until age 30, whereas the exposure to pollution is set to zero after the boom has passed. This "lucky" cohort experiences unusually high mortality at age 15 and until their mid thirties, resulting from exposure to high pollution, but it experiences substantially lower mortality thereafter, resulting from greater incomes.

Both Figures 1c and 1d show that the effects on mortality are dominated by the sign of the shock and rarely by negative selection–good shocks lowering mortality and bad shocks lowering it. Selection only "undoes" scaring for the very old. This occurs because after childhood, most individuals born with low stocks have died and investments have moved the health stock far from the dying threshold.

We do not observe all positive or negative inputs into health. Nor do we observe how they evolve in response to changes in economic conditions. Therefore we first look to study how unexpected aggregate shocks affect mortality and estimate the sign of the short- and long-term derivatives in equations 3 and 4. We also document heterogeneity by gender, age, period and level of government expenditures. We then look at how a few inputs respond to economic conditions and discuss the implications of the results.

IV. Mortality and Economic Fluctuations: Reduced form evidence

IV.A. Non-Parametric Evidence

We start by investigating the relationship between GDP fluctuations and adult mortality non-parametrically. For reasons noted above, our sample is the population aged 45 and older. To include populations where virtually all cohorts have GDP data, we work with mortality starting in 1860.[11] This includes a total of 245,512 observations.

Following the analysis above, 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.[12]

After de-trending mortality in this fashion, we relate mortality residuals to GDP fluctuations at different ages. We present these results graphically by dividing the sample into percentile bins, based on the relevant fluctuation distribution, either earlier in life or contemporary. For each bin, we calculate the average GDP fluctuation along with the average residual mortality.[13]

Figure 5 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

[11] In the original file, birth cohorts 1690 – 1799 (i.e., 110 cohorts) in Sweden, birth cohorts 1731- 1799 (i.e., 69 cohorts) in Belgium, cohorts 1725 – 1799 in Denmark, cohorts 1706 – 1799 in France etc. do not have early life GDP data and are omitted from those regressions.

[12] Because we have overlapping data on different cohorts in the same years, we can estimate separate cohort, age, and time fixed effects. However, trends which are common across time cannot be differentiated between cohort, age, and time effects.

[13] A full non-parametric approach would also regress GDP fluctuations on the same set of controls we used to de-trend mortality and plot the residuals of mortality against the residuals of GDP fluctuations. Because GDP fluctuations are already de-trended, proceeding this way changes very little to the results. This is shown in Appendix Figure B3.

negative relationship emerges between GDP fluctuations during adolescence and young adulthood (ages 10-25) and middle/late life mortality. While noisy, the relationship does not show any signs of being non-linear. After age 25 a positive relationship emerges, though it is not large. In total, good economic conditions while growing up are associated with lower mortality in adulthood.

The last panel in the figure shows the relationship between mortality residuals and contemporary GDP fluctuations. To smooth contemporary fluctuations, 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 80th percentile) lower mortality and very large busts (below the 20th percentile) increase it. But between the 20th and the 80th percentile (i.e., for relatively small fluctuations) there is a positive slope: small positive fluctuations increase mortality.

IV.B. Regression Analysis

We now estimate the formal relationship between mortality rates and unanticipated economic conditions throughout the lifetime using the following proportional hazard model, which corresponds to the reduced form equation from the model (equation 5):

$$\begin{aligned} ln(MR)_{bgct} &= \beta_0 + \beta_c GDPfluc_{ct} + \beta_{-1-0} GDPfluc_{bc}^{-1-0} + \beta_{1-5} GDPfluc_{bc}^{1-5} + \ldots \\ &\quad + \beta_{26-30} GDPfluc_{bc}^{26-30} + \theta_{agc} + \theta_{agc} * t + \theta_{agc} * t^2 + \theta_{gt} + \theta_{gb} + \varepsilon_{bct} \qquad (5) \end{aligned}$$

where 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. As in the non-parametric analysis, we include a full set of age-gender-country interaction dummies (θ_{agc}), along with their interactions with a time trend and that trend squared ($\theta_{agc} * t, \theta_{agc} * t^2$), gender-specific year dummy variables (θ_{gt}), and gender-specific year of birth dummy variables (θ_{gb}). This set of dummies fully accounts for the level and trend of GDP and therefore controls for secular improvements in mortality due to factors like nutrition. It also accounts for differential trends in mortality for different ages, gender and country, as suggested by the patterns in the data.

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 $GDPfluc_{ct}$, and lagged fluctuations. We divide lagged GDP fluctuations into GDP fluctuations at birth and in utero ($GDPfluc_{bc}^{-1-0}$) and in five year age groups up to age 30 ($GDPfluc_{bc}^{1-5}$,..., $GDPfluc_{bc}^{26-30}$). We interpret fluctuations as unexpected deviations from GDP trends. The identifying assumption is that these unexpected shocks are not caused my mortality itself (no reverse causality), and that all factors affected by economic fluctuations are inputs into health.

Our descriptive analysis suggests that contemporaneous GDP fluctuations have a non-linear effect on mortality. To address this, we model GDP fluctuations linearly within |5%| and effectively allow for a different line to be estimated in large booms and busts. To do so, we include non-linear terms in contemporary GDP fluctuations: a dummy for an economic boom (defined as GDP fluctuations > 5%) or a recession (GDP fluctuations < -5%) and the interaction of each of these with GDP fluctuations.

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, early life conditions are perfectly collinear with country specific cohort effects, so we cannot include these fixed effects in specifications with lagged GDP fluctuations. We can include then when examining the impact of contemporaneous GDP fluctuations alone. Finally following Ruhm (2000), we weight each observation by the square root of the corresponding population. The appendix shows that the results are invariant to the weights used. Standard errors are all clustered at country-level to allow for serial correlation within countries.

Table 2 shows the results from estimating equation (5), and Figure 6 displays the results graphically. The first rows of the table, along with Figure 6(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. To interpret the coefficient, note that a move from the 25th to the 75th percentile of GDP fluctuations raises GDP by about 5.4 percent. This translates into an increase in mortality of 0.92 percent. On average, mortality declines by about 0.6 percent annually. Hence, this effect 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 , pvalue = 0.31).

The second half of Table 2 (and Figure 6b), shows the coefficients for economic conditions at different ages, 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, similar to what model simulations predict.

The second and third columns examine the impact of contemporaneous GDP fluctuations and early life GDP fluctuations in more detail. In the second column, we control for country-by-birth-year fixed effects. This allows us to dummy out fully the impact of early life conditions. However, as noted above, we cannot include early-life GDP fluctuations in this specification. The coefficients on contemporaneous GDP are similar in this specification relative to that in the first column, as shown in Figure 6a. In particular, the coefficient on contemporary economic fluctuations is smaller (0.11) but not significantly different from that in the first column. The only change that results from this is that recessions are a little less harmful to health.

The third column includes country-by-year dummy variables, to control for contemporaneous economic and social conditions in a richer way. In this specification, we must of necessity exclude contemporary GDP fluctuations. The coefficients on GDP fluctuations in earlier life are very similar relative to those in the first column, or a bit larger in magnitude, as shown in Figure 6b. These results are consistent with the fact that (estimated) GDP fluctuations are not serially correlated over time.

We have explored the sensitivity of these findings in several ways, including excluding Eastern European countries and periods of global war, where mortality and economic conditions may both be influenced by other factors. The Appendix discusses these specifications; none of our results are materially changed by this, which suggests that the set of dummy controls we include capture the main differences across cohorts and time periods that we might worry about.

Columns 4 and 5 of Table 2 divide our results into two time periods: prior to 1945 and 1945 and later. One might imagine that the relationship between economic conditions and mortality was larger when GDP was smaller. Or it might be larger now, given that that we have new knowledge and technology on how to improve health. Empirically, we find a countercyclical but not significant relationship between contemporary economic conditions and mortality in the pre-1945 time period, and a strong pro-cyclical relationship post-1945. This finding is 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. It is also consistent with Gonzalez and Quast (2010)who find pro-cyclical mortality among the most developed states in Mexico and countercyclical mortality in the poorest states. Aside from selection, there are at least two reasons why this pattern might arise. One is that pollution (bad inputs) has increased over time; another is that as countries grow rich they provide (imperfect) insurance against (small) shocks. We explore these in the next sections of the paper.

The impact of early-life economic conditions becomes negative and much more significant in recent times. Again this is consistent with both larger insurance or larger pollution. Another possibility is selective survival—infant and child mortality decreased substantially for older cohorts, and as suggested by the model, shocks very early and very late in life have the largest negative selection effects. If frailer babies and children die when times are tough, those who survive maybe relatively healthier. We explore this next.

IV.C. Selection and Treatment

We investigate selection effects by examining how early life conditions affect the share of individuals that make it to adulthood. In most cohorts, we measure population size from birth. As we go back in time, population at birth becomes scarcer. We thus consider all cohorts for which we observe the population from age 10 or younger.

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 each of our 32 countries, for a total of 3,876 observations. The dependent variable is the share of the population born in a given gender and cohort that survived to age 45. We relate this share to the early life conditions faced by that cohort by estimating the following equation:

$$\begin{aligned} Prop_{cb} &= \beta_0 + \beta_{-1-0} GDPfluc_{bc}^{-1-0} + \beta_{1-5} GDPfluc_{bc}^{1-5} + \ldots + \\ & \beta_{26-30} GDPfluc_{bc}^{26-30} + \theta_{gc} + \theta_{gc} * t + \theta_{gc} * t^2 + \theta_{gb} + \theta_{gmin} + \varepsilon_{bct} \end{aligned} \tag{6}$$

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. We also include dummy variables for the earliest year at which population is measured (θ_{gmin})– birth, or up to age 10 as appropriate. All the regressions are weighted by the square root of cohort size and again all the standard errors are clustered at country level.

Table 3 shows the results of this estimation. Positive GDP fluctuations before age 30 increase the share of those who survive to age 45. The effects are roughly similar at all ages from 6-20. Columns 4 and 5 show these selection effects are similar for men and women, and the F-test fails to reject equality of those coefficients.

Columns 2 and 3 divide the sample by whether the cohorts were born before or after 1910. Consistent with our intuition, effects are much larger for early cohorts for whom mortality early in life is large. 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.

To test the extent to which selection explains the lack of a relationship between GDP fluctuations and mortality in our older data, we include terms for survival to age 45 in the regressions. The last two columns of Table 2 show the impact of including these terms in the main regression, and in the pre-1945 time period only. Particularly for the early years in the sample, the coefficients reject the simple hypothesis that more survivors leads to worse overall health and thus greater mortality after age 45. Indeed, more survivors before age 45 is associated with lower mortality after age 45. Our model shows how this can happen: the entire distribution of health changes with economic shocks making the selection effects small. Therefore larger effects today are more likely to stem from increases in bad inputs today (higher pollution), or smaller income today (due to insurance for example).

IV.D. Differentiation by Gender and Age

Figure 7 shows our results for contemporaneous and early life GDP fluctuations separately by gender and age. We divide ages into two groups: the younger ages (45-65) and older ages (66-89). Younger people of both genders experience similar impacts of contemporaneous economic shocks. In both cases, mortality increases with moderate expansions. It falls with big booms and rises with big recessions. These effects are somewhat muted for the older population. Moderate expansions are not associated with increased mortality for either older men or women. Our model shows that in general shocks earlier in life will have larger effects than effects later in life because of their cumulative impact on the health stock. But both groups do experience mortality increases in large booms, and older women experience mortality increases in big busts.

The impact of economic deprivation at birth is relatively similar for men and women, and also very similar for younger and older populations. This is consistent with the findings in Barker (1995) that fetal under-nutrition is associated with later coronary heart disease generally. However, among the younger population, bad economic conditions in young adulthood matter almost exclusively for men. There is no significant impact of economic fluctuations after age 6 on young women's mortality, but there is a pronounced U-shape for men. For both older men and women, poor economic conditions when young raise mortality. These findings are consistent with two facts. One is that mortality appears to be larger for men than for women, at every age. If this is due to lower depreciation rates among women, then the model predicts women will also be less sensitive to shocks early in life. It is also possible that men are more sensitive to early economic fluctuations because they enter the labor market in adolescence and therefore economic conditions in adolescence are larger predictors of their lifetime incomes, compared to women whose lifetime resources are tied to their husbands' incomes.

The finding that older women are more sensitive to economic fluctuations when young than younger women is consistent with the finding that the health-income gradient becomes larger with aging (Case et al., 2005). It is also again consistent with a relatively minor role of selection and a large scarring effect.

IV.E. Comparison with Previous Literature

Our results relating GDP fluctuations to mortality are not directly comparable to past literature, which generally relates mortality to unemployment rates. However, we can translate between our results and previous literature. As noted above, a 1 percent GDP fluctuation is associated with a 0.14 percentage point reduction in unemployment. As shown in table 2, it is also associated with a 0.17 percent increase in mortality. Thus, our result implies a 1.2 percent increase in mortality when unemployment falls by 1 percentage point (i.e., 0.17/0.14). This is reasonably close Ruhm (2000), who estimates an effect of 0.5 percent.

