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ABSTRACT

Mortality and the Business Cycle: Evidence from Individual and Aggregated Data*

There has been much interest recently in the relationship between economic conditions and mortality, with some studies showing that mortality is pro-cyclical whereas others find the opposite. Some suggest that the aggregation level of analysis (e.g. individual vs. regional) matters. We use both individual and aggregated data on a sample of 20-64 year-old Swedish men from 1993 to 2007. Our results show that the association between the business cycle and mortality does not depend on the level of analysis: the sign and magnitude of the parameter estimates are similar at the individual level and the aggregate (county) level; both showing pro-cyclical mortality.

JEL Classification: E3, I1, I12

Keywords: death, recession, health, unemployment, income, aggregation

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1. Introduction

There is a renewed interest in the relationship between mortality and economic conditions. Since the work by Ruhm (2000), showing that mortality increases in good economic times, many studies have attempted to replicate the findings using different datasets, different methods, and different outcomes of health and health behaviors. Their results are mixed, with some findings supporting the idea that health deteriorates, or mortality increases, with improvements in economic conditions (see e.g. Gerdtham and Ruhm, 2006; Neumayer, 2004; Tapia Granados, 2005, 2008), while others find the opposite (see e.g. Gerdtham and Johannesson, 2005; Svensson, 2007; Economou et al., 2008).

One of the differences between these studies is the level of analysis: studies using aggregated (macro-level) data tend to find that mortality is pro-cyclical (e.g. Ruhm, 2000; Gerdtham and Ruhm, 2006, Neumayer, 2004), whereas studies that use individual-level (micro) data tend to find the opposite (e.g. Gerdtham and Johannesson, 2005). Using both micro- and macro-level data, Edwards (2008) finds evidence of pro-cyclicality on the aggregated data, while the individual-level analyses provide more mixed results, finding different relationships for different subgroups. This would suggest that the level of analysis plays a crucial role in estimating the relationship between mortality and the business cycle. Haaland et al (2015) on the other hand, find that mortality is pro-cyclical both at the aggregate regional level as well as at the individual level. [1]

Our paper explores this issue in more detail on a large dataset. Using a random sample from the entire Swedish male population aged 20-64 between 1993 and 2007, we examine the relationship between transitory changes in economic conditions and *individual* as well as *regional* (county-level) mortality. We focus on the question of how accurately models using aggregate data infer effects of the business cycle on mortality at the individual level by comparing the analyses on the same underlying data, estimated at both levels. Our results at the individual level show evidence of pro-cyclicality, with temporary downturns in economic conditions decreasing mortality. These findings are robust to the inclusion of a set of covariates. We then collapse the data to the county-level and run the same analyses. The estimates on the aggregated data both share sign and yield similar magnitudes of the parameter estimates, suggesting that aggregate data indeed adequately infer the individual-level association between business cycles and mortality. Our analyses hence show that estimates of the relationship between mortality and the business cycle are not sensitive to the level at which the dependent variable is measured. This finding suggests that it is not the different levels of analyses that are likely to be driving some of the conflicting results found in the existing literature.

Our individual-level analyses show evidence of pro-cyclical mortality, driven by 20-44 year old men, with no significant effects among those aged 45-64. Subgroup analyses reveal that individuals with

[1] Lindo (2015) emphasizes the importance of the geographical level of aggregation used to capture aggregate economic conditions. Throughout the current paper we stick to the county level as the relevant unit.

the lowest incomes and the unemployed exhibit a pro-cyclical mortality pattern, but the effect of the business cycle is even larger among younger individuals in the highest income quartile. Thus, there is no clear social gradient in the response to the business cycle.

The structure of our paper is as follows: Section 2 gives the background to the study and discusses some of the existing literature. We then set out our methodology in Section 3 starting with the measurement of the business cycle after which we present an approach for comparing individual and county-level business cycle estimates. We describe the data in Section 4. The results are presented in Section 5. Section 6 concludes.

2. Background and literature

Various mechanisms have been suggested to explain why mortality may respond to fluctuations in the business cycle. Broadly speaking, however, the arguments that have been put forward for pro-cyclical mortality are similar to those for counter-cyclical mortality. For example, risky behaviors such as binge drinking and smoking have been argued to increase in economic expansions (Ruhm and Black, 2002; Dehejia and Lleras-Muney, 2004), as well as in economic downturns (Dee, 2001; Sullivan and von Wachter, 2009; Eliason and Storrie, 2009; Cotti, Dunn and Tefft, 2015; Hollingsworth, Ruhm and Simon, 2017). Similarly, although individuals may have less time to invest in their health when the economy is doing well (Ruhm, 2000), research suggests that individuals are happier and have a higher life satisfaction during economic booms (see e.g. Di Tella et al., 2003). Likewise, Ruhm (2000) argues that migration responds to local economic conditions by increasing the death rate in areas with larger numbers of migrants due to increased crowding, importing of disease, or unfamiliarity with the medical infrastructure, whereas others argue that migrants are generally high educated, healthy, and young (Kennedy et al., 2015). Finally, some argue that (job-related) stress increases in good economic times (Ruhm, 2000), whilst others suggest that there is more (job-related) stress in economic downturns (Brenner and Mooney, 1983). Yet, Miller et al. (2009) find that neither stress levels nor health behaviors contribute to mortality fluctuations. Additionally, Cutler et al (2016) argue that the contemporaneous impact of strengthened economic conditions on mortality is mixed due to a positive impact of greater income on health and a negative impact of pollution that accompanies more output.

Looking specifically at the relationship between macroeconomic conditions and health and health behaviors (rather than all-cause mortality), Dave and Rashad Kelly (2012) find that a one percentage point increase in the resident state’s unemployment rate is associated with a 3–6% reduction in the consumption of fruits and vegetables among those who are predicted to be at highest risk of being unemployed. Similarly, Ásgeirsdóttir et al. (2014) find that the Icelandic economic collapse in 2008 increased health-compromising behaviors, including smoking and heavy drinking, and decreased the consumption of fruit and vegetables. Tekin et al. (2013) find only weak evidence for a relationship between health behavior and economic activity around the time of the recent great recession.

A recent study by Ruhm (2013) finds that the procyclical relationship in Ruhm (2000) between the business cycle and mortality in the US has decreased in recent years. The study suggests that this is to some extent due to increases in countercyclical usage of medication and drugs that carry risks of fatal overdoses. Case and Deaton (2015) detect a dramatic rise in mortality among white midlife men in the US over the past 15 years and show that it is driven by similar causes. This rise in mortality is a secular phenomenon that took off in the 1990s, rather than a cyclical response. Case and Deaton (2015) show that this phenomenon was absent in Sweden, which means that our analysis is not affected by this.

