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Evidence from Norway

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Abstract:
Using variation across geographical regions, a number of studies from the U.S. and other developed countries have found more deaths in economic upturns and less deaths in economic downturns. We use data from regions in Norway for 1977-2008 and find the same procyclical patterns. Using individual-level register data for the same population, we then look at differences in pro-cyclicality across subsamples that are expected to be affected differently by the business cycle. Mortality is most pro-cyclical for young men (18-24), but there are also some indications of more pro-cyclical mortality for subgroups, such as the disabled, who are already dependent on the health-care system. Furthermore, the data allow us to look at pro-cyclicality in measures of morbidity, and we find pro-cyclicality in disability, obesity and traffic accidents in densely populated areas. Finally, we investigate pro-cyclical mortality across socioeconomic groups and find that mortality is more pro-cyclical for the well educated than the less educated, but it is less pro-cyclical for those with high earnings and more wealth than those with low earnings and less wealth. Overall, the observed associations between mortality and macroeconomic conditions seem to stem from a myriad of diverging mechanisms.

Keywords: mortality, morbidity, health, recession, unemployment, business cycle

JEL classification: I10, E32, J6

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Sammendrag

Ved å se på forskjeller mellom geografiske regioner har en rekke studier fra USA og andre utviklede økonomier funnet en økning dødeligheten i økonomiske oppgangstider og en reduksjon i nedgangstider. Dødeligheten samvarierer altså med konjunkturene – den er prosyklisk. Vi bruker norske regionale data for arbeidsledighet og dødelighet over perioden 1977-2008, og vi benytter samme metoder som de tidligere studiene og finner liknende pro-sykliske mønstre. Når vi i stedet bruker individdata for den samme populasjonen, kan vi se på prosyklikaliteten i dødelighet for undergrupper som forventes å bli påvirket ulikt av regionale konjunkturer. Dødeligheten er mer prosyklisk for unge menn (18-24), men det er også indikasjoner på høyere prosyklisk dødelighet for undergrupper som er avhengig av helsetjenester, for eksempel de uføretrygdede. Dataene gjør det også mulig å studere hvordan mål på sykelighet samvarierer med regionale konjunkturer, og vi finner at uføretrygding, fedme og trafikkulykker i tettbygde strøk er prosyklisk. Til slutt undersøker vi prosyklisk dødelighet for ulike sosio-økonomiske grupper, og vi finner at dødeligheten er mer prosyklisk for dem med høy enn for dem med lav utdanning, men mindre prosyklisk for dem med høy enn for dem med lav inntekt og formue. Den observerte samvariasjonen mellom dødelighet og regionale makroøkonomiske konjunkturer kan således synes å stamme fra en rekke ulike mekanismer.

1 Introduction

Numerous studies from the U.S. and other developed economies have documented that regional death rates are pro-cyclical — death rates tend to fall in economic recessions and rise in economic upturns.[1] Several mechanisms have been suggested to explain how the business cycle could affect death rates. High economic activity could raise mortality in several ways. More cars on the roads in economic upturns both increases traffic congestion and the population at risk of being involved in traffic accidents, and several studies have shown that fatal accidents are particularly pro-cyclical. Working conditions can also worsen during upturns, with associated detrimental effects on workers' health due to long hours, hazardous working conditions, worse diet, less exercise, less attention to safety routines, etc. Moreover, regional death rates are largely dominated by people outside of the labor force, meaning that macroeconomic cycles could affect death rates through effects on groups like children, students, disabled and elderly. Stevens et al. (2011) focus on possible effects of business cycles on congestion in and quality of the health-care system and find that the overall pro-cyclicality in the U.S. is driven by deaths among the elderly, who are likely to be dependent on the quality and capacities of the health-care system.

While these arguments suggest that economic upturns are bad for one's health, an increasing number of micro-studies on individual-level data document that job displacement has a negative effect on the workers' own mortality and health (Sullivan and von Wachter, 2009; Rege et al., 2009; Black et al., 2012; Eliason and Storrie, 2009a). Recent studies even suggest that the workers' families and peers are negatively affected by job displacement (Rege et al., 2011, 2012; Lindo, 2013b). As pointed out by other authors, the co-existence of these micro- and macro-results requires that the association between macroeconomic conditions and mortality rates operates through mechanisms outside the direct effect of job displacement on workers' health.

While previous studies have relied on state-level panel data,[2] we employ individual-level register data for every Norwegian resident over the period

[1] For U.S. studies see, for example, Ruhm (2000, 2003, 2005a, 2008); Miller et al. (2009); Stevens et al. (2011); Ruhm (2013); Lindo (2013a), and for studies from other countries see, for example, Gerdtham and Ruhm (2006); Neumayer (2004); Shin-Jong (2009).

[2] One exception is a study by Edwards (2008), who uses individual-level data from the U.S. (National Longitudinal Mortality Study) to look at differences across subgroups. As emphasized by the author, however, the relatively limited dataset disables him from confirming differential effects across interesting subsamples.

of 1977-2008. We start by replicating the methods of previous studies by aggregating our data to the regional level. The pro-cyclical pattern found for the U.S. is remarkably similar in Norway. A 1 percentage point increase in the regional unemployment rate leads to a 0.59 percent reduction in the regional mortality rates. This is practically the same estimate as Ruhm (2000) and Miller et al. (2009) find for the U.S., 0.54 and 0.43, respectively. Moreover, in line with the results of Miller et al. (2009) and Stevens et al. (2011), we too find that young adults have the most pro-cyclical death rates, and our results on cause of death also echo those of previous studies. These findings are important since they do not support previous suggestions that a strong welfare state safeguards against the pro-cyclical association between macroeconomic conditions and mortality (Gerdtham and Ruhm, 2006).