In addition, we consider directly how mortality relates to unemployment for the sub-sample of 31 countries with unemployment rates series. These data are generally available from about 1950. Table B5 shows the comparison of results using GDP fluctuations and unemployment rates over this time period. The first column replicates the above results for this subsample. The results are similar to our earlier findings, though less precise. In the next column, we investigate the relationship of contemporary unemployment with mortality rates. High contemporaneous unemployment reduces mortality, similar to Ruhm (2000). In contrast, unemployment rates up to age 25 are all associated with increased mortality, as subsequent columns show. Overall, we conclude that the results derived from GDP and unemployment are very similar.

V. Do government expenditures moderate the impact of economic conditions?

Government expenditures account for nearly half of GDP among many OECD countries. It is possible that this spending affects the link between economic conditions and health. One important policy that may influence the relationship between income and mortality is 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., $\frac{\partial Y_t}{\partial GDP_t}$ and $\frac{\partial B_t}{\partial GDP_t}$ – 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 permanent disability, poverty in childhood, or disease in old age. To the extent these programs succeed, the effect of economic conditions on long term outcomes will be smaller. We thus investigate the extent to which high levels of government spending reduce the impact of economic conditions on mortality. To examine this, we would ideally obtain long annual time series of government expenditures as a share of GDP for all the countries and cohorts in our studies and match that up to mortality rates at those times and later. Unfortunately these data are not consistently available on an annual basis. Instead we use recent OECD data to categorize countries into high and low spending countries. It has been documented that rich countries have both higher levels of spending and more countercyclical expenditures, whereas developing countries have lower levels of expenditures and these expenditures are pro-cyclical expenditures (see **?**, and references therein).Thus our categorization captures the extent to which levels and changes in expenditures differ across countries. Table 1 shows the countries in our sample by government spending in 2000. We divide the countries into two groups, based on whether government spending as a share of GDP is above or below 40 percent. Since government spending as a share of GDP is not well identified in communist countries, we exclude these countries from the analysis.

Table 4 and Figure 8 show the relationship between economic conditions and mortality for the two sets of countries. In countries where expenditures exceed 40 percent of GDP there is no effect of contemporary economic conditions on adult mortality. 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. The coefficients between the high and low spending countries are not statistically significant at the 10 percent level (p=0.12), but they are substantively large. In both sets of countries, large negative shocks to income increase mortality. Neither effect is statistically significant, but both are about the magnitude of the average across all countries.

VI. Why Do Economic Conditions Influence Health?

Our analysis so far has shown that mortality is related to economic conditions, but not why this is the case. In this section, we use a number of data sources to examine why mortality is related to economic conditions. We separate our analysis into the impact of early life economic circumstances and contemporaneous circumstances.

VI.A Understanding Early Life Conditions

To examine the relationship between early life economic circumstances and health, we use micro-level data from the 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.

For each individual, we start with GDP fluctuations early in life, for ages -1-0, up to 26-30. We relate these early life fluctuations to economic, social, and health outcomes later in life:

$$\begin{aligned} Y_{ibcg} = \quad & \beta_0 GDPfluc_{bc}^{-1-0} + \beta_{1-5} GDPfluc_{bc}^{1-5} + \ldots \quad + \beta_{26-30} GDPfluc_{bc}^{26-30} \\ & + \delta_{cgt} + \delta_{cag} + \delta_{bg} * HighG_c + \varepsilon_{bct} \end{aligned} \tag{7}$$

We control for country-year effects (θ_{cgt}, separately by gender). This fully absorbs current economic and social conditions in the country. With such a short panel and relatively little change in economic conditions across countries, we are loathe to examine the impact of contemporary GDP fluctuations. In addition to country-gender-year effects, we control for age-gender effects separate for each country, and gender effects by birth cohort. This latter variable is interacted with a dummy variable for living in a high government spending country, to presage our analysis of how the effects of early life fluctuations differ across countries with bigger and smaller governments.

GDP fluctuations are measured at the level of country-cohorts. To account for this, we cluster the standard errors at the country-cohort level.

We use several outcomes, shown in Table 5. The first outcome is the log of total personal income. We include this to examine whether early life economic shocks persist to middle and older ages. We also include variables for satisfaction with life. Satisfaction is measured for three domains: 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 between 3.7 for financial satisfaction to 4.6 for leisure time satisfaction.

We have two principle measures of health. The primary measure of health we employ is self-reported health status, scored on a basis from very good (1) to very bad (5). Self-reported health has been strongly related to subsequent mortality (Idler and Benyamini, 1997). The average person rates their health a 2.3 on the 1-5 scale. Since the survey is a panel, we can measure mortality as well, though the samples are not large enough for very accurate estimates at the country-cohort level. The average mortality rate is 0.5 percent.

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.

Table 6 starts by showing the relationship between each of these outcomes and GDP fluctuations early in life. Each column of the table is a different regression; the GDP fluctuations at different ages are shown in the various rows. The first column shows that economic conditions during childhood and young adult years are related to income throughout the working years. The largest effect is for economic conditions at ages 16-20, the age at which people typically leave school. This is consistent with other micro data (Oreopoulos et al., 2012).

The magnitude of the effects suggests that a one percentage point increase in GDP (above its long run level) around ages 16 to 25 increases income by one percent. The elasticity of adult mortality with respect to lifetime income is around -0.3 and -0.6 (Deaton and Paxson, 2001; Aizer et al., Forthcoming). If we assume these effects are causal, then a one percent increase in income would lower mortality by 0.3 percent or more. Therefore, this mechanism could explain our results on early life GDP fluctuations influencing health.

The next set of columns shows that economic conditions during childhood are significantly favorably associated with life satisfaction and financial satisfaction, though not leisure time satisfaction. As with income, the relationship is inverse U-shaped, with peak effects associated with fluctuations in the late teenage years.

The sixth column shows that a better economy when young leads to improved self-rated health at older ages. The effect is U-shaped: the largest coefficient is for economic conditions between the ages of 11 and 20. The magnitude of the coefficients implies that a 1 percent increase in GDP about trend in the teenage years increases self-rated health by .002, which is 2 percent of the standard deviation.

The next columns report the impact of economic conditions on health behaviors. None of the health behaviors are better for cohorts that experienced positive economic fluctuations when young. Indeed, current smoking is higher for these groups, consistent with a positive income effect for cigarettes (Townsend et al., 1994). The coefficients on obesity are not of consistent sign and are statistically insignificant.

In contrast to the health behaviors, individuals who grew up during good times are much more likely to have positive social interactions. They talk with others and meet with friends more. The effects for these variables are relatively constant across ages of early life GDP fluctuations. This suggests that social integration may be a part of how early life economic fluctuations affect health – though clearly it does not prove it.

Our findings in the previous section showed that economic fluctuations matter less in countries where government spending is a larger share of GDP. We consider whether this is the case here as well. Figure 9 shows the relationship between life satisfaction, self-rated health, and talking with others, separately for high and low government spending countries. The results are consistent with the findings for overall mortality. Virtually all of the effect of early life GDP fluctuations on outcome is in countries with low levels of government spending. Countries with larger public sectors have virtually no statistically significant relationship between GDP fluctuations and self-rated health or frequency of talking with others, and exhibit milder U-shape relationships with life satisfaction.

To examine how much of the impact of early life economic conditions can be explained by health behaviors and social interactions, we follow the methodology of Cutler and Lleras-Muney (2010). If social interactions are important mediators of how economic conditions affect health, the importance of early life economic conditions for health should decline when these mediating variables are included.

Table 7 shows this analysis. The first column shows the relationship between self-reported health status and GDP fluctuations at different ages, analogous to column 6 of Table 6. The second column includes the logarithm of total individual income in the regression. Individual income is not a perfect control variable, since it may be influenced by health in addition to influencing health. Still, it is important if income explains little of the relationship between early life conditions and later life health. This is indeed the case. Relative to the coefficients without including individual income, the coefficients on early life GDP fluctuations are virtually unchanged when individual income is included in the regression.

The third column shows that smoking and obesity are negatively related to self-reported health status. The impact of obesity in particular is large – about one-quarter of the way between two categories. However, including these variables has no significant effect on early life GDP fluctuations. This makes sense, since neither smoking nor obesity are strongly related to economic fluctuations early in life.

The next two columns consider the impact of social integration: talking with others and meeting friends. Health may influence social relationships in addition to social relationships influencing health. To explore the causal impact of social integration, we need to purge this endogeneity. We do so by including dummy variables for whether the person has a physical or mental problem that hampers their activity often, sometimes, or never. To the extent that these variables capture physical and mental health status, the impact of social integration is a better causal measure. Column 4 of the table includes the measure of handicap without the social integration variables. Not surprisingly, higher levels of impairment are negatively associated with self-rated health. The impact of early life conditions falls as well; the coefficients on GDP fluctuations in the teenage years are about one-third smaller when health impairments are included, and they are no longer statistically significantly related to self-rated health. As column 5 shows, however, social interactions are negatively associated with self-rated health, even conditional on reported impairment associated with physical and mental problems. The effects are reasonably large. Moving from never meeting friends to meeting friends daily improves self-rated health by one-third of a response category.

It is difficult to draw firm causal conclusions from this evidence. What is clear is that the impact of early life health conditions is not a function of improved health behaviors. There is suggestive evidence that social integration may explain this relationship, but we cannot be definitive with these data.

VI.B Contemporary Economic Conditions and Mortality

The literature suggests several reasons why contemporary economic growth may increase mortality. We investigate three explanations: pollution, additional time spent at work, and transport accidents.

Economic output increases in expansions, and so does pollution. People with cardiovascular and respiratory problems are particularly sensitive to small particulate matter, which can lodge in the lungs (thus making breathing difficult) or enter the bloodstream if small enough. 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. As a substitute, we use data on CO_2 emissions from 1960 on for 32 countries in our sample, obtained from the World Bank (Bank, 2015). CO_2 by itself is not harmful to health, but CO_2 is highly correlated with $PM_{2.5}$. Pollution may affect health with a lag. Thus, we average pollution in the current year and the two previous years (one previous year for the 1961 observation) to form a measure of contemporaneous pollution.

Figure 10 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, with the booming economy and subsequent recessions. After 1980, CO_2 emissions are generally flat, even as the world economy continued to grow. This may be a product of environmental regulations (e.g., the Clean Air Act of 1970 in the United States), which would have affected both CO_2 and $PM_{2.5}$. The relationship between GDP fluctuations and residual CO_2 emissions is shown in the top right panel of Figure

10.[14] There is a clear positive relationship between the two.

Changes in time use are a second reason why mortality might increase in booms. People work more in expansions, and this may be associated with increased stress. It may also reduce time available for other inputs that influence health, such as tending to elderly parents. We examine the labor supply consequences of GDP fluctuations using data on hours worked per worker. These data are available from 1981 on for 28 countries in our sample from OECD website. The middle panel of figure 10 shows that hours worked per worker are generally fairly constant over time. Hours fluctuate, but only in a small range. Further, the trend in residual hours is not correlated with GDP fluctuations.

Transport deaths are a third reason why mortality may increase in booms. More people drive in good times than in bad times, potentially leading to an increase in motor vehicle fatalities. Such deaths affect people driving for work, as well as others on the road who have difficulty navigating the greater amount of traffic. There may be more pedestrian deaths as well.

Data on millions of vehicle kilometers are available from the International Traffic Federation from 1970 on for 26 countries in our sample. We normalize these by population to get an average number of kilometers per capita by year. The lower panel of Figure 10 shows a steady increase in road use over time, with expected fluctuations around times of big recessions. The last panel shows that detrended vehicle kilometers driven are positively related to GDP fluctuations. This is particularly true in the tails – big booms are particularly associated with increase vehicle usage, and big busts have very significantly lower vehicle usage.

To examine whether these theories explain the relationship between strong economies and mortality, we include them in models along with GDP fluctuations. If these explanations explain why fluctuations matter for mortality, the coefficient on economic fluctuations should decline when these other variables are included.

Table 8 shows the results of this estimation. Our basic specification is as in column 2 of Table

[14]To form residual CO2 emissions, we regress per capita emissions on country and year dummy variables, and a quadratic time trend for each country. We use the same methodology to detrend work hours and vehicle kilometers per capita.

2. We relate mortality for the population aged 45 and older to non-linear contemporaneous GDP. Since we are not interested in early life GDP impacts in evaluating these theories, we include a complete set of country-gender-birth cohort fixed effects.

The first column of the table reports repeats the regression from column 2 of Table 2 for the period from 1961 on. Outside of big booms and busts, contemporaneous GDP has a positive relationship with mortality. The coefficient is similar to that in Table 2, though somewhat larger. Big booms still reduce mortality, but big busts are not associated with higher mortality in this sample. The second column adds the measure of CO_2 emissions. Including this variable significantly reduces the impact of economic booms on mortality. The coefficient on GDP fluctuations in the first row declines by two-thirds when the pollution variable is entered. Interestingly, including pollution does not affect the coefficients on big booms. The coefficient on boom * GDP fluctuations is virtually unchanged from the first column.

The next two columns repeat the analysis, looking at the impact of average hours worked on mortality. Surprisingly, more hours worked is associated with lower mortality. It is not entirely clear why this is the case. The coefficient on contemporary GDP fluctuations declines by 15 percent when work hours are included. This is relatively small. Thus, regardless of the reason why, increased hours of work do not explain a good deal of the impact of expansions on mortality.