We now briefly discuss the level of aggregation used in existing studies. As there is a vast literature on the relationship between mortality/health outcomes and the business cycle, we do not aim to give a comprehensive literature review, but instead discuss some of the key recent studies relevant to our paper. We generally distinguish between two types of studies, depending on the data used: those using aggregated (macro) data, and those using individual-level (micro) data. The studies we focus on that use macro-level (panel) data generally specify a fixed effects model, where regions (countries, states or counties) are observed over a number of years (see e.g. Ruhm, 2000; Gerdtham and Ruhm, 2006, Neumayer, 2004). These studies model the region-year-level mortality rate as a function of a measure of economic conditions, which also varies by region and year. Different measures have been used, including unemployment rates, and mean disposable incomes. The regional analyses then commonly control for other covariates, which are also averaged over regions and years, such as education (e.g. percentage high school dropouts, some college, college graduates), age groups, race and income.

The studies we focus on that use micro-level data typically observe a panel of individuals who are followed up for a number of years (see e.g. Gerdtham and Johannesson, 2005, Edwards, 2008). They model the binary indicator denoting whether the individual dies in that year as a function of a measure of economic conditions. Similar to the macro-level analysis, the latter is measured at a higher (e.g. state or county) level. They then commonly control for a similar set of covariates as above, but at the individual level (e.g. education, ethnicity, income and some polynomial in age).

Many factors may be able to explain the different, and sometimes opposite, findings in the literature. For example, the use of different regions, different time periods and business cycle indicators may lead to different findings. Similarly, the choice of covariates may affect the estimates of interest. Indeed, the studies mentioned above that use individual-level data generally do not include higher-level fixed effects, such as those at the state, region, or county level. Using individual-level data for example, Neumayer (2004) finds that mortality is pro-cyclical, but that the relationship is reversed when region fixed effects are not accounted for. Using both aggregate and individual-level data for the period 1977–2008, controlling for region fixed-effects, Haaland et al (2015) find that mortality is pro-cyclical both at the aggregate (regional) level as well as at the individual level. Not having access to regional unemployment rates for the period covered however leads the authors to use the number of registered unemployed in the region divided by the working-age population in the region rather than the labor force (those employed or seeking employment) as a proxy for regional economic conditions. The value of this measure is lower than the regional unemployment rates, as the working age population is larger than the labor force, which e.g. does not include students, disabled and housewives. Moreover, its cyclical fluctuations may differ and may reflect changes in the labor force participation not related to the business cycle.

3. Methodology

3.1. Measuring the business cycle

Most studies in the business cycle and health nexus literature rely on levels of macroeconomic time series as indicators of the business cycle; for example (the level of) the unemployment rate (e.g. see Ruhm 2000). In the macroeconomic literature however, the business cycle is defined as short-run fluctuations in economic activity *around* a long-term economic trend (see e.g. Sorensen & Whitta-Jacobsen, 2010). This definition states that there are (at least) two forces at play in most macroeconomic time series, as opposed to one (that is, as opposed to just the level of the variable). We capture these distinctly different behaviors in the observed macroeconomic time series, denoted E_t, using an additive model in which the time series is modeled as the sum of the two basic components: the time series long-run trend T_t and its short-run cyclical fluctuations BC_t:

$$E_t = T_t + BC_t \quad (1)$$

Thus, the observed macroeconomic time series is decomposed as the sum of a trend component T_t and a cyclical component BC_t; with the cyclical component BC_t representing the business cycle. Relying on E_t as the business cycle indicator is troublesome as it includes in addition to the cyclical variation also the contribution of the time series trend component T_t, confounding the measurement of the business cycle. We therefore identify the business cycle utilizing decomposed time series and exploit solely the cyclical component BC_t in the analyses that follow.

3.2. An approach for comparing individual and county-level business cycle estimates

Consider the following models for the association between the business cycle and health:

Individual (micro) level: $$y_{ijt} = \lambda_j^I + \tau_t^I + \delta^I BC_{jt} + \theta^I X_{ijt} + \epsilon_{ijt} \quad (2a)$$

Aggregate (macro) level: $$y_{jt} = \lambda_j^A + \tau_t^A + \delta^A BC_{jt} + \theta^A \bar{X}_{jt} + \epsilon_{jt} \quad (2b)$$

where the subscripts i, j and t refer to the individual, region and time respectively and where $\bar{X}_{jt}$ denotes the regional mean of the individual-level covariate X_{ijt}. The superscript refers to the individual (I) and aggregated (A) level of analysis. The micro-level dependent variable y_{ijt} is the binary indicator for individual i in region j having died at time t; the macro-level dependent variable y_{jt} is the mortality rate (the number of deaths per 100,000 individuals) in region j and year t. In all models, region and year fixed effects λ_j and τ_t respectively, are controlled for. The variable of interest, the business cycle (*BC*), is always measured at the county-level and varies with region and year. As argued by Ruhm (2000) and discussed above, the business cycle can affect mortality and health outcomes through its effect on individual behavior. For example, fluctuations in macroeconomic conditions may affect individuals' time use, their health-behaviors, stress or levels of anxiety. The parameters δ^I and δ^A pick up the effects of these changes in individual behavior due to macroeconomic fluctuations.

We note that these analyses are similar to those used in the existing literature: studies that use longitudinal individual-level data tend to estimate models like (2a) (see e.g. Gerdtham and Johannesson, 2005; Edwards, 2008). Due to data limitations, however, most studies use longitudinal aggregate data (e.g. on states, counties or countries) to estimate models such as (2b) (see e.g. Ruhm, 2000; Gerdtham and Ruhm, 2006; Neumayer, 2004). As the business cycle is hypothesized to affect health outcomes (mortality) through its effect on individual behavior, our preferred model for estimating the association between the business cycle and mortality is the one at the individual level, i.e. (2a). Studies using aggregate data estimating models such as (2b) aiming to draw conclusions about individual-level association between the business cycle and mortality can at best replicate the estimates of models like (2a). The natural question that arises is how accurately inference with aggregate data infers effects of the business cycle on mortality at the individual level; that is, how good of an approximation δ^A is of δ^I in terms of sharing sign and magnitude of parameter estimates.