Given that pro-cyclical mortality is largely driven by individuals outside of the labor market or by lower quality or congestion in the health-care system during economic upturns, we would expect to see more pro-cyclicality for groups like the non-employed or the disabled. Our individual-level data allow us to compare the pro-cyclical association across these groups, and we *do* find large associations for the disabled and the non-employed, but these associations are not significantly larger than the ones for the non-disabled and the employed. Still, it provides some support for the arguments of, for example, Stevens et al. (2011), namely that we should focus more on characteristics other than labor force attachment when trying to improve our understanding of pro-cyclical mortality.

As we would expect the mechanisms behind pro-cyclical mortality to also affect morbidity, pro-cyclical mortality should just be a reflection of a more general pro-cyclicality in morbidity. Our data allow us to look at the associations between the business cycles and disability, obesity and traffic accidents (fatal and non-fatal), and it is reassuring that we find pro-cyclical patterns for these proxies for morbidity too, although traffic accidents are only pro-cyclical in densely populated areas, where economic upturns appear more likely to result in congestion.

Finally, we study how pro-cyclical mortality has varying effects on different socioeconomic groups. We look at differences across education, earnings and wealth, but the results provide no clear patterns. Mortality is more pro-cyclical for the well educated than the less educated, but less pro-cyclical for those with high earnings and more wealth than those with low earnings and less wealth.

The rest of the paper is laid out as follows. In Section 2 we give an overview of mechanisms that can explain how the business cycle affects mortality. The empirical method is laid out in Section 3, where we try to align closely to the methods applied in previous studies while still allowing for the advantages of individual-level data. Our data are presented in Section 4, and the results appear in Section 5. Finally, in Section 6 we sum up by pointing at the main contributions of our analysis and suggest a few directions for future studies of the relations between macroeconomic fluctuations and health.

2 Theoretical Considerations and Previous Findings

Ruhm (2000) suggests several sets of mechanisms through which death rates could be affected by macroeconomic conditions. Although many of the mechanisms can affect both the employed and the unemployed, as well as persons outside the labor market, we start by presenting mechanisms at play mostly for those who loose their job in a recession. Then we recall that the vast majority of workers remain employed through business cycles, and we look at mechanisms particularly relevant for them. Finally, we summarize a set of mechanisms that is mostly unrelated to the labor market attachment of the individual. While we will focus on mortality, it is worth noting that all the mechanisms below should also affect morbidity. It thus strengthens the credibility of our results that our data allow us to check that the pro-cyclicality of mortality is also present for measures of morbidity.

2.1 Job loss

When analyzing the effect that job displacement has on mortality, Sullivan and von Wachter (2009) document that mortality rates for highly senior male workers are 50-100 percent higher the year after displacement. Moreover, they argue that for a displaced worker, the benefits from increased leisure time are not offset by the disadvantages that the individual experience from the long-term earnings reduction. Indeed, a strong negative correlation has been shown between income and mortality (Deaton and Paxson, 2001). If job loss imposes stress that affects health for the individuals experiencing displacement, then we should expect that death rates are counter-cyclical for these individuals, since displacements are more common in recessions. The empirical evidence also demonstrates a deteriorated self-reported mental health when the unemployment rate increases (Charles and DeCicca, 2008; Ruhm, 2003), and this is most pronounced for employed individuals, for males and for individuals with more cyclical employment probabilities, such as African-Americans and those with low levels of education (Charles and DeCicca, 2008).

As noted by, for example, Ruhm (2000), Stevens et al. (2011) and Lindo (2013a), the pro-cyclical effect on mortality can be reconciled with the literature showing that job displacement increases mortality *if* the aggregate effect on mortality is not mainly concentrated among those being displaced. In reconciling these two strands of literature, it is crucial to remember that only a very small proportion of the employed, and an even smaller proportion of the overall population, are in fact laid off and unemployed during recessions. Thus, even though the displaced could face detrimental causal health effects, small beneficial effects that affect large parts of the population, like the employed or the elderly, would easily dominate the overall population association between mortality and business cycles. Our data allow us to see how associations between business cycles and mortality vary across such groups. This enables us to obtain estimates that makes it possible to compare the effects of macroeconomic fluctuations across groups that tend to loose their job in recessions and groups that do not (elderly, children, disabled).

2.2 Workload and liquidity

2.2.1 Health and stress

The workload of the employed could vary with the business cycle. Those retained in recessions and those employed in economic upturns could face extended work hours, with associated job-related stress and hazardous working conditions, which in turn could have a negative effect on health (e.g., Sparks et al., 1997). For example, we could expect work-related accidents to increase when the economy is booming or in recessions if one tries to cut costs by lowering safety. Miller et al. (2009) and Ruhm (2000) find some indication of increasing accident-related deaths during economic booms. The evidence is not clear-cut, however, since 63 percent of the increase in accident-related deaths are among those outside the prime working age populations (ages of 25-65) (Miller et al., 2009).

In the epidemiological literature, work hours have been related to myocardial infarction (e.g., Sokejima and Kagamimori, 1998), and work-related stress has been suggested to increase deaths from cardiovascular diseases (e.g., Kivimaki et al., 2002). Stressful and unsafe working conditions have been linked to, among other things, ischemic heart diseases and intervertebral disk problems (Price and Kompier, 2013). Ruhm (2003) also shows that a booming economy is related to an increase in the estimated prevalence of such diseases. The pro-cyclical death rates from heart (Ruhm, 2007) and cardiovascular (Stevens et al., 2011; Ruhm, 2000) diseases provide additional support for this hypothesis. As stressed by the authors, however, this work-related mechanism may not be of primary importance since overall death rates (Stevens et al., 2011) and deaths due to heart diseases (Ruhm, 2007) are also shown to be pro-cyclical for those over the age of 65.