The final columns examine the impact of kilometers driven on mortality. There is no significant relationship between increased miles driven and mortality; indeed, the coefficient is negative (more miles driven is associated with lower mortality), although not significant. Thus, the regression does not attribute any of the impact of GDP fluctuations to increased automobile travel.

Overall, the strongest link between economic fluctuations and mortality is found through the pollution channel. As much as two-thirds of the adverse effect of contemporaneous economic fluctuations may be a result of increased pollution.

VII. Conclusion and Discussion

Forthcoming

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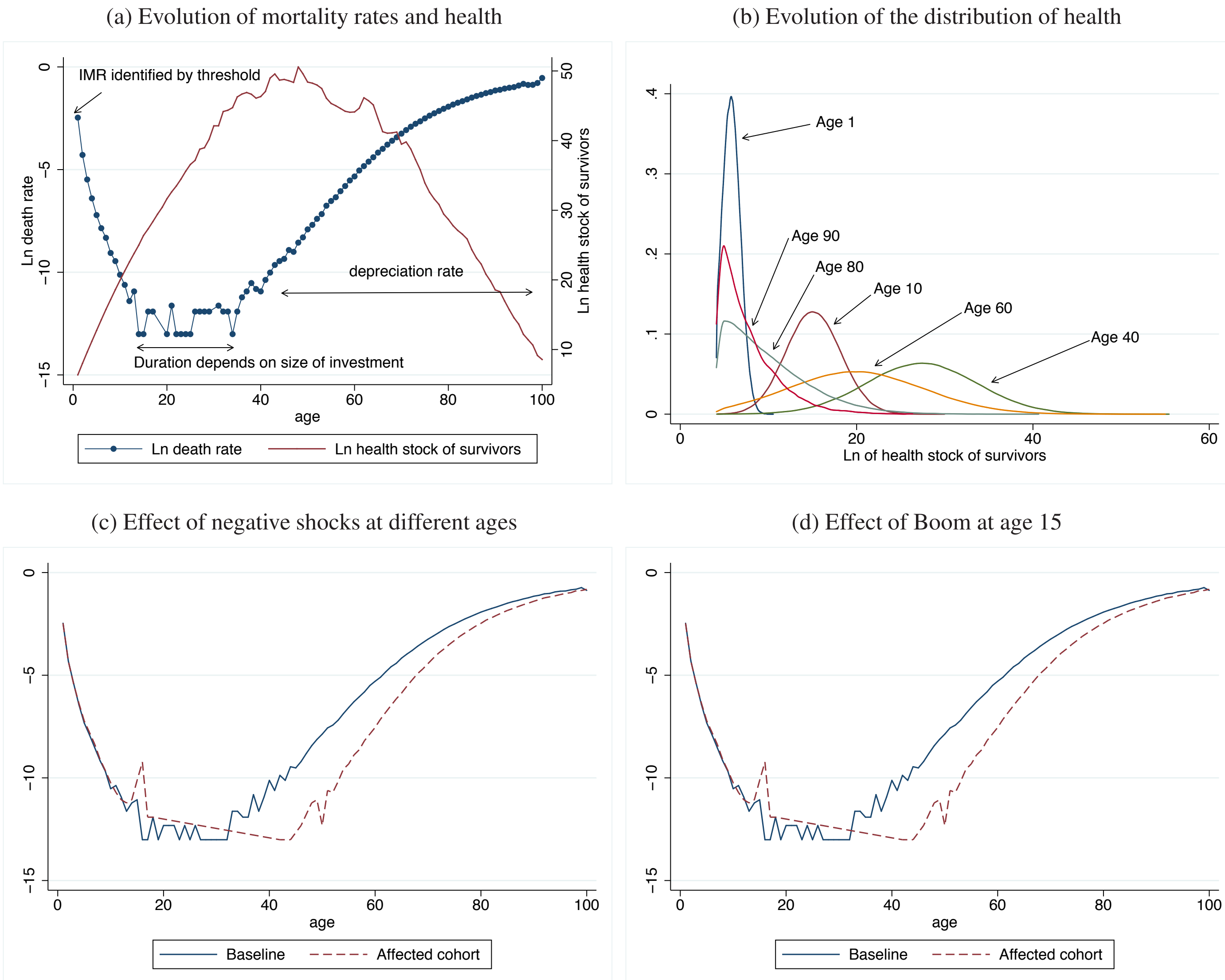
Figure 1: Model Simulations



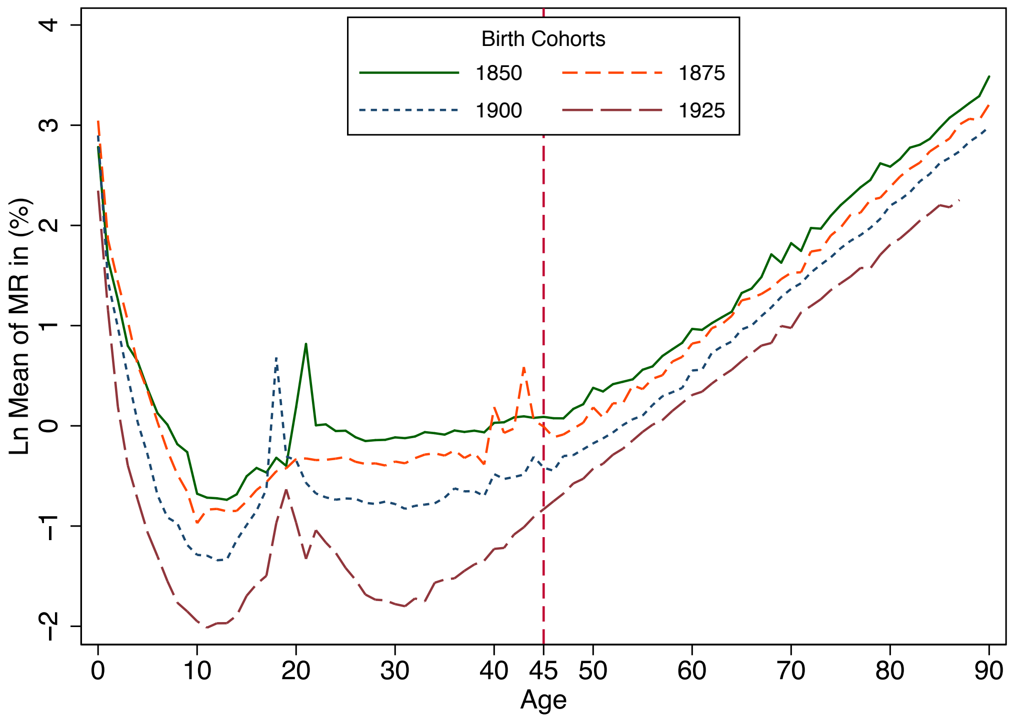
(a) Evolution of mortality rates and health

(b) Evolution of the distribution of health

(c) Effect of negative shocks at different ages

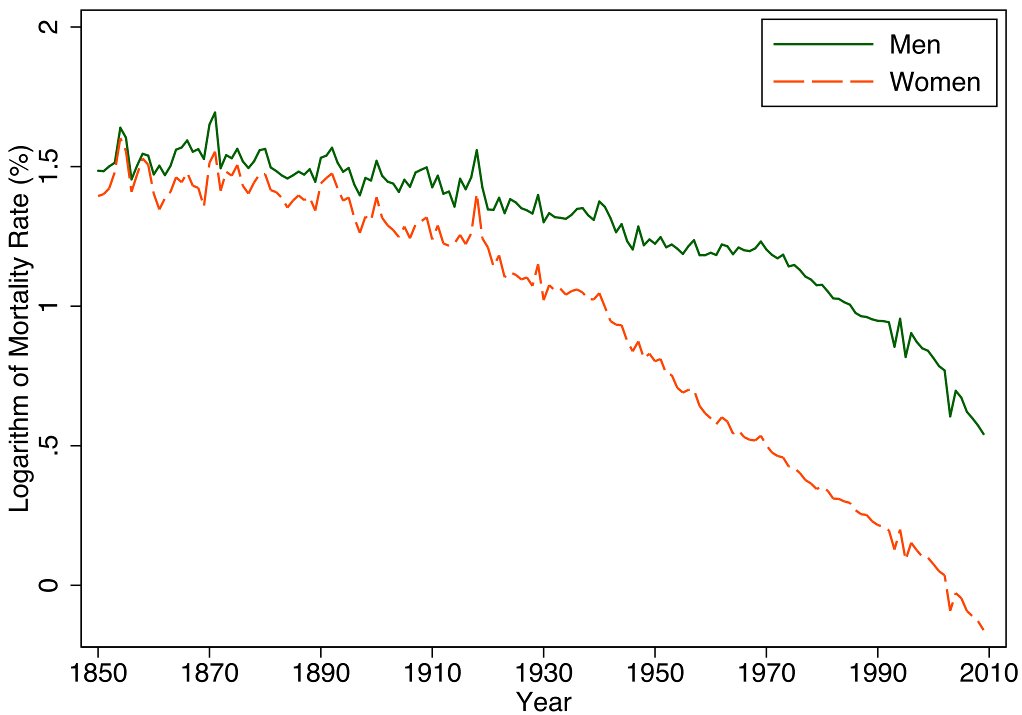
(d) Effect of Boom at age 15

Figure 2: 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. Table 1 shows the countries and years represented.

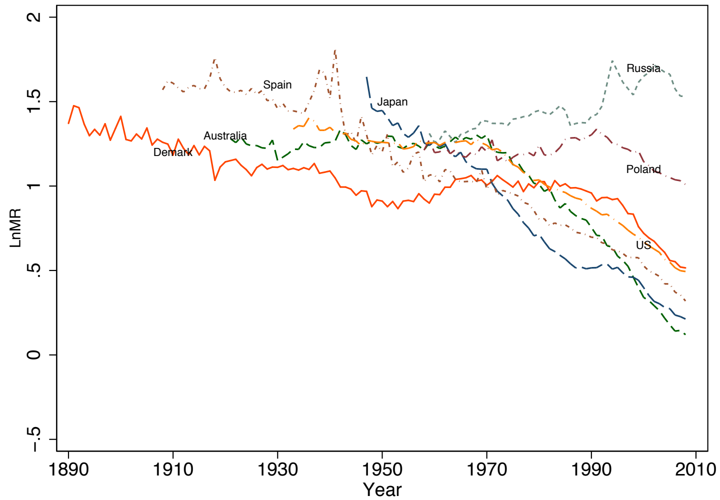
Figure 3: Logarithm of Mortality Rates Age 60-69, by Gender



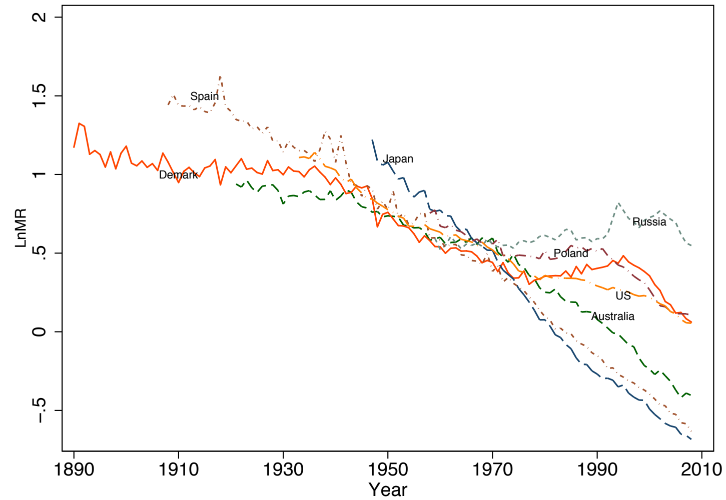
Notes: Authors' calculations from Human Mortality Database (HMD). Logarithm of the population- weighted mean mortality rates are plotted. We average mortality across all countries with data for each cohort. Thus, there are more countries represented for more recent cohorts. Table 1 shows the countries and years included in the figure.