We start by estimating the following models:

Individual (micro) level: $y_{ijt} = \alpha_j^I + \beta_t^I + \gamma^I BC_{jt} + e_{ijt}$ (3a)

Aggregate (macro) level: $y_{jt} = \alpha_j^A + \beta_t^A + \gamma^A BC_{jt} + e_{jt}$ (3b)

where the subscripts i, j and t refer to the individual, region (county) and time respectively. To allow for comparability between the models, the underlying data of the two specifications are identical, where (3b) is estimated on the micro data that has been collapsed to the regional level. In addition, to allow for a comparison of the magnitude of the model-coefficients, we estimate (3a) as a logit model, and (3b) as a Generalised Linear Model (GLM) using a logit link function with a Bernoulli distribution. In both analyses, we cluster the standard errors by region. Hence, the coefficients γ in (3a) and (3b) are identical, since variation at the region-year level (BC_{jt}) cannot explain variation at the individual level $\left(y_{ijt}\right)$ within regions and years. This also implies that the inclusion of any additional covariates at the higher level (that are thus identical in the two models) will not lead to differences in the estimated coefficients between the individual and aggregate level. In other words, *only* the inclusion of individual-level covariates X_{ijt} (and the corresponding $\bar{X}_{jt}$ at the aggregate level) can lead to differences between the micro and macro point-estimates.

This is key to understanding why results could potentially vary with the degree of aggregation when using a cyclical business-cycle indicator in our model setting. Notably, from an econometric point of view, this can be driven by unobserved compositional changes over the cycle, by measurement errors in covariates, by covariates that are endogenous at the individual level, by using different data sources for covariates at different aggregation level, or by heterogeneity of business-cycle effects across individuals. To proceed, we add covariates to the model, arriving at models (2a) and (2b) introduced above; that is, the models typically used in the literature. Employing models (3a) and (3b), yielding identical parameter estimates, provides a common point of reference for the parameter estimates which in turn allows us to study the extent of similarity between the models once further covariates are added. With this methodology we aim to close in on an answer to the question of how accurately models using aggregate data infer effects of the business cycle on mortality at the individual level.

4. Data

The analyses are mainly based on data from Statistics Sweden (population data) and the National Board of Health and Welfare (mortality). The main source of data from Statistics Sweden is the database "Longitudinal integration database for health insurance and labor market studies" (LISA by Swedish acronym), 1993 to 2007. The LISA database presently holds annual registers since 1990 and includes all individuals from 16 years of age and older that were registered in Sweden as of December 31 for each year. The database integrates existing data from the labor market, educational and social sectors. LISA is updated each year with a new annual register. We use a 20% random sample of the total male population in Sweden, aged 20-64[2], located in the 21 counties of Sweden. In addition to the individual-level data, county-level macroeconomic data on unemployment rates is collected from Statistics Sweden.

The upper part of table 1 presents the descriptive statistics on mortality for the full sample, and by the two age groups we consider. The mean mortality rate for 20-44 and 45-64 year old Swedish men, averaged over all years, is 0.0009 and 0.0054; or 90 and 540 deaths per 100,000 population, respectively.

[2] Our access to these data is restricted to the male working-age population; we therefore cannot show similar analyses on the female population, or on different age groups.

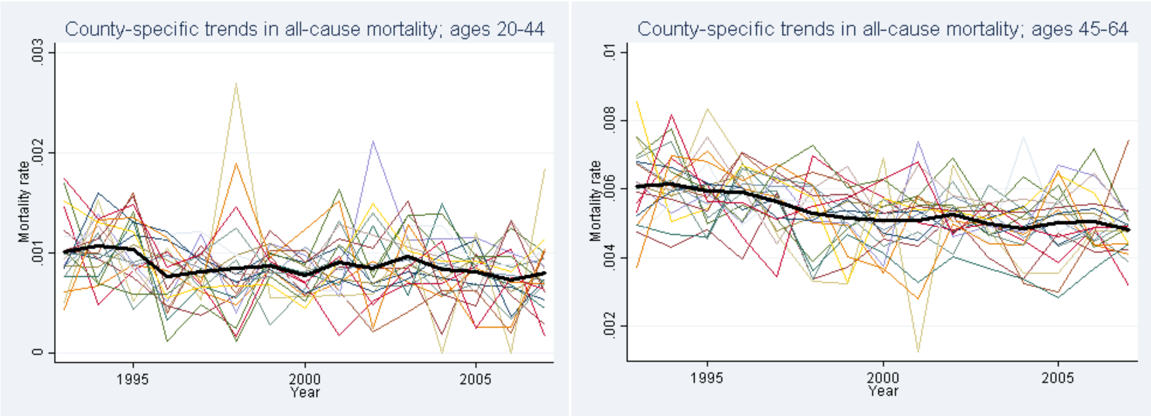
Table 1: Descriptive statistics on individual characteristics; mean (standard deviation)

	All		Age 20-44		Age 45-64		Alive		Dead	
Dependent variable										
All-cause county-level mortality rate	0.0031	(0.0024)	0.0009	(0.0004)	0.0054	(0.0010)				
Covariates										
Age	41.53	(12.53)	32.27	(7.01)	53.92	(5.61)	41.51	(12.52)	53.15	(10.03)
9- 12 years education	0.614	(0.42)	0.678	(0.46)	0.529	(0.49)	0.61	(0.48)	0.55	(0.49)
13-15 years education	0.133	(0.33)	0.155	(0.36)	0.103	(0.30)	0.133	(0.34)	0.07	(0.25)
16+ years education	0.136	(0.34)	0.129	(0.33)	0.146	(0.35)	0.137	(0.34)	0.074	(0.26)
Employed	0.854	(0.35)	0.875	(0.33)	0.825	(0.37)	0.85	(0.35)	0.55	(0.49)
Single	0.455	(0.49)	0.652	(0.47)	0.1943	(0.39)	0.456	(0.49)	0.35	(0.47)
Divorced	0.102	(0.30)	0.051	(0.22)	0.170	(0.37)	0.102	(0.30)	0.23	(0.42)
Widowed	0.006	(0.07)	0.001	(0.02)	0.013	(0.11)	0.006	(0.07)	0.01	(0.13)
Family income (x100, in SEK)	2722	(5388)	2529	(5463)	3110	(5268)	2780	(5395)	2107	(1981)
# Days PT unemployed per year	2.94	(26.57)	3.61	(28.12)	2.013	(22.91)	2.93	(26.05)	1.39	(17.61)
Registration at AF per year	3.20	(25.57)	3.36	(24.89)	2.987	(26.47)	3.19	(25.53)	6.56	(38.39)
# Days unemployed per year	21.11	(61.86)	25.81	(65.15)	14.85	(56.58)	21.12	(61.86)	19.98	(63.86)
Number of observations	711 599		499 594		380 586		709 973		22 245	

Notes: reference categories are less than nine years education and married. The variable “Registration at AF per year” represents a registration for at least one of the following five sub-variables: Number of days unemployed, part time unemployed, registered at employment services, labor market activities or activity studies.