2.2.2 The opportunity cost of time

For employed workers, a booming economy might affect the opportunity cost of time through a change in employment status or work hours. During economic upturns work hours are often extended. Consequently, leisure time declines, and thereby the costs of undertaking healthy activities increase. Ruhm (2003) has documented that higher unemployment rates are associated with increased physical activity, improved diet, and reduced smoking and obesity. Moreover, Ruhm (2000) shows that death from preventable diseases, such as cardiovascular disease or influenza/pneumonia, are pro-cyclical,[3] while no such clear pattern is identified among deaths due to cancer.[4] Ruhm (2007) also demonstrates that death from heart attacks are especially pro-cyclical. However, including controls for obesity and smoking did not change the magnitude of the estimated pro-cyclical mortality rates from heart attack (Ruhm, 2007). It has also been shown that rising unemployment rates result in an increase in both doctor visits and hospitalizations, and this is most apparent among the employed individuals (Ruhm, 2003).[5]

2.2.3 Liquidity

If the opportunity cost of time or work-related stress are important explanations for the pro-cyclical mortality, why are mortality rates also pro-cyclical among those who are not in their prime working age? Evans and Moore (2011) suggest that short- to medium-term change in liquidity—possibly

[3]Preventable diseases are classified as such because it is likely that they respond to short-term changes in lifestyle or health investment.

[4]Miller et al. (2009) and Ruhm (2013) find that the relation is counter-cyclical for cancer, while Lindo (2013a) does not find significant results, and the sign differs with the aggregation level of his measure of macroeconomic conditions.

[5]As underlined by the author, these results should be interpret with caution as large standard errors give imprecise estimates.

resulting from business cycles—could effect death rates, as more people go to the cinema or retail establishments, travel or go out eating when liquidity is improved. The authors show a within-month mortality cycle, where mortality declines before the first day of the month and increases after the first day of the month. Consistent with this, they also show a short-term increase in mortality just after a paycheck is received. Evans and Moore (2011) argue that the paycheck-induced change in liquidity over the month leads to increased activity, which explains the increase in mortality rates. Relevant to our setting, they suggest that pro-cyclical mortality rates are explained by increased activity, since the same mortality pattern for different death categories are found in the within-month mortality cycle.[6] We note that improved liquidity may not only affect the worker, but also those dependent on or affected by the worker's liquidity, like family and friends.[7]

Increased food consumption (Lipovetzky et al., 2004) or increased activity (Paffenbarger et al., 1978) could affect mortality rates, as both could trigger heart attacks or strokes.[8] A number of studies from the U.S. have also uncovered a pro-cyclical pattern in alcohol consumption (Evans and Graham, 1988; Wagenaar and Streff, 1989; Freeman, 1999; Ruhm, 1995; Ruhm and Black, 2002) and found that the increase in alcohol consumption during a boom stems from the intensive margin (not the extensive), i.e. that people move from lighter alcohol use to heavier use (Ruhm and Black, 2002). Moreover, Ruhm and Black (2002) argue that a change in income seems to explain much of the pro-cyclical alcohol consumption.

On the other hand, it is also possible that more liquidity improves consumption of safety precautions, like safer child care and safer cars.

The degree of liquidity constraints differs across socioeconomic groups. We should expect the liquidity for the young or for those with low education or low socioeconomic status to be mostly affected by the business cycle, although it is notoriously difficult to measure liquidity constraints

[6]As discussed by Evans and Moore (2011), for example, a temporary increase in activity could trigger causes of death other than those related to accidents. For instance, eating a heavy meal (Lipovetzky et al., 2004) or the Christmas season (Phillips 2004) could be triggers for hearth attacks.

[7]Consumption could also fluctuate among the elderly or the non-employed if their wealth or the "willingness to consume" is correlated with the local unemployment rate. In particular, Stephens (2003) found that seniors increased their consumption after they received their social security checks.

[8]We can explore the relevance of liquidity further by looking at the the pro-cyclicality of weight among high-school-aged males. Given their increased liquidity during economic upturns (e.g. because of higher parental income), we would expect them to increase consumption. Thus, their weight is pro-cyclical. The higher value of time for parents during booms might also affect their children's weight, for example, if the family has less healthy meals. This would also suggest that weight is pro-cyclical.

in observational data. It is also hard to separate effects of liquidity constraints from other variables, as the group of individuals who are unable to smooth consumption through business cycles are also more likely to experience job loss when unemployment rates are high (Hoynes et al., 2012). It might still be informative to see if groups that are less likely to be able to smooth consumption have the most pro-cyclical death rates (Gourinchas and Parker, 2002). Consistent with this, Evans and Moore (2011) show that the within-month mortality pattern is strongest for young males, blacks, Hispanics and high-school dropouts. This is also consistent with the strong pro-cyclicality observed among young adults (Stevens et al., 2011; Miller et al., 2009; Ruhm, 2000). With our data we can identify groups for whom earnings are particularly pro-cyclical and then see if this corresponds to pro-cyclicality in mortality too, although it would clearly be more informative if we had information about consumption.

2.3 Factors unrelated to the individual's labor market attachment

Groups other than the employed and displaced, along with their immediate dependents,are heavily represented in the regional death rates. So, how might groups outside of or in the fringes of the labor market, like the children, the disabled or the elderly, be affected by the business cycle?

If the health of the worker him/herself is affected by the business cycles, the change in the worker's behavior or health could also affect his/her family and friends. We have already mentioned how changes in the worker's liquidity across the business cycle can also affect the worker's family and friends. Moreover, Lindo (2013b) finds that parental job loss reduces the health of their infants, and Rege et al. (2009) find that paternal job loss reduces the school performance of his children. Furthermore, Rege et al. (2012) find strong social interaction effects in entry onto disability pension, which suggest that if a worker becomes disabled, for example in association with a job loss, then this will cause more of the worker's peers to also become disabled. These results suggest that the deleterious effect of job losses, which are more common during recessions, is not only affecting the worker himself, but also the worker's family, friends, colleagues and neighbors. It thus appears that this will affect the worker's peers countercyclically.