Figure 4: Logarithm of Mortality Rates over Time, by Gender, Age Group and Country

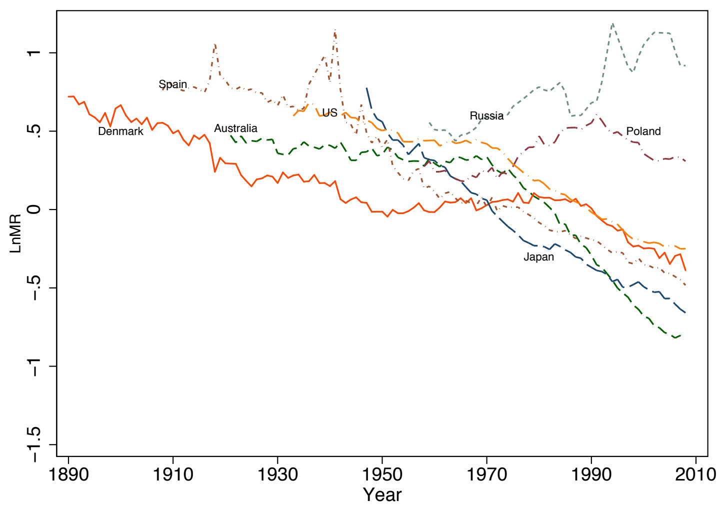
(a) Men, 60-69



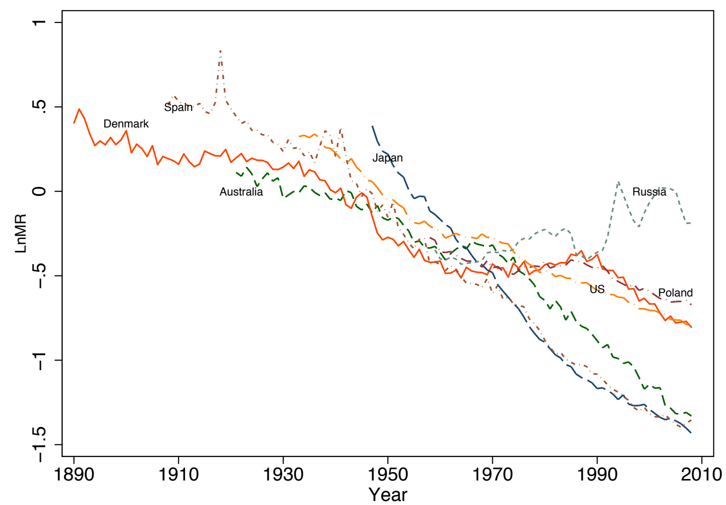
(b) Women, 60-69



(c) Men, 50-59



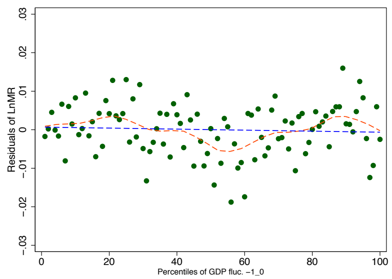
(d) Women, 50-59



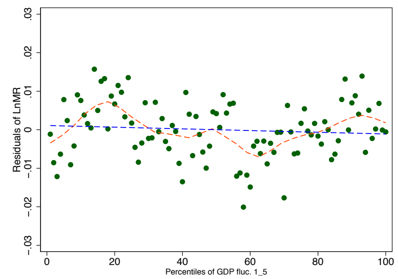
Notes: Authors' calculations from Human Mortality Database (HMD).

Figure 5: GDP fluctuations during the lifetime and residual mortality

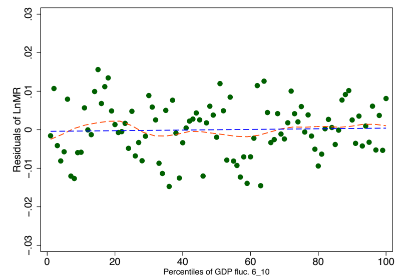
(a) GDP fluc. at ages -1 - 0



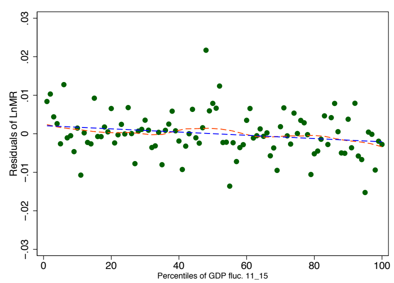
(b) GDP fluc. at age 1-5



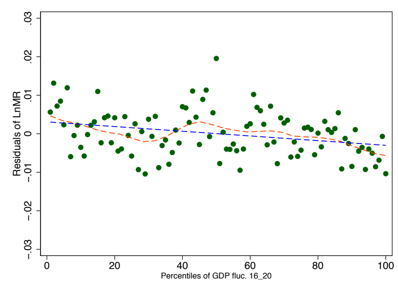
(c) GDP fluc. at age 6-10



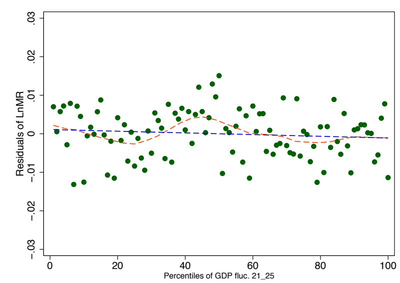
(d) GDP fluc. at ages 11-15



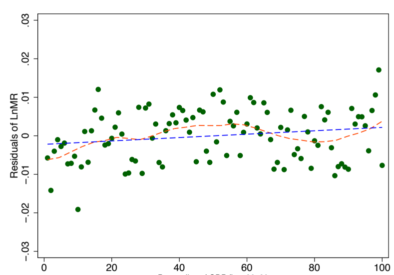
(e) GDP fluc. at age 16-20



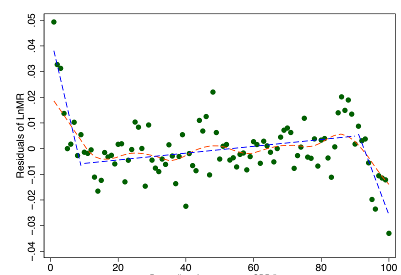
(f) GDP fluc. at ages 21-25



(g) GDP fluc. at age 26-30



(h) Contemporary GDP fluc.

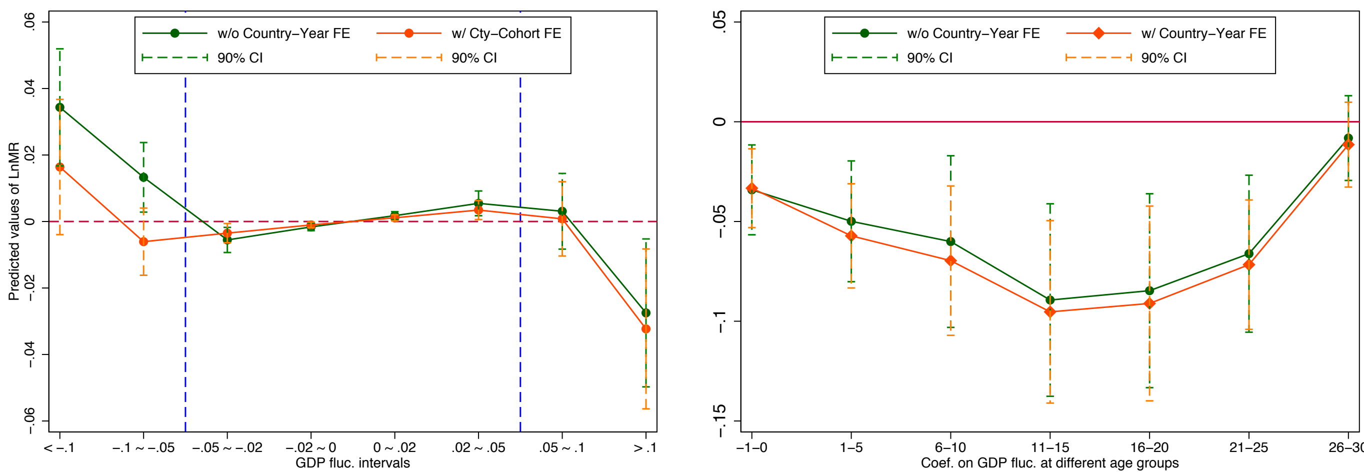


Notes: Mortality is detrended by regressing the logarithm of the mortality rate on country-age-gender fixed effects, those fixed effects interacted with a linear and quadratic term in time, gender-year of birth fixed effects, and gender-year fixed effects. GDP is detrended using a Hodrick-Prescott filter 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 6: Contemporary and Long-term effects of GDP fluctuations on adult mortality

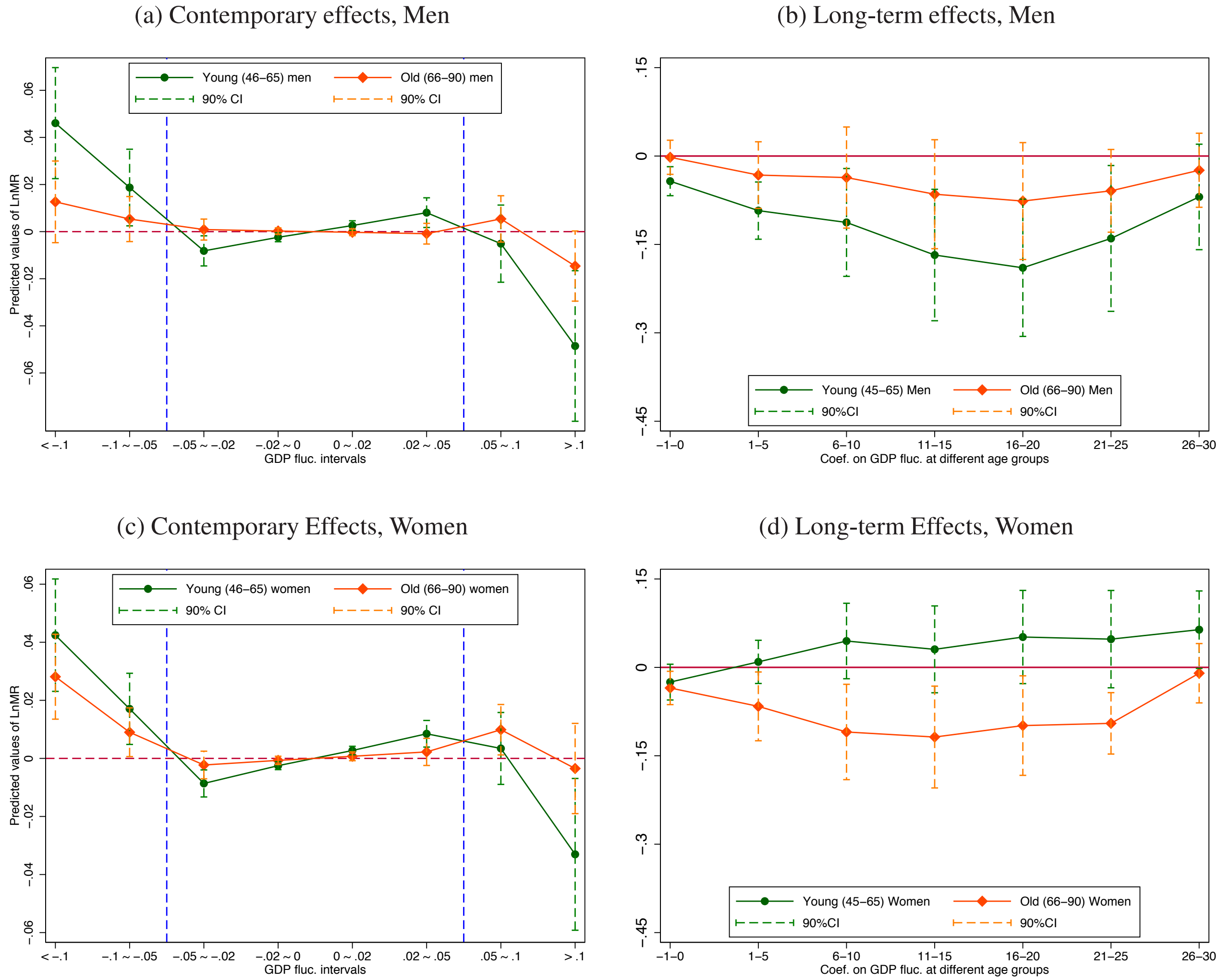
(a) Contemporary GDP fluctuations and Mortality

(b) GDP fluctuations in Early Life and Mortality



Notes: Panel (a) shows the relationship between contemporary GDP fluctuations and mortality, and panel (b) is the relationship between early life GDP Fluctuations and mortality. Each point is the coefficient from a regression of the logarithm of the mortality rate on a dummy variable for the contemporaneous GDP fluctuation being in a particular interval defined on the X-axis of panel (a) and the early life GDP fluctuation in the ages indicated in panel (b). The regression also includes country-age-gender dummy variables, those variables interacted with a time trend and its square, gender-specific year of birth dummy variables, and gender-specific year dummy variables. The dashed lines in panel (a) are the predicted values from the regression in table 2.