Figure 1 shows the county-specific mortality rates for the two age groups over our observation period, showing considerable variation both within and between counties. The mortality rate over time, averaged over the 21 counties, is presented by the thick solid line, showing a slight reduction over time, particularly for 45-64 year olds.

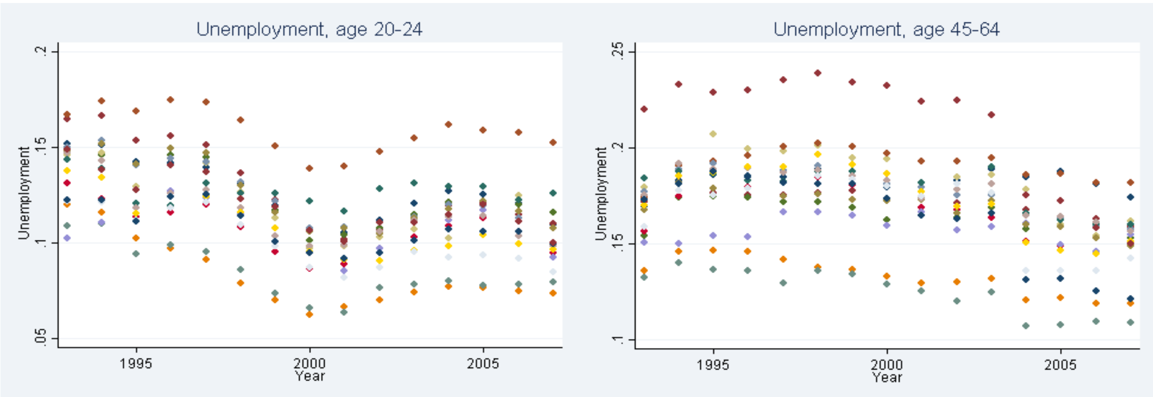
Figure 1: County-specific trends in all-cause mortality by age group



Notes: The figures show the county-level mortality rates over time by age group. The thick solid line is the average across the 21 counties.

Figure 2 presents individual-level unemployment status collapsed to the county-level by age group over our observation period. As shown, there is much variability both between counties and within counties across time. There is a clear cyclical pattern, particularly for unemployment among the younger age group. This shows a downturn in the late 1990s/early 2000s, with a rise in unemployment rates, which falls again towards the middle of the 2000s.

Figure 2: Trend in county-level employment rates

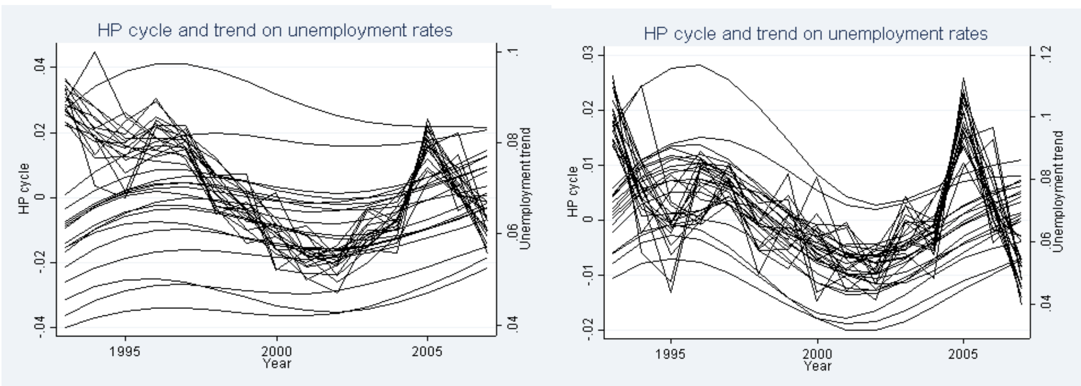


Notes: The figures show the average county-level unemployment rates over time by age group.

We use official county-level unemployment rates collected from the statistical database of Statistics Sweden to construct the measure of the business cycle. Recall that we use the cyclical component of decomposed unemployment rates to identify the business cycle and that for this we need to *tease out* the trend component T_t and the cyclical component BC_t from the observed time series. To this end, we use the Hodrick-Prescott (HP) filter. In this context, one advantage of official unemployment rate data, rather than collapsing the individual-level unemployment indicator, is that the former cover a longer time series, which allows us to run the HP filter on a longer time interval (1976-2014), increasing the accuracy of the filter[3]. Moreover, using official unemployment rates, rather than collapsing the individual-level unemployment indicator, circumvents the problem of having to measure which of the non-working individuals are a member of the labor force and which are not. The estimated cycles and trends of the HP filter using county-level unemployment rates are presented in figure 3 using a smoothing parameter of 100 and 6.25 respectively; the means and standard deviations of our business cycle measures are shown in appendix in table 2. A smoothing parameter of 6.25 is suggested by Ravn and Uhlig (2002) for annual data. However, plotting the estimates using this smaller smoothing parameter shows clear cyclicality in the trend estimates, as shown in the right panel of figure 3, suggesting it is not sufficient to smooth out all cyclicality. Our preferred specification therefore applies more smoothing. A sharp improvement (i.e. reduction) in cyclical unemployment is shown from the early 1990s until early 2000s after which cyclical unemployment increases for a few years to drop again after 2005. The smooth lines show that the county-level trends during the observation period are similar across all counties, albeit the levels of the trends differ across regions.

Figure 3: Trend and cycle using unemployment rates

HP smoothing parameter 100 | HP smoothing parameter 6.25



Notes: The figures show the county-level unemployment trend and cycle obtained from the HP filter over time. Data on county-level unemployment rates is obtained from Statistics Sweden.

The lower part of table 1 presents the descriptive statistics on the covariates, including individual age, educational level (less than 9 years of education, 9-12 years, 13-15 years, or 16+ years), family income (in 100s SEK), binary indicators for being employed, being single/cohabiting, married, divorced and widowed, the number of days spent in part-time unemployment, full-time unemployment, and used to retrain for other jobs. We also observe and control for the industry the

[3] The HP filter output is unreliable near the endpoints of the data set. Increasing the observation window around our period of interest (1993-2007) in the macroeconomic county dataset deals with this.

individual is employed in (not shown here). Column 1 shows the descriptive statistics for the 20% random sample of 20-64 year old men, with columns 2 and 3 distinguishing between the two age groups (20-44 and 45-64 year olds). Columns 4 and 5 show the summary statistics for the sample that is alive and those who die within our observation period.

The average age in our sample is 41.5 (it is 53 among those who die). The majority have 9-12 years of education, 85 % are employed, and the average annual income is 277,200 SEK (approximately € 24,000). The average person is almost 3 days a year part-time unemployed, and 21 days fully unemployed.