Some mechanisms are not so clearly connected to the labor market attachment of the individual and his/her peers. For example, more cars on the road caused by increased activity could raise traffic accidents, either simply because the population at risk of an accident is larger or because the likelihood of accidents increases with congestion. Ruhm (2000) and Miller et al. (2009) demonstrate that motor vehicle fatalities are the most pro-cyclical cause of death. Additionally, drinking and driving is shown to increase when the economy is booming (Evans and Graham, 1988; Ruhm, 2000). Congested traffic could also increase pollution, which could affect health (Heutel and Ruhm, 2013). To explore this further we will see if traffic accidents in general (both fatal and non-fatal) are pro-cyclical, and we will study whether accidents in urban areas—where congestion problems are more likely—are more pro-cyclical than accidents in rural areas.

As another example, an increase in accidents or hospital visits induced by an economic boom could deteriorate the availability of high-quality health care if hospitals do not adjust staffing levels accordingly. Consistent with this, Ruhm (2007) finds that less unemployment reduces the likelihood that senior citizens receive health checks, like coronary angiography, coronary artery bypass grafting and percutaneous coronary interventions. Similarly, Miller et al. (2009) and Stevens et al. (2011) argue that the quality of health-care services fluctuates through the business cycle because a booming economy causes shortages of health-care personnel. In particular, Stevens et al. (2011) show that higher unemployment rates are associated with better staffing levels in nursing homes through, for example, more nurses or certified aides. They also show that pro-cyclical death rates are particularly high among elderly women, arguing that they tend to live longer than their husbands and are therefore more likely to spend their final years in a nursing home. Moreover, using place of death as a proxy for where the elderly population was living before death, Stevens et al. (2011) find that deaths occurring in nursing homes are more pro-cyclical than deaths occurring elsewhere. A concern regarding these estimates is, first, that the living arrangement might be endogenous. In particular, if health among seniors is pro-cyclical, we might expect that their health also affects choice of living arrangements. Second, when the economy is booming, individuals of relatively poor health might be more likely to reside in a nursing home, as it is affordable—either through an increase in own wealth or if their children now can afford sending their parents to a nursing home instead of taking care of them (or if the alternative value of the children's time is higher in a booming economy).

We would expect that it is particularly those with health impairments who would be vulnerable to reductions in health-care quality or congestion. In addition to the elderly, we are able to check whether the disabled are also more likely to die during economic upturns.

2.4 Summing up mechanisms

Factors not related to the individual's labor market attachment would largely apply to everyone, regardless of labor market status. The employed, just like children or elderly, may suffer more traffic accidents in economic upturns, since the roads are more congested. The quality of health care, however, may affect those with health impairments more than the healthy workers, possibly implying that this mechanism is stronger for the disabled and the elderly. Thus, if the health-quality mechanism is important, we would expect more pro-cyclicality for the disabled than for the non-disabled, and maybe also for the elderly than for the non-elderly.

The liquidity mechanism might also affect those outside the labor market (through family members who are directly affected by job displacement), but it primarily speaks to those in the labor market. It is not obvious, however, whether workers in stable jobs or workers who are frequently unemployed are most affected by this mechanism. One might argue that going from unemployment to employment in economic upturns affects liquidity more than possible wage increases for the always-employed (and those with stable jobs may on average also hold higher wealth, which helps smooth consumption). Overall, the liquidity mechanism provides weak empirical predictions, although it might be taken to suggest more pro-cyclical patterns for those in the labor market, especially those with fluctuating employment, than for those permanently outside the labor market.

The mechanisms related to job stress and opportunity costs of time apply the most to those employed through the business cycle. If this mechanism is important, we thus predict more pro-cyclical mortality for the employed than for the non-employed.[9]

[9]Since the displaced are presumably a negatively selected group, even with respect to health, it is hard to know what we would learn by comparing the pro-cyclicality of the displaced workers with the pro-cyclicality of the retained workers. A few previous studies (on weight-related health and mental health or eating habits) have tried to circumvent this by using predetermined characteristics to predict workers into one group with stable employment and one with unstable employment (Charles and DeCicca, 2008; Dhaval and Inas, 2010).

3 Empirical Methods

3.1 Regional data

We start by investigating whether the relationships between macroeconomic conditions and mortality is the same in Norway as what was found in previous influential studies. For comparability, it is crucial that we employ the same panel data methods as in prior studies (e.g. Ruhm 2000, Miller et al. 2009, Stevens et al. 2011 and Ruhm 2013). The regression models applied in prior studies can be illustrated by the following ordinary least squares (OLS) regression model estimated on annual data for each region:

$$\overline{y}_{j,t} = \alpha_t + R_j + \beta UR_{j,t} + \lambda x_{j,t} + \varepsilon_{j,t}, \tag{1}$$

where $\overline{y}$ is typically the natural logarithm of the mortality rate in region j in year t; α_t is a vector of calendar year fixed effects included to control for national time trends; R_j is a vector of region fixed effects included to control for time-invariant regional characteristics; and x is a vector of region-time demographic controls (age, gender, education, etc.) included to control for compositional differences (and changes). The error term ε_{jt} is assumed to have a conditional expectation of zero. We also follow the convention of weighting each observation by the number of individuals in the region-year cell.[10]

The parameter of interest β captures the relationship between the regional unemployment rate and regional mortality. This estimate is identified from within-regional variations in mortality rates, so the discussions of macroeconomic effects on mortality refer to changes within regions rather than at the national level. When the regression is run on the log of the mortality rate, the estimate readily provides the semi-elasticity of mortal-

[10]With regional data it is hard to ensure that the estimated effect of the unemployment rate on mortality (β) is not biased by migration. For example, the healthiest individuals could be migrating to booming regions, leaving the non-healthy in the non-booming regions. This would imply that death rates decline in booming regions and increase in non-booming regions. If so, this would lead to less pro-cyclical death rates, that is, the observed pro-cyclical death rates could be biased downwards. On the other hand, migration flows into booming regions could raise death rates through increased crowding on roads or hospitals. Ruhm (2000) argues that if the latter mechanism is explaining the pro-cyclical mortality rates, then we would expect a stronger correlation between the unemployment rate and mortality in fast growing states than in slow growing states. Consistent with this, Ruhm shows that mortality rates are most pro-cyclical in fast growing states. However, he also demonstrates that mortality rates are strongly pro-cyclical in slow growing states, and he argues that this gives somewhat inconclusive evidence on how migration flows bias estimates of the effects of unemployment rates on mortality. When we use individual-level panel data below, we can follow each individual over time and space, enabling a better control of how migration affects the estimates.

ity with respect to unemployment rates, which can be thought of as the percentage change in the death rate from a 1 percentage point change in the unemployment rate.