Figure 7: Contemporary and Long-term Effects of Economic Fluctuations, by Gender and Age Group



(a) Contemporary effects, Men

(b) Long-term effects, Men

(c) Contemporary Effects, Women

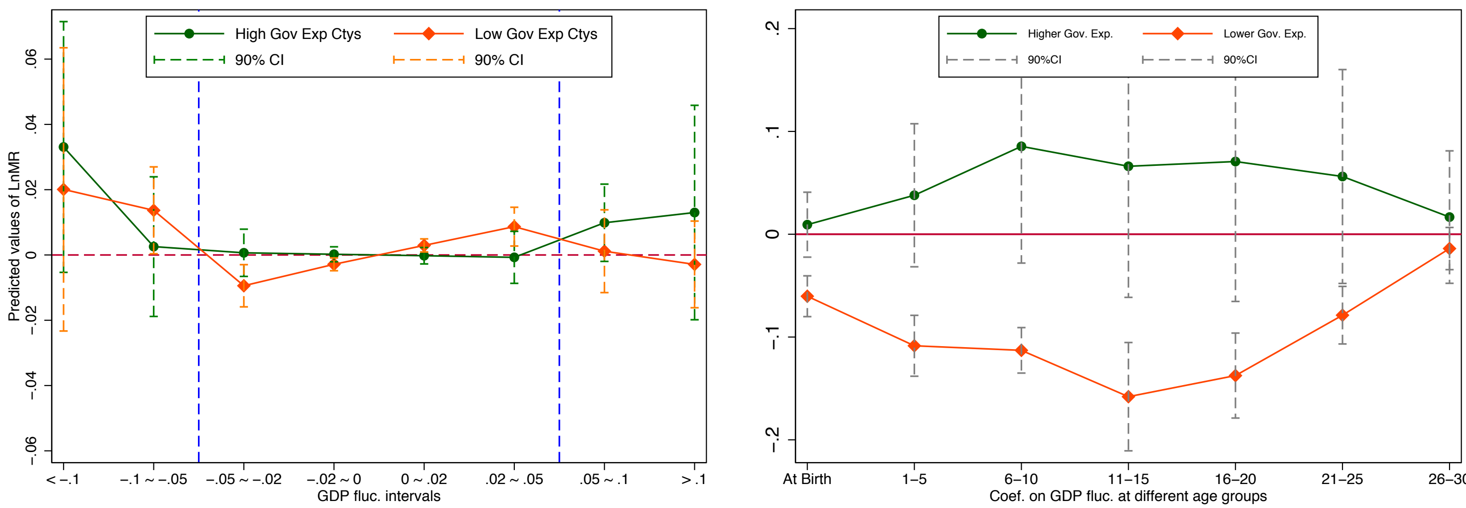
(d) Long-term Effects, Women

Notes: These figures are analogous to those in Figure 6, with the exception that the regression is estimated separately for men and women of different ages. Younger men and women are those aged 45-65. Older men and women are aged 66-90.

Figure 8: Impact of GDP fluctuations in High and Low Government Spending Countries

(a) Contemporary GDP

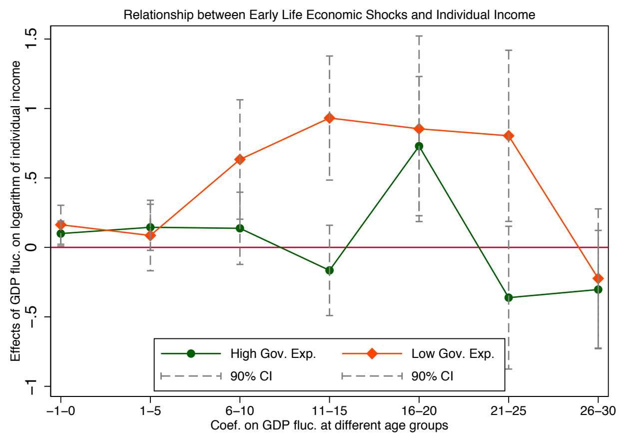
(b) Early Life GDP



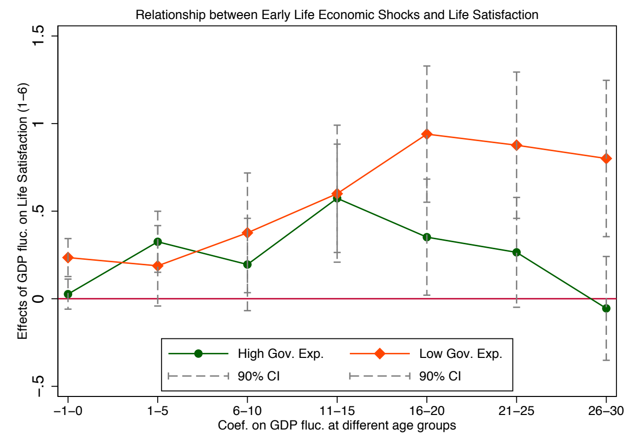
Notes: These figures are analogous to those in Figure 6, with the exception that the regression is estimated separately for countries with government spending as a share of GDP that is above and below average. Government spending as a share of GDP is shown in Table 1.

Figure 9: The Impact of Early Life GDP on Quality of Life at Older Ages

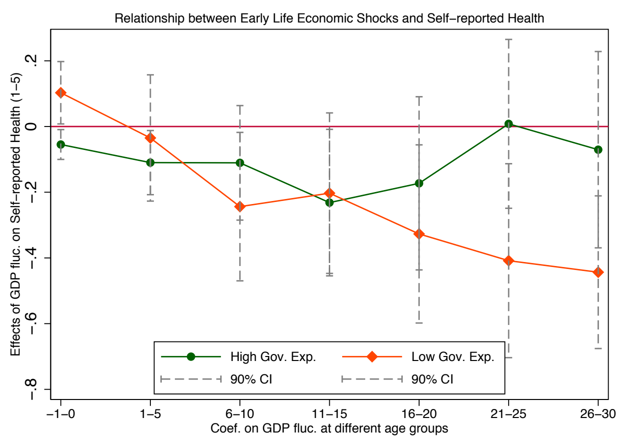
(a) Income



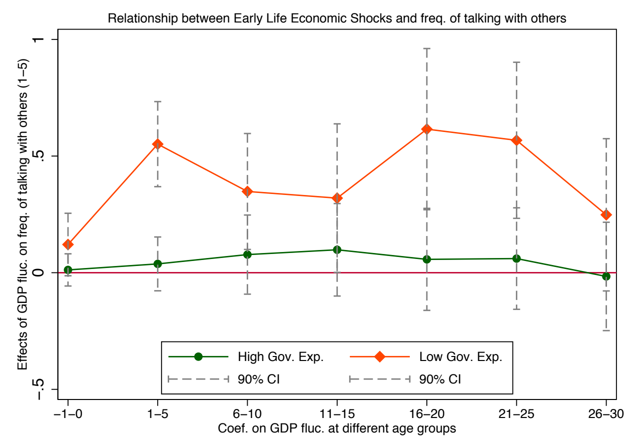
(b) Life Satisfaction



(c) Self-reported health



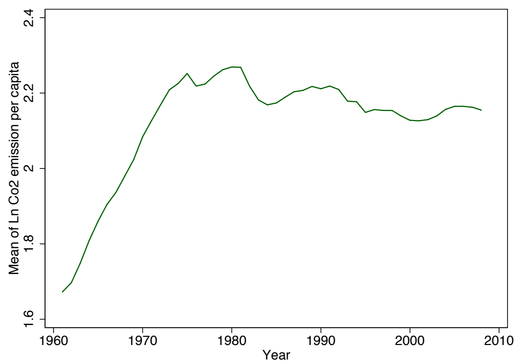
(d) Frequency of talking with others



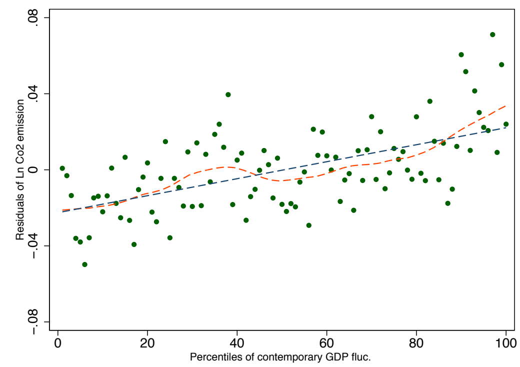
Note: Results are from the European Community Household Panel.

Figure 10: Pollution, Work Hours, and Motor Vehicle Usage

(a) Pollution Time Series Trend

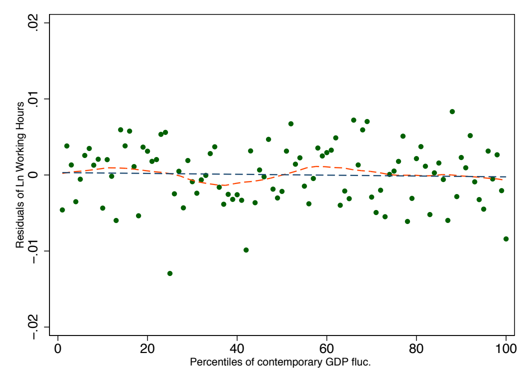


(b) Pollution and GDP fluctuations

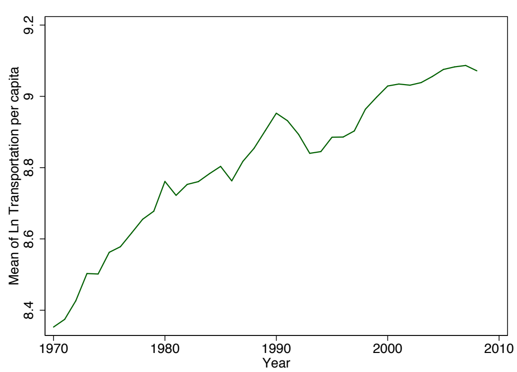


(c) Working Hours Time Series Trend

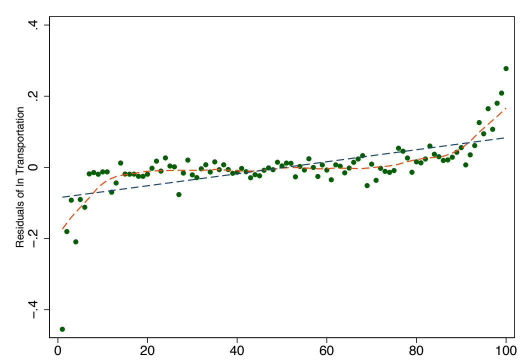
(d) Working Hours and GDP fluctuations



(e) Vehicle Miles Driven Time Series Trend



(f) Vehicle Miles Driven and GDP fluctuations



Notes: Data source of CO2 emission is World Development Indicators. Working hours and vehicle miles driven are from OECD website.

Table 1: Countries in Human Mortality Database

Country	Earliest Year	Latest year	Gov. exp as share of GDP in 2000
Sweden	1800	2011	55%
France	1816	2012	52%
Denmark	1835	2011	54%
Iceland	1838	2010	42%
Belgium	1841	2012	49%
Norway	1846	2009	42%
Netherlands	1850	2009	44%
Italy	1872	2009	46%
Switzerland	1876	2011	35%
Finland	1878	2009	48%
Spain	1908	2009	39%
Australia	1921	2009	36%
Canada	1921	2009	41%
United Kingdom	1922	2011	39%
United States	1933	2010	34%
Portugal	1940	2012	41%
Austria	1947	2010	52%
Bulgaria	1947	2010	—
Japan	1947	2012	39%
New Zealand	1948	2008	38%
Czech Rep.	1950	2011	42%
Hungary	1950	2009	47%
Ireland	1950	2009	31%
Slovak Republic	1950	2009	52%
Poland	1958	2009	41%
Belarus	1959	2012	—
Estonia	1959	2011	—
Latvia	1959	2011	—
Lithuania	1959	2011	—
Russia	1959	2010	—
Ukraine	1959	2009	—
Luxembourg	1960	2009	38%

Notes: The values in blue 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 2: 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	Original	With country - cohort FE	With country -year FE	Year < 1945	Year >= 1945	With selection controls	With selection controls & Year < 1945
Mean	0.700	0.700	0.700	1.088	0.594	0.700	1.088
Contemporary Economic Conditions							
Contemp. GDP fluc.	0.170**	0.109**	–	-0.104	0.221***	0.164**	-0.100
	(0.070)	(0.053)		(0.102)	(0.070)	(0.071)	(0.097)
Big Boom	0.030***	0.031***	–	0.014	0.040***	0.030***	0.014
	(0.007)	(0.007)		(0.011)	(0.009)	(0.007)	(0.010)
Boom* Fluctuations	-0.559***	-0.536***	–	0.048	-0.756***	-0.549***	0.057
	(0.133)	(0.134)		(0.124)	(0.140)	(0.133)	(0.122)
Big bust	0.003	-0.017*	–	-0.017	0.013	0.003	-0.017
	(0.009)	(0.010)		(0.018)	(0.011)	(0.009)	(0.018)
Bust * Fluctuations	-0.326***	-0.275***	–	-0.148	-0.351***	-0.314***	-0.142
	(0.090)	(0.100)		(0.156)	(0.113)	(0.087)	(0.155)

(Continue on next page)

Table 2: (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(Mortality rate)						
Settings	Original	With country - cohort FE	With country -year FE	Year < 1945	Year >= 1945	With selection controls	With selection controls & Year < 1945
Mean	0.700	0.700	0.700	1.088	0.594	0.700	1.088
Economic Conditions in Earlier Life							
GDP Fluc. Age -1-0	-0.034**	–	-0.033***	0.052	-0.043***	-0.031*	0.049
	(0.014)		(0.012)	(0.053)	(0.013)	(0.015)	(0.048)
GDP Fluc. Age 1-5	-0.050**	–	-0.057***	-0.104**	-0.056***	-0.040**	-0.106***
	(0.018)		(0.016)	(0.043)	(0.017)	(0.017)	(0.028)
GDP Fluc. Age 6-10	-0.060**	–	-0.070***	0.104	-0.076***	-0.035	0.046
	(0.026)		(0.023)	(0.091)	(0.028)	(0.026)	(0.070)
GDP Fluc. Age 11-15	-0.089***	–	-0.095***	0.056	-0.100***	-0.062**	0.008
	(0.029)		(0.028)	(0.070)	(0.031)	(0.026)	(0.048)
GDP Fluc. Age 16-20	-0.085***	–	-0.091***	0.108	-0.096***	-0.057**	0.114
	(0.030)		(0.030)	(0.095)	(0.031)	(0.027)	(0.089)
GDP Fluc. Age 21-25	-0.066***	–	-0.072***	0.032	-0.071**	-0.049**	0.035
	(0.024)		(0.020)	(0.060)	(0.027)	(0.023)	(0.060)
GDP Fluc. Age 26-30	-0.008	–	-0.011	-0.028	-0.011	0.005	-0.013
	(0.013)		(0.013)	(0.031)	(0.015)	(0.013)	(0.042)
Percent surviving to 45	–	–	–	–	–	-0.112	-0.424**
						(0.100)	(0.150)
Observations	245,512	245,512	245,512	75,052	170,460	245,512	75,052
R^2	0.995	0.996	0.996	0.993	0.997	0.995	0.993