5. Results

We start by presenting our results from the individual-level analysis, as in equation (3a), distinguishing between the two age groups. Next, we present the findings from the county-level analysis, collapsing the individual-level data to the county-level.

5.1 Individual-level analysis

Table 3 shows the findings for the analyses at the individual-level. Our baseline measure of economic conditions uses the cycle component obtained from the HP filter on regional unemployment rates. The robustness of the results to different business cycle indicators is shown below (Section 5.3). We report the results controlling for county and year fixed effects as well as county-specific time trends, though the findings are robust to the exclusion of county-specific time trends.

Column 1 in Table 3 shows the raw correlation between individual-level mortality and the business cycle for 20-44 year old men, controlling only for county and year fixed effects and county-specific time trends. Column 4 shows the same analysis for the 45-64 year old group of men.

Table 3: Individual-level analyses with cyclical unemployment rate as BC indicator

	20-44 year olds			45-64 year olds		
	1	2	3	4	5	6
County-level measure of the business cycle	-8.047*	-7.967**	-8.207**	1.436	1.549	1.512
	(4.106)	(4.058)	(4.135)	(1.759)	(1.806)	(1.721)
Log-Likelihood	-31649	-30663	-29690	-113777	-108827	-106609
Region and year fixed effects and regional time trends	Y	Y	Y	Y	Y	Y
Individual age, education, marital status	N	Y	Y	N	Y	Y
Individual employment and income	N	N	Y	N	N	Y

Note: The measure of the business cycle is obtained from the HP filter on regional unemployment rates. Individual employment controls in specification (3) refer to employment status, number of days in unemployment, retraining and industry employed in. Number of (individual*year) observations for 20-44 year olds is 4, 538, 832 and for 45-64 year olds 3,398,161. Robust standard errors in parentheses, clustered by county. * p<0.10; **p<0.05;***p<0.01.

The findings indicate a pro-cyclical association between individual-level mortality and the business cycle for the younger age group, although significant only at the 10 percent significance level. A one standard deviation increase in cyclical unemployment is associated with an odds of dying of 0.883 ($e^{-0.124}$) for 20-44 year olds, or a reduction in mortality of 12 %[4]. For 45-64 year olds, the parameter estimate has a positive sign and is not significant. Columns 2 and 5 then account for age, educational level and dummies for marital status. As such, the model comprises the demographic covariates typically controlled for in the literature on business cycles and mortality (Ruhm, 2000). Controlling for these individual-level background characteristics produces estimates similar in magnitude to those in column 1 and 4 for both age groups. However, the business cycle effect is now significant at the 5 percent level for 20-44 year olds. In columns 3 and 6 the control strategy goes one step further compared to what covariates that are typically controlled for by in addition including employment controls in terms of employment status, the number of days in the year that the individual is in part-time unemployment, in full-time unemployment, and retraining for other jobs and dummies indicating the industry the individual is employed in, as well as family income. The parameter estimate for age group 20-44 increases somewhat in magnitude and remains significant at the 5 per cent level. Similar to the first specification presented in column 1, a standard deviation increase in cyclical unemployment is associated with a 12 % reduction in mortality. Colum (6) indicates that mortality among men in age group 45-64 is not influenced by the business cycle. Hence, the findings suggest that macroeconomic conditions mainly affect the younger working-age population, rather than those closer to retirement.

5.2 County-level analysis

We now turn to the county-level analysis, using the mortality rate at the county-year as the dependent variable. The measure of economic conditions remains the same as that above. Table 4 below presents the results for the county-level analyses, with columns 1-3 showing the estimates for the group of 20-44 year olds, and columns 4-6 showing that for 45-64 year olds.

Table 4: County-level analyses with cyclical unemployment rate as BC indicator

	20-44 year olds			45-64 year olds		
	1	2	3	4	5	6
County-level measure of the business cycle	-8.047*	-6.155*	-7.614**	1.436	2.154	2.212
	(4.106)	(3.485)	(3.632)	(1.759)	(1.809)	(1.957)
Log-Likelihood	-1.923	-1.923	-1.922	-8.861	-8.860	-8.859
Region and year fixed effects and regional time trends	Y	Y	Y	Y	Y	Y
Regional mean age, education, marital status	N	Y	Y	N	Y	Y
Regional income trend and employment controls	N	N	Y	N	N	Y

Note: The measure of the business cycle is obtained from the HP filter on regional unemployment rates. Regional employment controls in specification (3) refer to county-level collapsed individual number of days in unemployment, retraining and industry employed in. Regional income refers to trend in mean regional income obtained from the HP filter. Number of (region*year) observations for 20-44 year olds as well as 45-64 year olds is 315. Robust standard errors in parentheses, clustered by county. * p<0.10; **p<0.05;***p<0.01.

[4] That is, a 12 % reduction in the odds of dying, calculated as $1 - e^{(coefficient\ estimate\ x\ standard\ deviation\ of\ variable)}$

With the same underlying data to that used in the analyses presented in Table 3, but collapsed to the county-level, the estimates in columns 1 and 4 are identical to the individual-level findings described above (i.e. columns 1 and 4 of Table 3); hence again indicating a pro-cyclical association between mortality and the business cycle for men of 20-44 years of age.

Turning to columns 2 and 4, covariates of mean regional demographics are introduced as control variables. As shown, the parameter estimates share the same sign and are rather close in magnitude to those in the individual-level analysis, although the effects of the business cycle on mortality for 20-44 year old men is associated with a higher p-value yielding significance at the 10 percent level compared to the 5 percent level in the individual-level analysis. Column 3 and 6 add individual-level employment and income controls collapsed to the county level. In order to avoid including covariates that may themselves capture the business cycle effect however, regional employment is excluded from model, as this is clearly highly correlated to our business cycle measure. The cyclical variation in regional income is teased out of the collapsed individual-level income so that the variables only account from the trend in mean regional income using the HP filter. Compared to specification 2 and 4 the estimates increase somewhat in magnitude while the effects become significant at the 5 percent level for 20-44 year olds. A one standard deviation increase in cyclical unemployment is associated with an 11 percent reduction in mortality. In other words, mortality is significantly pro-cyclical among the younger working-age population while the effect is absent among the population closer to retirement. Our analyses suggest indeed that using aggregate regional-level data accurately captures the association between the business cycle and mortality at the individual level.

5.3 Robustness analysis

Table 5 presents the estimates from the *individual*-level analyses that specify different measures of macroeconomic conditions. In panels A to C, we test the robustness of the results using different measures of the business cycle based on unemployment rates. In addition, in panels D to F, we present measures of the business cycle based on the Gross Regional Product (GRP).