3.2 Individual-level data

With individual-level data, we can estimate the analogous linear probability model[11] (using OLS):

$$y_{i,j,t} = \alpha_t + R_j + \beta UR_{j,t} + \lambda x_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where i indicates the individual and y is a binary variable indicating if individual i is alive or dead in calendar year t. The term α_t is a vector of year fixed effects included to control for national time trends; R_j is a vector of region fixed effects included to control for time-invariant regional characteristics; x is a vector of (possibly time varying) individual characteristics (age, gender, education, etc.) included to control for compositional differences (and changes); and the error term $\varepsilon_{i,t}$ is assumed to have a conditional expectation of zero. When run on individual-level data there is no need to use weights since each individual receives the same weight. It is worth noting that equation (1) and equation (2) can be run on the exact same underlying set of individuals. If the outcome variable in equation (1) is death rate (not log of death rate), the two models would yield identical results as long as we weight with the number of individuals in the region-year cell in equation (1) and as long as the control variables in equation (2) are included in a sufficiently flexible way in equation (1) .

Following the tradition in the literature, we will also present results from individual-level data on the relationship between macroeconomic conditions and mortality as semi-elasticities. When $\overline{y}$ in equation (1) is the natural log of the mortality rate, the parameter of interest β provides the semi-elasticity of mortality with respect to the unemployment rate. To ensure that specification (1) and (2) are in fact providing almost identical results, we will also estimate equation (1) by using the mortality rate (not the log), and we then calculate the semi-elasticity by dividing the estimate of β by the regional death rate. To obtain a comparable semi-elasticity from equation (2), we follow the same procedure and divide the estimate

[11] We also tried running some logit models on individual-level data, but this took an excessively long time and also resulted in us losing observations via separations given all the fixed effects included. For the logit models that did in fact converge, the implied mean marginal effects (and corresponding semi-elasticities) were similar to those produced by OLS.

of β by the regional death rate.[12] We will also follow the tradition in the literature and report standard errors that account for correlations between observations within regions (cluster on region).

4 Data

4.1 Data sources and definitions

Our analysis utilizes a dataset provided by Statistics Norway containing annual records on vital statistics for every Norwegian resident. From this data source we obtain for each person the year of birth, death and emigration, as well as sex, the municipality of residence in every year and the identity of each person's parents. A unique personal identifier is provided to every Norwegian resident at birth or immigration, and this enables us to follow the same individual over time and across registers, and to link children to parents. We start with the entire Norwegian resident population in 1977. From that point until 2008, newborns are included in the dataset the year they are born, and residents are excluded from the dataset when they die or emigrate. Immigrants are not included in the dataset. We will follow every individual in this population from 1977 (or birth) until he/she drops out of the sample, i.e. he/she dies or emigrates (or is right-censored in 2008). Overall, this leaves us with a dataset of more than 5.4 million individuals, each observed for an average of about 23 years.

To this population, we include information from several other data sources. Macroeconomic conditions, which is the explanatory variable we are mainly interested in, are captured by annual regional unemployment rates. The regions, of which there are 89 in Norway, are defined by Statistics Norway to capture local labor markets. The main criteria used by Statistics Norway for defining the regions are travel distances and trade. By using regions instead of, for example, municipalities, the potential problem of migration between geographic areas is reduced.[13] The unemployment rate is defined consistently over all years as the number of registered unemployed in the region divided by the working-age population of the region.

[12] This can also be interpreted in the framework of a linear probability model as the semi-elasticity of the probability of dying with respect to the unemployment rate, which can thus be thought of as as the percentage point change in the probability of dying from a 1 percentage point change in the unemployment rate.

[13] We have also explored the relevance of migration for our main results by assigning an individual to the region of residence at age 10 and at birth (without any updating), which yielded very similar results as those reported. In addition, we explore if migration is pro-cyclical; see Table 10 below.

Data on cause of death is obtained from The Norwegian Cause of Death Register, where the cause is coded using ICD 8, 9 and 10.[14] To have comparable codes for our entire time period, we have recoded to the 20 aggregate causes used by Statistics Norway (see Appendix A).

Data on weight, height and ability test scores (IQ) are retrieved from the Norwegian Armed Forces, which collects this information at the time of military conscription (normally at age 18).[15] Military conscription is mandatory for every Norwegian man, but not for the cohorts of women in our data period. Therefore, we will only use this information for men. The test is based on the sum of scores from three tests: math, figures and word similarities. The score ranges from 1 to 9, and follows the Stanine method (Standard NINE), which scales test scores with a mean of five and a standard deviation of two. In addition to IQ, weight (in kg) and height (in cm), we also construct a body mass index (BMI, i.e. weight in kilograms divided by squared height in meters). Base on BMI, we construct the indicator variables *overweight* ($BMI \geq 25$), *obesity* ($BMI \geq 30$) and *underweight* ($BMI \leq 18.5$).

Data on traffic accidents involving personal injuries are maintained by Statistics Norway and are available for all our years except 1979 (data is missing for 1979 in the data source). The dataset includes date and type of every accident in Norway resulting in personal injuries, as well as the personal identifier of all involved persons. From this source we construct a dummy set to 1 if the individual was involved in a traffic accident in the year. We also have a variable showing whether the traffic accident occurred in a densely or non-densely populated area.