Notes: Column 1 includes 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. Column 2 further controls for country-cohort fixed effects. Because early life conditions are collinear with country-cohort effects, these are omitted. Column 3 controls for country-year. Contemporaneous GDP is perfectly collinear with country-year fixed effects and so is omitted. Columns 4 and 5 divide the sample by whether calendar year is before 1945 or not. Columns 6 and 7 include the share of the population surviving to age 45. This is not known for all birth cohorts. We include birth cohorts where survival is known from age 30 or earlier. A set of dummies is included for the beginning year. All the regressions are weighted by the square root of the population size in the corresponding observation. Standard errors are clustered at country level. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Selection Effects - Effects of Early Life GDP fluctuations on Survival to Age 45

	(1)	(2)	(3)	(4)	(5)
	Proportion Living to Age 45				
Sample	Full sample	Cohorts <= 1910	Cohorts > 1910	Men	Women
Mean	0.782	0.576	0.876	0.760	0.805
Economic Conditions in Earlier Life					
GDP Fluc. Age -1-0	0.029*	0.039	0.023	0.029	0.030*
	(0.017)	(0.032)	(0.014)	(0.018)	(0.016)
GDP Fluc. Age 1-5	0.053	0.188**	-0.004	0.053	0.052
	(0.032)	(0.071)	(0.022)	(0.034)	(0.031)
GDP Fluc. Age 6-10	0.154***	0.249*	0.030	0.155***	0.154***
	(0.045)	(0.118)	(0.030)	(0.048)	(0.042)
GDP Fluc. Age 11-15	0.126***	0.242**	-0.011	0.118**	0.134***
	(0.041)	(0.105)	(0.030)	(0.045)	(0.039)
GDP Fluc. Age 16-20	0.137***	0.226**	-0.015	0.125**	0.149***
	(0.049)	(0.087)	(0.042)	(0.050)	(0.051)
GDP Fluc. Age 21-25	0.102***	0.123*	-0.020	0.092**	0.112***
	(0.030)	(0.066)	(0.030)	(0.035)	(0.029)
GDP Fluc. Age 26-30	0.076	0.116**	-0.013	0.067	0.084*
	(0.047)	(0.048)	(0.053)	(0.049)	(0.046)
Observations	3,876	1,476	2,400	1,938	1,938
R^2	0.977	0.960	0.971	0.971	0.982

Notes: The table includes all cohorts for which survival from age $\leq$ 10 to age 45 is known. Robust standard errors in parentheses. The F-test for the difference between the coefficients in columns 2 and 3 is 3.23 (p = 0.01). The F-test for the difference between columns 4 and 5 is 1.67 (p = 0.15).

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

Table 4: Government Spending and the Impact of Economic Fluctuations on Mortality

	(1)	(2)	(3)
		ln(Mortality rate)	
Settings	Original	High government spending	Low government spending
Mean	0.700	0.765	
Contemporary Economic Conditions			
Contemp. GDP fluc.	0.170**	-0.023	0.280**
	(0.070)	(0.144)	(0.116)
Big Boom	0.030***	0.007	0.005
	(0.007)	(0.017)	(0.013)
Boom* Fluctuations	-0.559***	0.067	-0.336**
	(0.133)	(0.223)	(0.148)
Big bust	0.003	-0.014	0.010
	(0.009)	(0.015)	(0.010)
Bust * Fluctuations	-0.326***	-0.202	-0.339
	(0.090)	(0.179)	(0.242)
Economic Conditions in Earlier Life			
GDP Fluc. Age -1-0	-0.034**	0.026	-0.081***
	(0.014)	(0.026)	(0.017)
GDP Fluc. Age 1-5	-0.050**	0.044	-0.123***
	(0.018)	(0.046)	(0.019)
GDP Fluc. Age 6-10	-0.060**	0.101	-0.129***
	(0.026)	(0.075)	(0.015)
GDP Fluc. Age 11-15	-0.089***	0.078	-0.175***
	(0.029)	(0.083)	(0.035)
GDP Fluc. Age 16-20	-0.085***	0.083	-0.149***
	(0.030)	(0.088)	(0.025)
GDP Fluc. Age 21-25	-0.066***	0.064	-0.088***
	(0.024)	(0.066)	(0.016)
GDP Fluc. Age 26-30	-0.008	0.021	-0.023
	(0.013)	(0.041)	(0.013)
Observations	245,512	112,912	104,790
R^2	0.995	0.995	0.996

Notes: High and low government spending countries are identified in Table 1. 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. The F-test for the equality of the coefficients on contemporary GDP fluctuations is F=1.96 (p=0.12). The F-test for the equality of the coefficients on early life GDP fluctuations is F=2.81 (p=0.03). All regressions are weighted by the square root of the population size in the corresponding observation. Standard errors are clustered at country level. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Summary Statistics for ECHP Data

Variable	Observations	Mean
ln(Total Individual Income)	529,376	11.37
Health		
Self-reported health status (1=very good; 5=very bad)	746,712	2.41
Die (yes=1)	—	—
Satisfaction (1= not satisfied; 6=very satisfied)		
Life satisfaction	637,846	4.18
Financial satisfaction	670,227	3.62
Leisure time satisfaction	637,386	4.19
Health behaviors		
Current smoker (yes=1)	241,128	0.33
Obese (yes=1)	212,102	0.13
Social relationships: Freq. of the activity (1=Never; 5=On most days)		
Talking with others	658,761	4.18
Meeting friends	729,166	4.01

Notes: The data 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.

Table 6: Early Life Economic Conditions and Middle and Late Life Outcomes

	Income	Satisfaction			Health	Health Behaviors		Social relations	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Ln(Total ind. income)	Life & main activity	Financial situation	Leisure time	Self-reported health	Current smoker	Obese	Talking with others	Meeting friends
Mean	11.39	4.175	3.622	4.197	2.418	0.323	0.126	4.178	4.001
Economic Conditions in Earlier Life									
GDP fluc Age -1-0	0.121***	0.093**	0.060	0.030	-0.024	0.050**	-0.002	0.043	0.009
	(0.046)	(0.044)	(0.043)	(0.042)	(0.026)	(0.023)	(0.030)	(0.039)	(0.030)
GDP fluc Age 1-5	0.192**	0.278***	0.366***	0.148*	-0.087*	0.001	-0.053	0.185***	0.124**
	(0.085)	(0.087)	(0.085)	(0.080)	(0.052)	(0.054)	(0.059)	(0.062)	(0.054)
GDP fluc Age 6-10	0.329**	0.277**	0.244**	-0.009	-0.125	0.091	0.097	0.172**	0.178**
	(0.134)	(0.128)	(0.120)	(0.123)	(0.084)	(0.087)	(0.083)	(0.087)	(0.081)
GDP fluc Age 11-15	0.188	0.591***	0.533***	0.029	-0.235**	0.157	-0.061	0.196*	0.154
	(0.170)	(0.149)	(0.145)	(0.143)	(0.106)	(0.108)	(0.100)	(0.105)	(0.101)
GDP fluc Age 16-20	0.929***	0.542***	0.437***	0.013	-0.226*	0.216**	0.009	0.226**	0.188*
	(0.252)	(0.160)	(0.163)	(0.153)	(0.122)	(0.106)	(0.109)	(0.115)	(0.113)
GDP fluc Age 21-25	0.196	0.415***	0.547***	0.032	-0.077	0.075	-0.000	0.205*	-0.006
	(0.245)	(0.155)	(0.154)	(0.146)	(0.124)	(0.096)	(0.096)	(0.113)	(0.120)
GDP fluc Age 26-30	-0.231	0.216	0.355**	-0.007	-0.157	0.084	-0.133	0.074	-0.182
	(0.203)	(0.153)	(0.159)	(0.147)	(0.147)	(0.092)	(0.083)	(0.116)	(0.111)
Observations									
Total	529,375	637,841	670,223	637,381	746,706	241,123	212,098	658,755	729,160
Unique individuals	120,115	132,517	136,291	134,537	149,126	79,768	65,423	136,160	148,519
Country-cohort cells	585	831	831	830	849	671	549	831	847
R^2	0.796	0.143	3.623	4.190	0.257	0.190	0.035	0.173	0.199

Notes: The data are from the European Household Community Panel, from 1994-2001. The sample is people aged 30-84 with the exception of individual income, which is for people aged 30-64. 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

Table 7: Understanding How Early Life Conditions Affect Self-Reported Health

	Self-Reported Health Status				
	(1)	(2)	(3)	(4)	(5)
Economic Conditions in Earlier Life					
GDP fluc Age -1-0	-0.024	-0.020	-0.023	-0.003	-0.002
	(0.026)	(0.026)	(0.026)	(0.021)	(0.021)
GDP fluc Age 1-5	-0.087*	-0.083	-0.076	-0.057	-0.037
	(0.052)	(0.052)	(0.052)	(0.041)	(0.041)
GDP fluc Age 6-10	-0.125	-0.123	-0.116	-0.089	-0.062
	(0.084)	(0.084)	(0.085)	(0.064)	(0.065)
GDP fluc Age 11-15	-0.235**	-0.233**	-0.224**	-0.137	-0.114
	(0.106)	(0.105)	(0.106)	(0.087)	(0.088)
GDP fluc Age 16-20	-0.226*	-0.214*	-0.219*	-0.136	-0.096
	(0.122)	(0.121)	(0.123)	(0.101)	(0.103)
GDP fluc Age 21-25	-0.077	-0.077	-0.073	-0.071	-0.100
	(0.124)	(0.122)	(0.124)	(0.105)	(0.105)
GDP fluc Age 26-30	-0.157	-0.154	-0.156	-0.119	-0.160
	(0.147)	(0.145)	(0.146)	(0.118)	(0.116)
ln(Total Individual Income)	—	-0.064***	—	—	—
		(0.002)			
Current smoker	—	—	0.056***	—	—
			(0.008)		
Obese	—	—	0.235***	—	—
			(0.012)		
Frequency of talking with others (ref = never)					
Less often than once	—	—	—	—	-0.019
a month					(0.013)
Once or twice a month	—	—	—	—	-0.048***
					(0.012)
Once or twice a week	—	—	—	—	-0.071***
					(0.012)
On most days	—	—	—	—	-0.074***
					(0.012)

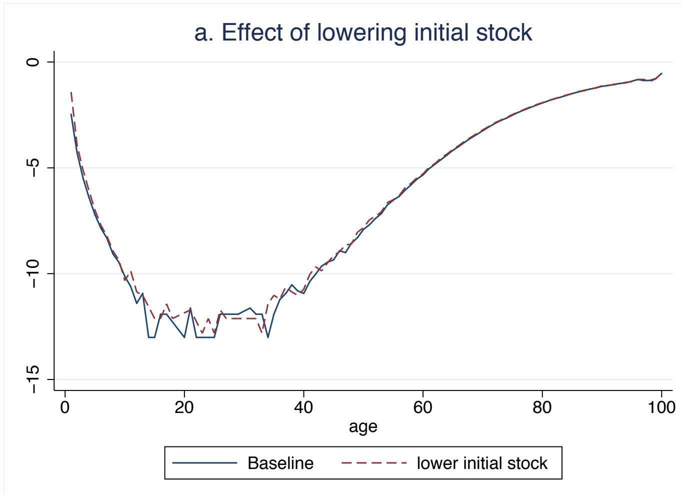
(Continue on next page)

Table 7: (Continued)

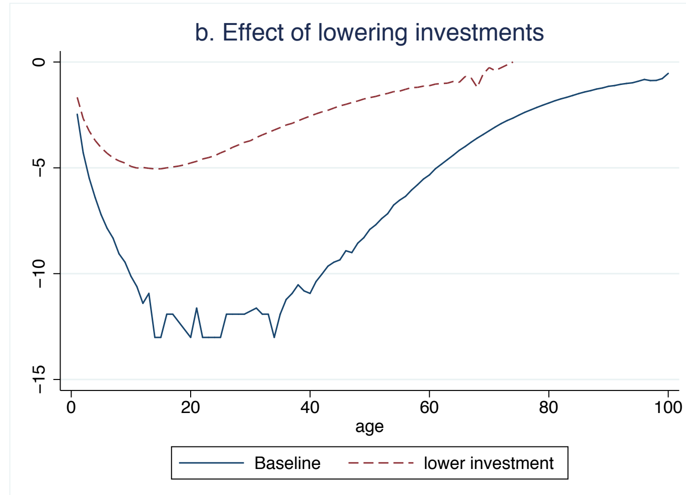
	Self-Reported Health Status				
	(1)	(2)	(3)	(4)	(5)
Frequency of meeting friends (ref = never)					
Less often than once	—	—	—	—	-0.158***
a month					(0.016)
Once or twice a month	—	—	—	—	-0.240***
					(0.016)
Once or twice a week	—	—	—	—	-0.281***
					(0.016)
On most days	—	—	—	—	-0.295***
					(0.016)
Any physical or mental problem and hampered activity (ref = none)					
Have problem but not	—	—	—	0.422***	0.415***
hamper activity				(0.008)	(0.008)
Have problem and hamper	—	—	—	0.886***	0.882***
activity sometimes				(0.008)	(0.009)
Have problem and hamper	—	—	—	1.565***	1.549***
activity often				(0.011)	(0.011)
Observations					
Total	746,706	746,706	746,706	746,706	746,706
Unique individuals	149,126	149,126	149,126	149,126	149,126
Country-cohort cells	849	849	849	849	849
R^2	0.257	0.262	0.259	0.461	0.465