Turning to panel A to C, using measures based on unemployment rates, the findings are similar to those presented in Table 3 in terms of sharing sign albeit the magnitude of the parameters estimates differ somewhat. Panel A displays the results using the unemployment rates, that is, the measure typically employed in the literature, which indicate pro-cyclical mortality while significant at the 10-percent level only. In panel B we show that the results are robust to applying less smoothening (λ=6.25 as suggested by Ravn and Uhlig, 2002), in which a lower weight is to given to the trend. A standard deviation increase in cyclical unemployment is associated with a reduction in mortality for 20-44 year olds by approximately 7% (i.e. an odds of dying of 0.933 (or $e^{(-8.314 \times 0.0082)} = e^{-0.068}$, where 0.0082 is the standard deviation of cyclical unemployment taken from Table 2): an approximately 60 percent lower effect compared to the one presented in the main analyses where more smoothing was applied to the time series.

However, as indicated in figure 3, displaying the HP filter outcomes using this smaller smoothing parameter, the trend estimates clearly contain cyclical variation hence absorbing information of the business cycle that we wish to capture by the cyclical component; again, suggesting such value of the smoothing parameter is not sufficient to smooth out all cyclicality in this case. Interestingly, we note that once we let the trend spill over to the business cycle measure in utilizing cyclical variation extracted using this smaller smoothing parameter, the effect of macroeconomic conditions on mortality decreases. This suggests indeed that it is the cyclical variation in unemployment rates that affects health. In panel C, we go one step further by noting that the levels of the trend components differ across regions, as shown in figure 3. An absolute cyclical deviation might differently yield an influence depending on the level of the trend at the county. For example, an absolute deviation of 2 units might signal a larger impact on the regional economy in counties where the trend averages at 3 units compared to 8 units. We test for this line of reasoning by estimating the effect using the unemployment gap which is defined by normalizing the cyclical component with the trend component. A standard deviation increase in the gap reduces mortality for 20-44 year olds with 10%, increasing to 12% as more covariates are added to the model. The effect is thus similar to that of using the solely the cyclical component in Table 3.

Next, we examine the robustness of the results an alternative measure of economic activity; the Gross Regional Product (GRP). In panel D, the estimates from the natural logarithm of the GRP are displayed, followed by using cyclical variation in GRP in panel E. None of these measures indicate an association between the business cycle and mortality. As for the GRP, there might be a problem with using the level or the additive cyclical variation. To clarify, assume that the cyclical component fluctuates around a long run mean value of 0, and assume further that the amplitude of the cyclical component remains constant in proportion to the trend. Then the absolute amplitude of the business cycle fluctuations will rise over time. For this reason, dividing the cyclical component with the trend component, as done in the "GRP-gap", allows for more meaningful comparisons over time. Also, when comparing the macro economy across counties, normalizing the cyclical component with the trend component may make comparisons more meaningful. The estimates based on the GRP-gap are displayed in panel F. As shown, nor this way of accounting for the GRP suggests a significant impact of fluctuations in regional income on mortality. While cyclical fluctuations in terms of modest increases in regional income may not be bad for health, it is arguably more intuitive that fluctuations in macroeconomic conditions related to the labor market affect health. One reason for this is that the unemployment indicator is a better indicator for how people may use their time. For example, job hours may extend during short-lasting economic expansions that in combination with physical exertion of employment and job-related stress have negative health effects. When the economy slows

Table 5: Robustness analyses at the individual-level, using different business cycle indicators

	20-44 year olds			45-64 year olds		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Individual-level analysis, county-level business cycle						
Measure of the business cycle, unemployment rate	-6.999*	-7.004*	-7.363*	1.663	1.555	1.516
	(4.023)	(3.986)	(4.082)	(1.567)	(1.565)	(1.483)
Log-Likelihood	-31649	-30663	-29690	-113777	-108827	-106609
Panel B: Individual-level analysis, county-level business cycle						
Measure of the business cycle, cyclical unemployment rate (HP $\lambda = 6.25$)	-8.487**	-8.360**	-8.314**	1.589	1.743	1.821
	(4.283)	(4.209)	(4.222)	(2.095)	(2.128)	(2.093)
Log-Likelihood	-31649	-30664	-29691	-113777	-108827	-106609
Panel C: Individual-level analysis, county-level business cycle						
Measure of the business cycle, unemployment gap (HP 100)	-0.487**	-0.500**	-0.545**	0.073	0.091	0.069
	(0.226)	(0.228)	(0.239)	(0.083)	(0.085)	(0.081)
Log-Likelihood	-31648	-30663	-29689	-113777	-108827	-106609
Panel D: Individual-level analysis, county-level business cycle						
County-level measure of the business cycle, ln of GRP	-0.153	-0.112	-0.087	-0.034	-0.062	0.011
	(0.620)	(0.609)	(0.625)	(0.321)	(0.316)	(0.297)
Log-Likelihood	-31651	-30665	-29692	-113777	-108828	-106609
Panel E: Individual-level analysis, county-level business cycle						
County-level measure of the business cycle, cyclical variation in GRP (HP 100)	-0.094	-0.074	-0.050	-0.002	-0.018	0.027
	(0.697)	(0.690)	(0.707)	(0.345)	(0.339)	(0.327)
Log-Likelihood	-31651	-30665	-29692	-113777	-108828	-106609
Panel F: Individual-level analysis, county-level business cycle						
County-level measure of the business cycle, GRP-gap (HP 100)	-0.495	-0.383	-0.260	-0.094	-0.186	0.056
	(3.822)	(3.783)	(3.881)	(1.876)	(1.842)	(1.774)
Log-Likelihood	-31651	-30665	-29692	-113777	-108828	-106609
Region and year fixed effects and regional time trends	Y	Y	Y	Y	Y	Y
Regional mean age, education, marital status	N	Y	Y	N	Y	Y
Regional mean employment and income	N	N	Y	N	N	Y

Note: The measure of the business cycle is obtained from the HP filter on regional unemployment rates and gross regional product (GRP). (HP) refers to the value of the smoothing parameter in the HP filter. The series gap refers to the cyclical component being divided by the trend component in the decomposed time series. Individual employment controls in specification (3) refer to employment status, number of days in unemployment, retraining and industry employed in. Robust standard errors in parentheses, clustered by county. * p<0.10; **p<0.05;***p<0.01.

down on the other hand, firms may put less pressure on employees to work overtime and employees have more time for health-promoting activities. Moreover, during economic booms, hazardous working conditions accompanied by work-related accidents may increase, especially in cyclically sensitive sectors such as construction that have pro-cyclical accident rates (Ruhm, 2000). For these reasons, the unemployment indicator ought to be a more relevant indicator compared to the GRP measure for capturing the association between the business cycle and health. This may explain why capturing the business cycle by way of the unemployment indicator yields significant results whereas the regional income measure remains insignificant.