Data on drawing of disability pensions (labeled DP) are retrieved from historical records received from the Norwegian National Insurance Scheme. Disability pensions havebeen available for every Norwegian resident aged 16-67 who is permanently medically disabled and thus unable to work. We have coded an indicator variable to one if the person is disabled in the given year.[16] Since it can sometimes take a couple of years from the onset of a disability to formal entry into a disability pension (Rege et al., 2009),

[14]We would like to thank the Cause of Death Registry (Dødsårsaksregisteret) for access to the data. Views and conclusions expressed in this paper are those of the authors and cannot in any way be attributed to the registry.

[15]We would like to thank the Norwegian Armed Forces for access to these data. Views and conclusions expressed in this paper are those of the authors and cannot in any way be attributed to the Norwegian Armed Forces.

[16]In the regression where disability pension is the outcome variable, we have censored individuals from the year after entry onto a disability pension. Since it is rare to exist from a disability pension, our results are essentially the same if we allow individuals to escape disability pensions (and thus re-enter the dataset).

we are using the year of the occurrence of the disability that led to the disability claim (rather than the year in which the disability pension was granted).

Data on earnings, employment and wealth are from the tax register (maintained by Statistics Norway) and available for residents aged 16-67. We use a measure of labor-related income, which forms the basis for calculations of pensions in the universal and public Norwegian pension system. It includes wages and income from self-employment, but also sick-leave compensation and unemployment benefits from the national welfare insurance. Recalling that this measure does not include long-term welfare benefits (like disability or elderly pensions), income from capital (dividends and interests) or child-care allowances, we will refer to this labor-related income as *earnings*. In line with previous studies using the same variable (Havnes and Mogstad, 2011a,b), we will define an individual as non-employed if his/her earnings in a year are below two “basic amounts”. The “basic amount” determines the magnitude of current and future pensions in the universal (and mandatory) Norwegian National Insurance Scheme. It is adjusted annually by the Norwegian Parliament, and it has typically been growing more than the prices but less than wages. In 2008 the mean and median earnings in our sample was NOK 315,613 and 317,274, and two basic amounts was 138,216 NOK (approximately 23,000 U.S. dollars at the time). Our measure of wealth captures net taxable wealth.

Data on migration are retrieved from the vital statistics using information on region of residence. We create a dummy set to 1 if the individual moved from one region to another during the year.

Data on completed education come from the Norwegian National Education Database (maintained by Statistics Norway), from which we obtain the individual's highest completed years of education in each calendar year (four indicator variables, <11, 11-13, ≥14 and missing).[17]

Control variables in the analyses on data aggregated to the regional level (Equation 1) include (in addition to region and calendar year dummies) the fraction of the population aged 0-4, 5-17, 18-30, 31-64 and 65+;

[17]In Norway compulsory education decomposes into seven years in primary school and three years in secondary school. In 1997 a large primary school reform was implemented, where school starting age changed from seven years to six years. The new reform thus increased years in primary education from nine to ten years. The difference in years of schooling for individuals born before and after the reform is adjusted for. A large school reform was also implemented between 1961 and 1972, changing the years of mandatory education from seven to nine. Secondary education was either a three- or five-year track for the cohort born before 1965. Hence, for the individuals born before 1965 the completed high school variable takes on the value one if individuals have at least 12 years of schooling (and one if at least 13 years for later cohorts).

the mean of a gender dummy; and the mean education level (years of completed schooling). In the individual-level analyses (Equation 2), we always include region and calendar year dummies, a gender dummy and yearly age dummies, and if indicated, also education dummies (the aforementioned four categories).

4.2 Summary statistics

Table 1 presents summary statistics for our sample. We have 5,419,848 different individuals in the dataset, and each are in for 23 years on average. Our dataset thus includes more than 125 million person-year observations, and the mean death rate is 1.1 percent. The average age in the overall sample is 39, and there are slightly more women than men. From Table 2 we see that there are a substantial number of deaths in all given age intervals, but the number of deaths is obviously dominated by deaths among the elderly. The most common causes of death are from cardiovascular diseases and cancer.

Table 1: Summary statistics

	Mean	Standard deviation
Death	0.0107	
Unemployment rate	2.2591	1.2595
Men	0.4943	
Age	38.83	23.60
Education in years[a]	11.35	2.90
Alternative outcome variables:		
Earnings[b]	265,987	221,354
DP[c]	0.0101	
Traffic accident[d]	0.0033	
Over weight (BMI≥25)[e]	0.1402	
Migration[f]	0.0280	

The sample includes every Norwegian resident from 1977-2008, in total 5,419,848 different individuals observed for 23 years on average, yielding N=125,779,446 person-year observations. Individuals are excluded from the sample in the calendar year after death or emigration. See Section 4.1 for details.

[a]Calculated over individuals above the age of 30 with non-missing data on education

[b]Available for those aged 16-67 only (N=82,175,948). Measured in fixed 2009 NOK (adjusted using the "basic amount", see Section 4.1). The annual exchange rate has fluctuated between approximately 5 to 9 NOK per U.S. dollar since 1977.

[c]Available for 1977-2007 only, and only for those aged 16-67. When DP is used as an outcome variable (and only then) individuals are excluded from the sample in the year after entering disability (N=68,908,049).

[d]Not available for 1979 (N=121,965,271).

[e]Available for men at age 18 only (N=824,831).

[f]Available for 1977-2005 only.