Theory Appendix

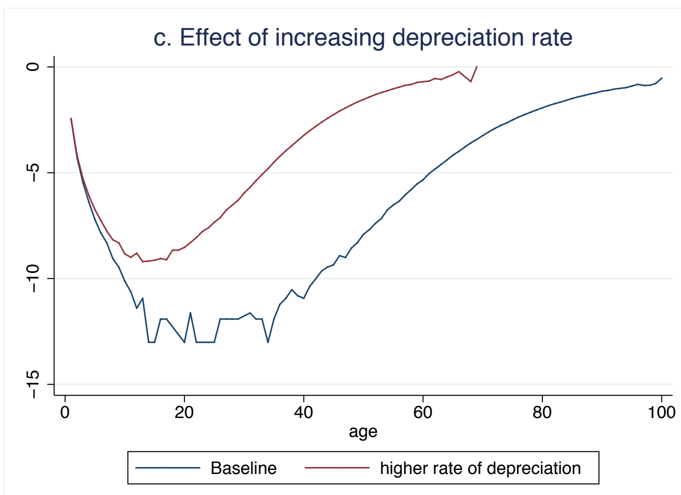
Figure A1: How the Different Parameters Affect the Shape of Mortality



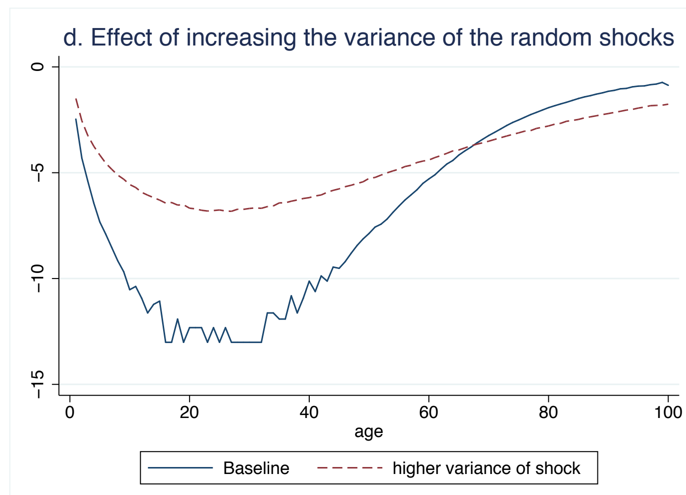
(a) Effect of lowering initial stock



(b) Effect of lowering investment



(c) Effect of increasing depreciation rate



(d) Effects of increasing variance of random shocks

Data Appendix

This appendix has two parts. First, we consider alternative ways of measuring trend GDP and mortality. Second, we present additional results related to the results reported in the paper.

Measuring Trend GDP and Mortality

A central issue in our analysis is measuring trend GDP. Trend GDP is important because we wish to relate mortality fluctuations to GDP fluctuations. The most common method to form trend GDP is using a Hodrick-Prescott (1997) filter. This method locally smooths GDP to form trend. Figure B1 shows actual values of ln(GDP per capita) in the United States along with trend formed using the Hodrick-Prescott filter, with a smoothing parameter of 500.

An alternative way to measure trend is to model GDP as a function of time. Implicitly, this is how we measure trend mortality rates. For example, in equation (5), mortality trends for country-cohort-gender cells are fit using a quadratic time trend. Figure B1 also shows predicted GDP using a second-order polynomial in time. Figure B2 shows residual GDP using the different methods. The Hodrick-Prescott filter adjusts more to the fluctuations in GDP than does the polynomial in time. The biggest difference between the two is in the 1920s. The Hodrick-Prescott filter views the late 1920s as a period of very high GDP fluctuations, since it adjust downward trend GDP over the 1920s to explain the Great Depression. The time trend does this to a much smaller extent.

Our results are sensitive to the choice of which filter to use. Figure B3 shows comparisons of the relationship between contemporaneous GDP fluctuations and mortality, and between GDP fluctuations at ages 16-20 and mortality, using both trend measures. The impact of early life GDP shows the same downward shaped pattern in both cases for much of the distribution. The relationship is smoother using the Hodrick-Prescott filter and statistically significantly negative. The trend filter is not.

The impact of contemporaneous GDP is even more different in the two methods. The HP filter implies a clear positive relationship between GDP fluctuations and mortality outside of large booms and busts, while the time-trend method suggests a negative relationship throughout the distribution.

This raises the obvious question of which method is more accurate. We take two approaches to answer this question. First, we examine how sensitive each method is to fluctuations in the smoothing parameters. Table B1 shows the relationship between contemporaneous mortality and contemporaneous GDP fluctuations and GDP fluctuations at ages 16-20 using different trend methods. The first three columns report estimates employing different Hodrick-Prescott smoothing parameters: the base case of 500, 100, and 1000. The results about contemporary and early life GDP fluctuations are insensitive to this choice. The last three columns report results for the time trend method using polynomials of different orders: second, third, and fourth order. The results again change very little. We have explored even higher order polynomials in time to form the time series filter. As the number of non-linear terms in time increases, the results approach those of the HP filter.

The second way to judge the models is to see which is more correlated with other macroeconomic indicators. Table B2 shows the relationship between unemployment rates and GDP residuals formed using the various methods. The sample is the 1,234 observations with data on GDP and unemployment. In univariate regressions, unemployment rates are strongly negatively related to GDP fluctuations no matter how they are measured. When residuals from the two methods are included jointly, the models uniformly prefer the HP residuals. The coefficients on the HP residuals are relatively constant, while those on the time trend residuals change more. For this reason, we believe that forming trend using the Hodrick-Prescott filter is a preferred to using non-linear time trends.

Figure B4 shows 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 time series mean and standard deviation of GDP fluctuations measured using the HP filter are shown in Figure B5. These mirror the results in Figure B4.

Additional results

We have explored the sensitivity of our main results in Table 2 in several ways. Table B3 shows many of these specifications. For convenience, the first column of Table B3 repeats column 1 of Table 2. 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 by 1959. Consistent with Table 2, we find both short- and long- term effects are more salient in recent years. Then the next column shows that our results are not sensitive to the exclusion of these 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 Appendix Table B3 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.

Figure B1: Actual and Smoothed GDP in the United States

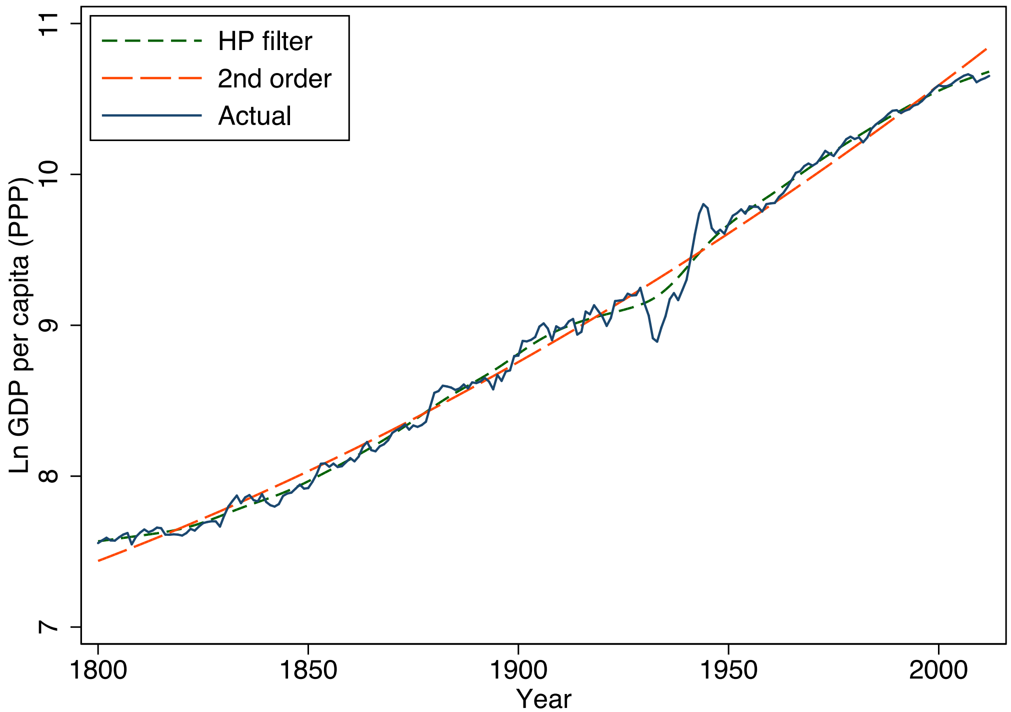


Figure B2: GDP Residuals

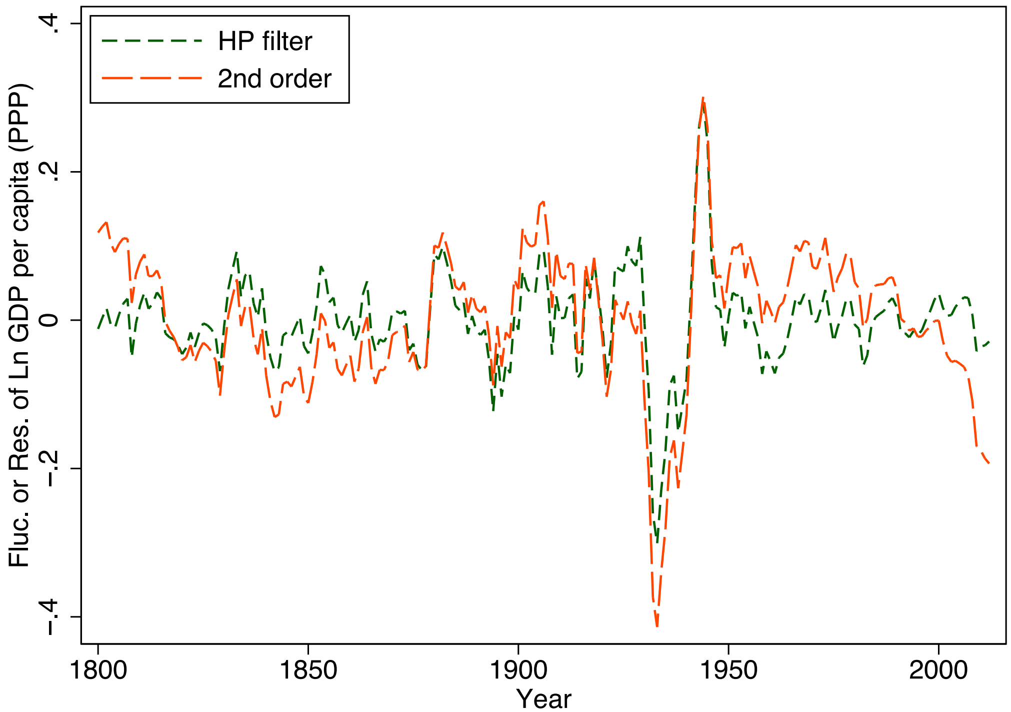
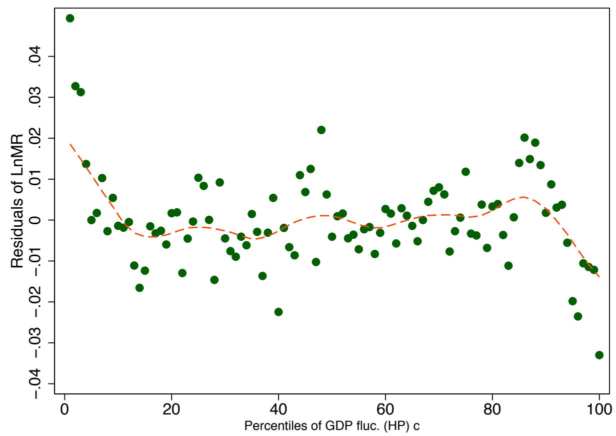
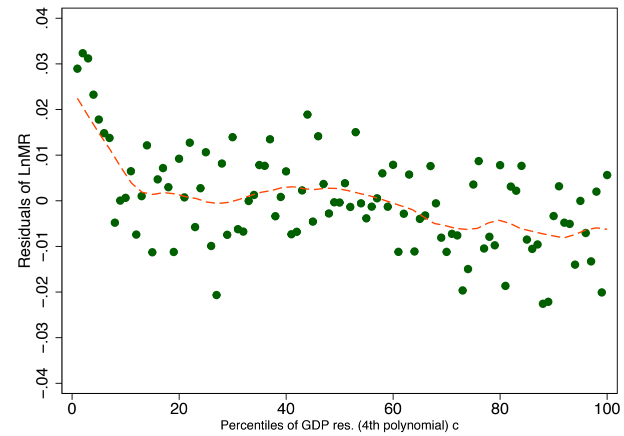