Table 6 below presents the results using the different measures of the business cycle, estimated on the region-year level data. Similar to Table 5, panels A to C specify the business cycle based on unemployment rates whereas the measurement of the business cycle in panels D to F are based on the GRP. The estimates confirm our earlier analyses: with identical estimates in columns 1 and 4 to those in Table 5 (by construction), providing us with a reference point for comparing estimates of subsequent models, we find that mortality is pro-cyclical, accounting for regional economic activity using measures based on unemployment rates. Once we adjust for average regional-level demographics the estimates change only somewhat in magnitude while sharing the same sign (although one can note that the effect of the unemployment rate displayed in panel C now is significant at the 1-percent level rather than 5-percent level). This suggests that an analysis based on aggregated region-year level data indeed provides adequate estimates for the individual-level association between the business cycle and mortality. This also holds when controls for individual (and their county-level counterparts) employment characteristics and income are added to the models. Therefore, perhaps in contrast to what one may expect *ex ante*, the inclusion of additional higher-level covariates that are correlated with the business cycle measure does not seem to confound higher-level business cycle estimates. This would suggest that we in this context can rely on *aggregated* analyses to infer associations between the business cycle and health at the *individual* level.

5.4 Subgroup analyses

To explore whether the effect of macroeconomic conditions differentially affects different types of individuals, we run a set of subgroup analyses. As our preferred specification is at the individual level, using the business cycle obtained from the HP filter on unemployment rates, we only report the estimates for the individual-level analyses. Table 7 presents the estimates by subgroup. We show the findings for four separate income quartiles, four education groups, by marital status, and by employment status. All analyses control for the full set of individual-level background characteristics discussed above. Columns 1-4 show the findings for 20-44 year old men; columns 5-8 present the results for men aged 45-64.

Table 6: Robustness analyses at the county-level, using different business cycle indicators

	20-44 year olds			45-64 year olds		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: County-level analysis, county-level business cycle						
Measure of the business cycle, unemployment rate	-6.999*	-5.581*	-7.675**	1.524	2.316	2.306
	(4.023)	(3.274)	(3.289)	(1.527)	(1.645)	(1.813)
Log-Likelihood	-1.923	-1.923	-1.922	-8.861	-8.860	-8.859
Panel B: County-level analysis, county-level business cycle						
Measure of the business cycle, cyclical unemployment rate (HP 6,25)	-8.487**	-7.408*	-8.775**	1.589	2.308	2.769
	(4.283)	(3.958)	(4.269)	(2.095)	(2.125)	(2.369)
Log-Likelihood	-1.923	-1.923	-1.922	-8.861	-8.860	-8.859
Panel C: County-level analysis, county-level business cycle						
Measure of the business cycle, unemployment gap (HP 100)	-0.487**	-0.497**	-0.621***	0.073	0.106	0.098
	(0.226)	(0.220)	(0.217)	(0.083)	(0.097)	(0.141)
Log-Likelihood	-1.923	-1.923	-1.922	-8.861	-8.860	-8.859
Panel D: County-level analysis, county-level business cycle						
County-level measure of the business cycle, ln of GRP	-0.153	0.041	-0.137	-0.034	0.095	0.031
	(0.620)	(0.548)	(0.773)	(0.321)	(0.289)	(0.350)
Log-Likelihood	-1.924	-1.923	-1.922	-8.861	-8.860	-8.859
Panel E: County-level analysis, county-level business cycle						
County-level measure of the business cycle, cyclical variation in GRP (HP 100)	-0.094	-0.068	-0.113	-0.002	0.118	0.031
	(0.697)	(0.627)	(0.872)	(0.345)	(0.333)	(0.403)
Log-Likelihood	-1.924	-1.923	-1.922	-8.861	-8.860	-8.859
Panel F: County-level analysis, county-level business cycle						
County-level measure of the business cycle, GRP-gap (HP 100)	-0.495	-0.289	-0.510	-0.094	0.555	0.055
	(3.822)	(3.398)	(4.708)	(1.876)	(1.805)	(2.160)
Log-Likelihood	-1.924	-1.923	-1.922	-8.861	-8.860	-8.859
Region and year fixed effects and regional time trends	Y	Y	Y	Y	Y	Y
Regional mean age, education, marital status	N	Y	Y	N	Y	Y
Regional income trend and employment controls	N	N	Y	N	N	Y

Note: Number of (county*year) observations for 20-44 as well as 45-64 year olds is 315. The measure of the business cycle is obtained from the HP filter on regional unemployment rates and gross regional product (GRP). (HP) refers to the value of the smoothing parameter in the HP filter. The series gap refers to the cyclical component being divided by the trend component in the decomposed time series. Regional employment controls in specification (3) refer to county-level collapsed individual number of days in unemployment, retraining and industry employed in. Regional income refers to trend in mean regional income obtained from the HP filter. Robust standard errors in parentheses, clustered by county. * p<0.10; ** p<0.05; ***p<0.01.

Panel A, columns 1-4, show significant pro-cyclical variation in mortality for individuals in both the lowest and the highest income quartile, with mortality in the higher socio-economic group being more sensitive to macroeconomic fluctuations compared to the lower socio-economic group. A standard deviation increase in the unemployment rate is associated with an 18 % ($e^{-0.203}$) reduction in mortality among the lowest income quartile, and a 36 % reduction ($e^{-0.45}$) reduction in mortality among the highest income quartile. Thus, this indicates that socioeconomic inequality in mortality increases in downturns while it decreases during economic booms. As for the two different age groups, the findings are consistent in that it is only the younger age group with 20-44 year old men that is affected by the business cycle.

The analyses by education, presented in Panel B, show a similar pattern to that in prior analyses in that a business cycle effect only is present in the lower age group, albeit it is only individuals with 9-12 years of education that is affected.

Panel C presents the results for subgroups based on marital status. The findings show that the pro-cyclical effect indicated by prior analyses is present only for single 20-44 year olds. Interestingly, a counter-cyclical effect is visible for divorced 45-64 year olds, but the effect is rather small. Of course, marital status can be affected by the expectation of future mortality, and therefore these results should be interpreted with caution. The same applies to the analysis by employment status. We find that mortality among unemployed 20-44 year olds is sensitive to variations in the business cycle. There is no effect among the 45-64 year olds, confirming that economic conditions do not affect mortality in this age group.