Table 2: Mortality rates in sample by age

Age	Death rate per 100,000 population		Number of deaths	Number of deaths by causes of death						
	Mean	SD		Cardio vascular	Accidents, falls, poisoning	Respiratory	Suicide	Cancer	Mental and behavioral	Derma-tological
All	1070.2	1880.7	1,346,106	598,371	29,717	128,081	16,543	312,886	28,548	1577
0-17	55.36	32.38	15,912	261	159	480	401	1,105	24	2
18-24	72.26	46.98	8,496	258	404	86	1,948	668	414	1
25-44	103.9	35.38	36,121	4682	2,117	529	5,698	8,137	2,615	14
45-64	581.3	165.3	166,727	54,588	3,023	6,540	5,318	63,772	3,478	52
65+	5124.1	455.3	1,118,850	538,582	24,014	120,446	3,178	239,204	22,017	1508

5 Empirical Findings

5.1 Pro-cyclical mortality rates

In Table 3 we present associations between regional unemployment rates and mortality. All estimates are adjusted for region and calendar year fixed effects, and we have weighted with the number of residents in the region. Models 1-4 show the estimated associations between regional unemployment rates and the regional death rates (i.e. equation (1)), and the dependent variable in models 1-3 follow previous studies by using the natural log of the regional mortality rate. The OLS estimate shown is thus the semi-elasticity, and the estimate in model 1 means that a 1 percentage point increase in the unemployment rate reduces mortality rates by 2.3 percent. But model 1 includes only region and year fixed effects, and once we add the regional controls for age, education and sex in model 2, the estimated semi-elasticity declines to 0.50 percent. In line with results in previous studies (like Ruhm 2013), the estimate increases somewhat (to 0.59 percent) when we also control for region-specific time trends in model 3. The changes in the estimate from adding in controls and secular trends may suggest that the estimated association between business cycles and mortality is confounded by compositional changes in the population of the regions. With individual-level data we can control for characteristics of every individual, and thus handle compositional changes more flexibly (using a rich set of dummies instead of regional means).

To be able to compare results on individual-level data (cf. equation (2)) with those on aggregate data, we first rerun model 2 on the regional mortality rates instead of the log of the regional mortality rates. In model 4 we keep the exact same (regional) control variables as in model 2, with regional mortality rates as the outcome variable. The estimate in model 4 is thus the marginal effect, and we see that the implied semi-elasticity of 0.65 percent is in line with the results of models 2 and 3. The results in model 4 can now be compared directly with results from linear probability models on individual-level data where mortality is captured by a dichotomous variable. Since the regional data are nothing other than aggregates of the individual-level data, running an OLS model (model 4) directly on individual-level data, instead of on data that we have first aggregated, will yield numerically identical point estimates (although standard errors need to be clustered on regions).

To better capture compositional changes, we can make the control variables more flexible by using the individual-level data. This is done in model

Table 3: Overall regression results of regional unemployment rates on mortality

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Unemployment rate	-0.02303*	-0.00495+	-0.00585*	-0.00007*	-0.00014**	-0.00015**	-0.00031+	-0.02610*
	(0.01086)	(0.00290)	(0.00253)	(0.00003)	(0.00004)	(0.00005)	(0.00016)	(0.01208)
Aggregated data (vs. micro)	x	x	x					
Dependent variable	Ln(mort.rate)	Ln(mort.rate)	Ln(mort.rate)	Mort.tate	Dummy	Dummy	Dummy	Dummy
Estimation method	OLS	OLS	OLS	OLS	OLS	OLS	OLS	Logit
Additional covariates:								
Mean age		x	x	x				
Mean education		x	x	x				
Mean number of females		x	x	x				
Fixed effects age					x	x		
Gender					x	x		
Fixed effects education					x			
Region specific time trend			x					
Implied semi-elasticity				-0.0065	-0.0128	-0.0138	-0.0287	-0.0258
Observations	2,759	2,759	2,759	2,759	125,779,446	125,779,446	125,779,446	125,779,446

Estimation results for the association between regional unemployment rates and mortality (mean=0.0107), presented as semi-elasticities (models 1-3), marginal effects with implied semi-elasticities (models 4-7) and log odds ratio with implied semi-elasticities (model 8). All estimates are adjusted for region and calendar year fixed effects, as well as other control variables as indicated. Regressions on regional data (models 1-4) are weighted with the number of residents in the region, and standard errors in regressions on individual-level data (models 5-8) allow for dependent observations within regions (clustering on region). Mean of mortality rate is 0.0107. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by **, * and +, respectively.

5, where we abandon the rough regional controls for age, sex and education, and instead use dummies for age (annually), sex and education (five categories). Here, and in all results that follow, we present standard errors that allow for correlations within regions (clustered on regions). We see that adding these more detailed controls doubles the estimated semi-elasticity (to 1.3 percent).[18] This underlines that it can be crucial to control very flexibly for characteristics of the regional populations in studies on aggregate data.

In model 6 we run the same model, but drop the control for education (since education could itself be affected by the business cycle for some age groups). This has almost no impact on the estimate. In the following we will use model 6 as our model of reference, meaning that we will—unless otherwise explicitly noted—run the linear probability model with the same controls as in model 6, i.e. the detailed dummies for age, sex, region and year. Models 7 and 8 are included to check that our linear probability model produces similar results as the logit model, and from implied semi-elasticities we see that this is the case.[19]

All these models show that the association between the regional unemployment rate and mortality is negative, meaning that mortality is pro-cyclical in Norway too. The results from models run on aggregate data, which are comparable to previous studies, imply that a 1 percentage point increase in the regional unemployment rate decreases the regional death rate by 0.50-0.59 percent. These estimates of semi-elasticity are remarkably similar to the semi-elasticities of 0.54 and 0.43 percent reported for the U.S. by Ruhm (2000) and Miller et al. (2009), respectively.