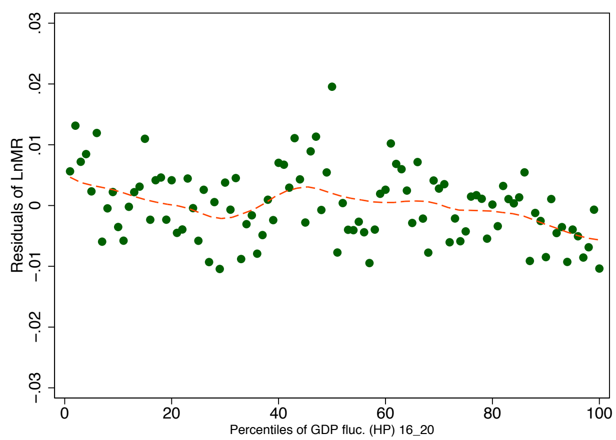
Figure B3: The Impact of Alternative Measures of Trend



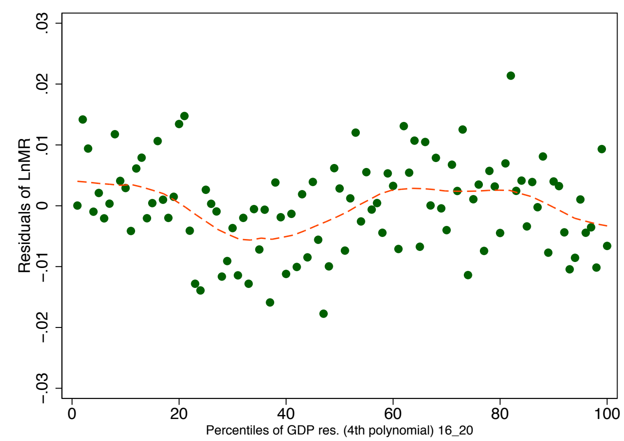
(a) Contemporaneous GDP, HP Filter



(b) Contemporaneous GDP, Non-linear time trend



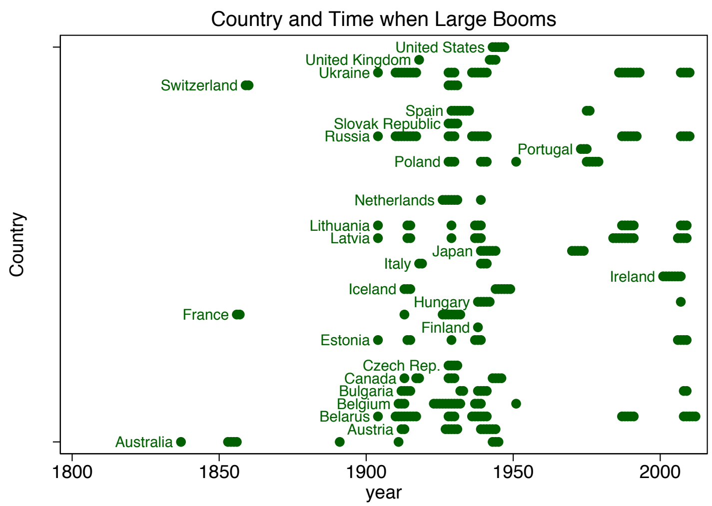
(c) GDP at Ages 16-20, HP Filter



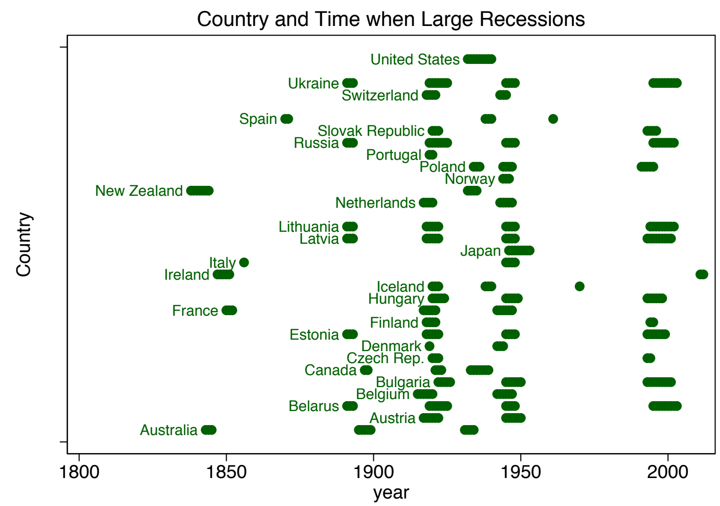
(d) GDP at Ages 16-20, Non-linear time trend

Notes: The upper figures show the residuals of mortality against contemporaneous GDP fluctuations, where GDP fluctuations are defined using the HP filter (panel (a)) and a non-linear time trend (panel (b)). The lower figures show the relationship between GDP fluctuations at ages 16-20 and mortality over age 45, again using the two methods.

Figure B4: Large Booms and Recessions in the 32 countries



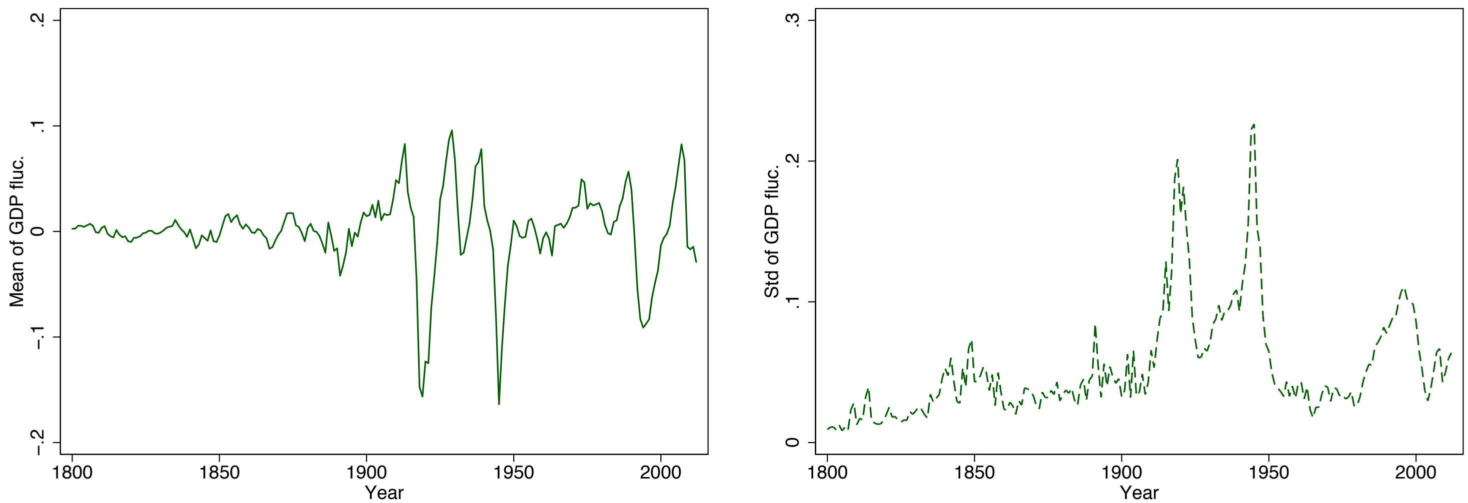
(a) Booms



(b) Busts

Notes: 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.

Figure B5: Mean and Standard Deviation of GDP Fluctuations

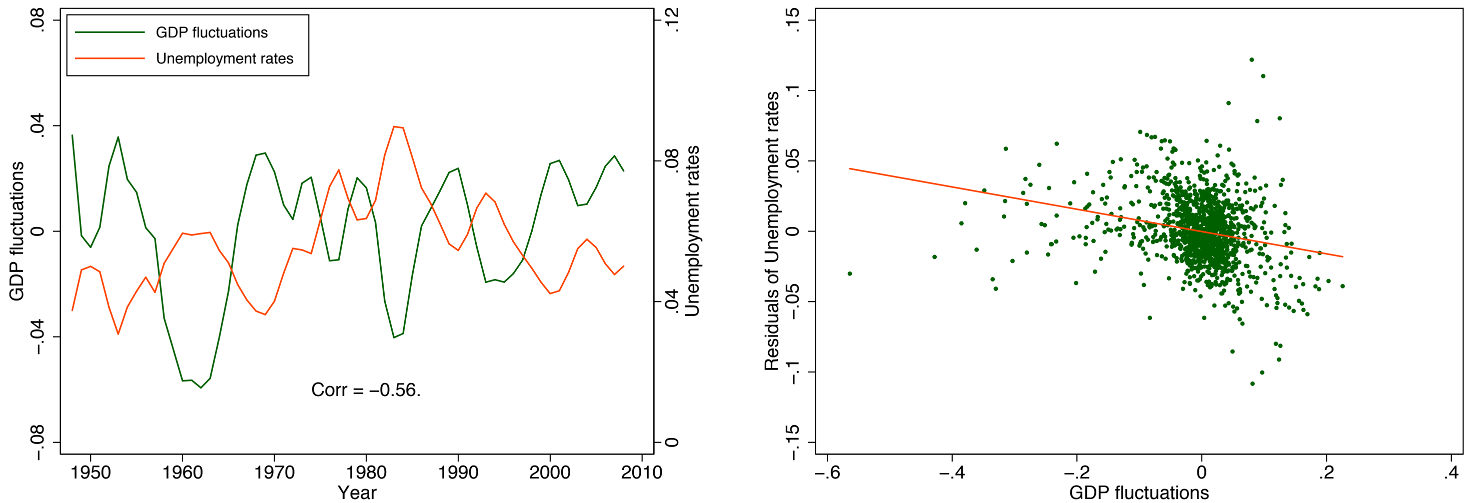


(a) Mean

(b) Standard Deviation

Notes: The left and right figures show the mean and standard deviations of the 32 countries used in the study over time.

Figure B6: Comparison of Unemployment Rate and GDP Fluctuations



(a) Time Series in United States

(b) (b) GDP fluc. and unemployment rate residuals

Notes: The residuals of unemployment rate are from regressions controlling for country dummies, year dummies, and country specific linear and square trends in years.

Table B1: Comparison of Alternative Methods of Forming Trend

	ln(Mortality Rate)					
	Hodrick-Prescott Filter Smoothing Parameter			Time Trend Polynomial Order		
Variable	500	100	1000	2nd	3rd	4th
Contemporaneous GDP fluctuation	0.170**	0.150**	0.266***	-0.090**	-0.073**	-0.095**
(non-boom or bust)	(0.070)	(0.0634)	(0.0762)	(0.037)	(0.035)	(0.041)
GDP fluctuation ages 16-20	-0.085***	-0.258***	-0.108***	0.013	-0.017	-0.022
	(0.030)	(0.0881)	(0.0343)	(0.018)	(0.019)	(0.018)
N	245,512	245,512	245,512	245,512	245,512	245,512
R2	0.995	0.995	0.995	0.995	0.996	0.997

Notes: The sample for each regression is ages 45-90.
*** p<0.01, ** p<0.05, * p<0.1

Table B2: Relationship Between Unemployment Rates and GDP Residuals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Unemployment Rate							
Time trend residual (2nd order)	-3.036	—	—	—	-0.00653	—	—	1.626
	(2.094)				(3.177)			(4.541)
Time trend residual (3rd order)	—	-3.620*	—	—	—	2.440	—	-11.81
		(2.007)				(3.977)		(7.864)
Time trend residual (4th order)	—	—	-1.849	—	—	—	8.841**	17.68***
			(1.596)				(3.530)	(5.701)
HP Filter residual	—	—	—	-11.37***	-11.36**	-14.74**	-24.94***	-24.21***
				(3.203)	(4.981)	(6.115)	(6.618)	(6.571)
N	1,428	1,428	1,428	1,428	1,428	1,428	1,428	1,428
R2	0.670	0.670	0.666	0.680	0.680	0.681	0.691	0.697

Notes: The sample for each regression is country-year observations with both unemployment rates and GDP residuals. Standard errors are clustered at country level.
*** p<0.01, ** p<0.05, * p<0.1

Table B3: Alternative Subgroups

	(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)

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Table B3: 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

Notes: 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 are clustered at country level. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table B4: 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					
GDP Fluc. Age -1-0	-0.0376***				
	(0.0114)				
	[0.0139]				
GDP Fluc. Age 1-5	-0.0281**				
	(0.0132)				
	[0.0202]				
GDP Fluc. Age 6-10	-0.0215				
	(0.0148)				
	[0.0288]				
GDP Fluc. Age 11-15	-0.0407***				
	(0.0155)				
	[0.0288]				
GDP Fluc. Age 16-20	-0.0276*		-0.00537		
	(0.0160)		(0.0509)		
	[0.0380]		[0.0538]		
GDP Fluc. Age 21-25	-0.0117			0.169***	
	(0.0140)			(0.0370)	
	[0.0370]			[0.0596]	
GDP Fluc. Age 26-30	0.0242*				0.0796**
	(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

Notes: 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. Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$