Overall, while singles and the unemployed exhibit pro-cyclical mortality patterns, there does not seem to be a social gradient in the response to macro-economic fluctuations. Indeed, the largest effects are found for younger individuals in the highest income quintile. However, quantifying the response in terms of a change in the *number* of deaths in each subgroup suggests that a one standard deviation increase in unemployment rates leads to a reduction of 32 deaths in the lowest income quintile (an 18% reduction for a mortality rate of 0.0018, see Table 7), and a reduction of just 18 deaths in the highest income quintile (a 36% reduction for a mortality rate of 0.0005). Vice versa, a one standard deviation *decrease* in unemployment rates leads to an increase of 32 deaths for the lowest income quintile and an increase of 18 deaths in the highest income quintile. In other words, an improvement in the economy (a reduction in unemployment rates) widens the social gradient in mortality rates, with a deterioration in the economy reducing the gradient.

Table 7: Individual-level analyses, using the county-level business cycle, obtained from the HP filter using county unemployment rate, by subgroups

	20-44 year olds				45-64 year olds			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Individual-level analysis, by income quartiles	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
All-cause county-level mortality rate	0.0018	0.0007	0.0006	0.0005	0.0107	0.0053	0.0033	0.0023
County-level measure of the business cycle, cyclical unemployment	-13.163***	8.762	4.173	-29.374**	1.812	-0.896	2.216	3.369
	(5.079)	(9.383)	(7.266)	(13.504)	(3.402)	(3.436)	(5.084)	(5.025)
No. of observations	1 134 272	1 134 667	1 134 204	1 133 241	849 543	849 500	849 121	849 381
Panel B: Individual-level analysis, by education group	< 9 years	9-12 years	13-15 years	>15 years	< 9 years	9-12 years	13-15 years	>15 years
All-cause county-level mortality rate	0.0017	0.0010	0.0005	0.0004	0.0085	0.0052	0.0035	0.0029
County-level measure of the business cycle, cyclical unemployment	-2.432	-9.446**	-8.943	-6.059	1.940	2.336	6.907	-9.699
	(14.267)	(4.330)	(18.435)	(12.862)	(2.983)	(1.960)	(6.372)	(6.663)
No. of observations	161 471	3 080 290	702 556	576 716	747 278	1 799 639	352 006	498 487
Panel C: Individual-level analysis, by marital status	Married	Single	Divorced	Widowed	Married	Single	Divorced	Widowed
All-cause county-level mortality rate	0.0005	0.0094	0.0018	-	0.0038	0.0077	0.0084	0.0085
County-level measure of the business cycle, cyclical unemployment	4.752	-10.802**	-9.851	-	0.048	0.344	6.713**	-9.012
	(11.633)	(5.392)	(9.233)	-	(2.829)	(3.608)	(3.404)	(10.298)
No. of observations	1 339 556	2 960 500	232 506	-	2 111 764	660 482	579 717	44 582
Panel D: Individual-level analysis, by employment status	Unemployed	Employed			Unemployed	Employed		
All-cause county-level mortality rate	0.0028	0.0006			0.0139	0.0036		
County-level measure of the business cycle, cyclical unemployment	-14.554**	-3.664			-0.287	3.128		
	(7.259)	(4.390)			(1.981)	(1.950)		
No. of observations	564 514	3 972 266			592 774	2 805 387		
Region and year fixed effects and regional time trends	Y	Y	Y	Y	Y	Y	Y	Y
Regional mean age, education, marital status	Y	Y	Y	Y	Y	Y	Y	Y
Regional income trend and employment controls	Y	Y	Y	Y	Y	Y	Y	Y

Note: Robust standard errors in parentheses, clustered by county. * p<0.10; ** p<0.05; ***p<0.01.

6 Conclusion

There has been a renewed interest in the relationship between economic conditions and mortality. The literature provides mixed evidence, with some studies finding support for the suggestion that mortality increases with improvements in economic conditions, and others finding the opposite. One of the differences between these studies is level of analysis: studies using aggregated data tend to find that mortality is pro-cyclical, whereas studies that use individual-level data tend to find the opposite.

Using both individual-level and aggregated data on a sample of Swedish working-age men sheds light on this issue. With pro-cyclical mortality effects of similar magnitude at both the individual level and the regional level, our analyses show that estimates of the relationship between mortality and the business cycle are not sensitive to the level at which the dependent variable is measured. This finding suggests that it is not the different levels of analyses that drive some of the conflicting findings in the literature. As a side issue, we report that capturing current economic conditions by cyclical deviations extracted from decomposed time series is preferred over the usage of the raw non-decomposed time series.

Our estimates at both the individual and regional level suggest that a 1 standard deviation increase in the unemployment rate reduces mortality by around 12% among 20-44 year old men. In contrast, we find no differences in mortality for 45-64 year old men, suggesting that the business cycle mainly affect the younger working-age population, rather than those closer to retirement. One reason for this may be the fact that older workers are more likely to have permanent positions, and with that increased job security. Any deteriorations in the business cycle are therefore less likely to affect older workers' (e.g.) levels of stress of anxiety, compared to the younger working-age population. Furthermore, we find no clear social gradient in the *response* to the business cycle, with both high and lower socio-economic groups being affected. However, given their different baseline mortality rates, the actual reduction in mortality due to a one standard deviation increase in the unemployment rate is higher for the low income group compared to the higher income groups. In other words, an improvement in the economy (a reduction in unemployment rates) increases the differential mortality rates between the highest and lowest income quintile, with a deterioration in the economy leading to the differential mortality rates converging.

Our results suggest some topics for future research. First, the results in the paper as well as those in the literature depend on the additive functional form for the relation between mortality and its determinants. It is an open question to what extent the empirical findings generalize to more flexible specifications. Furthermore, in a longitudinal setting, time-invariant unobserved heterogeneity (or an individual-specific fixed effect) leads to dynamic mortality selection over time. It is conceivable that the speed of selection within a cohort depends on the state of the business cycle, leading to systematic changes in the composition of survivors. It is not straightforward to reconcile this with the commonly used model specification, but it may go some way in explaining that while we find strong pro-cyclical effects for the ages up to 44, the effects are counter-cyclical and insignificant for the ages 45-65. Clearly, it would be interesting to explore this empirically in a more formal fashion.

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Appendix

Table 2: Descriptive statistics of business cycle measures

Unemployment rate	0.0642	(0.019)
HP 100		
Cyclical unemployment	0.0029	(0.0154)
Trend unemployment	0.0612	(0.0108)
Unemployment gap	0.0491	(0,2656)
HP 6.25		
Cyclical unemployment	0.0013	(0.0082)
Trend unemployment	0.0628	(0.0140)
ln(GRP)	5.4928	(0.0229)
HP 100		
Cyclical GRP	0.0047	(0.0259)
GRP-gap	0.0008	(0,0047)

Notes: Means and standard deviations (in parentheses) of the business cycle indicators. GRP stands for Gross Regional Product. Number of (county*year) observations is 315.