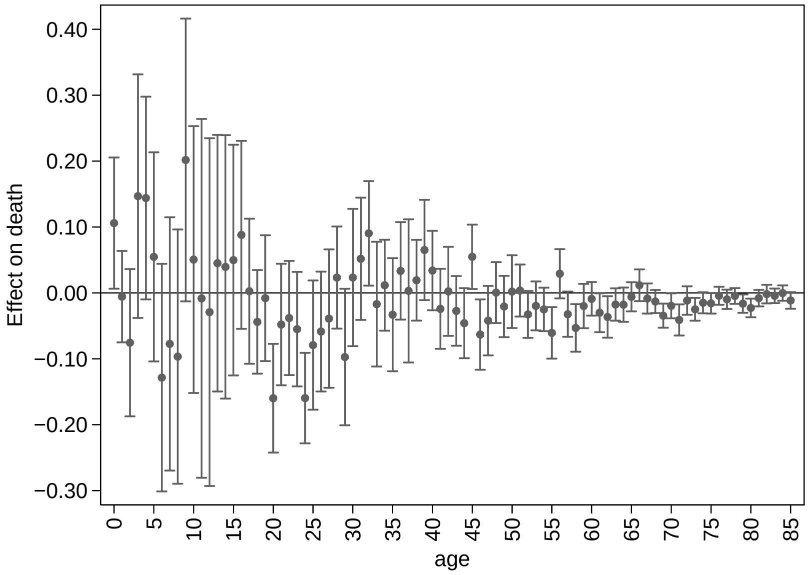
Despite using the exact same data and model, our estimated semi-elasticities increase when we include more flexible controls in the individual-level data model. This also echoes previous findings on U.S. data, where Edwards (2008) finds somewhat higher semi-elasticities when using individual-level data, suggesting a general pattern where pro-cyclicality is more pronounced in individual-level data than in aggregate data.[20] In general our

[18] Of course, we would have obtained the exact same point estimate in the corresponding model on regional data, i.e. the regional model including the large number of controls for the regional mean of all of these individual-level dummies.

[19] We make this comparison by using the model without control variables since we were not able to have the logit model converge when including the huge number of dummy variables.

[20] Note that we maintain a constant method for measuring the unemployment rate. Lindo (2013a), however, uses U.S. data and finds that changes in the aggregation level of the variable corresponding to our unemployment rate, with associated changes in aggregation level of the analyses, affect the estimated semi-elasticities considerably. He reasonably interprets this variations as indication that economic conditions at different

Figure 1: Semi-elasticities by age



Point estimates of log of regional mortality rates on the regional unemployment rates from regressions for each year of age separately, with point-wise 90 percent confidence intervals. Estimates weighted with the number of residents in region, and adjusted for regional controls for region (dummies), calendar year (dummies) and sex (dummy).

estimates show pro-cyclical death rates that are remarkably similar to the findings based on U.S. data.[21]

5.2 Age patterns in pro-cyclicality

We now investigate whether the age profile for the Norwegian population is also similar to the one in the U.S., and start by presenting a similar plot as in Figure 1 in Miller et al. (2009), where the semi-elasticities are estimated for age groups. Figure 1 shows the semi-elasticity of the regional unemployment rate and mortality, as estimated when applying our reference model (model 6 of Table 3) separately for each age group.

In line with Miller et al. (2009) death rates are most pro-cyclical for young adults at ages just below 20 to below 30. Table 4 shows analogous

levels (region, state and county) affect mortality differently, although our findings might suggest that his results could also be affected by the aggregation level of the control variables.

[21]Recently, Ruhm (2013) has argued that from the 1970s to today, the pro-cyclicality in the U.S. has declined and maybe even evaporated entirely. We find few similar signs in our data, and if anything, the pro-cyclicality might have increased slightly over time in our data.

results where we have run regressions separately by gender and for five age groups: children (0-17 years), young adults (18-24 years), young prime age adults (25-44 years), prime age adults (45-64 years) and elderly (65+ years). The estimated semi-elasticities echo the pattern from Figure 1 and emphasize the fact that mortality of young adults, especially men, are the most pro-cyclical.

In general, Table 4 shows that death rates for the men are pro-cyclical in all the age groups except for children, although the estimated coefficient is not statistically significant[22] for men aged 25-44 (model 4). These results line up well with those of Stevens et al. (2011), except that Stevens et al. (2011) found pro-cyclical death rates for the children. Other U.S. studies have also shown pro-cyclical infant morality rates (Ruhm, 2000; Dehejia and Lleras-Muney, 2004), but infant morality seems unrelated to labor market conditions in Germany (Neumayer, 2004) and other OECD countries (Gerdtham and Ruhm, 2006).

When splitting the sample into age groups defined by five-year intervals, Stevens et al. (2011) demonstrated that many of the point estimates in the ages between 30-64 are near zero, and none of them are statistically different from zero. For the women in Table 4, death rates are only significantly pro-cyclical for those aged 45-64. Moreover, in contrast to our estimates, Stevens et al. (2011) show that death rates are stronger among elderly woman than men.

Although there are some deviations, in general our estimates reveal patterns of pro-cyclical death rates over age and gender that are largely in line with studies from the U.S.

5.3 Cause of death

A number of previous studies have used cause of death data to investigate what diagnoses categories are more pro-cyclical (Lindo, 2013a; Stevens et al., 2011; Edwards, 2008). Two consistent findings are that cardiovascular deaths and fatal accidents are pro-cyclical. The result for cardiovascular deaths could be explained by, for example, more stress, less exercise or less healthy diets in economic upturns. The result for accidents would be explained by less safety precautions or from a larger population at risk, for instance, due to more people in the traffic during in economic upturns.

In Table 5 we present cause of death results. Cardiovascular deaths are pro-cyclical, and especially so for those aged 45 and above, where the

[22] In discussing results in the paper, we will describe a finding as statistically significant if the p-value is below 0.05.

Table 4: Pro-cyclical mortality for age and gender groups

	(1)	(2)	(3)	(4)	(5)	(6)
	All ages	0-17	18-24	25-44	45-64	65+
			Male and Female			
Unemployment rate	-0.00014**	0.00003+	-0.00004**	-0.00000	-0.00014**	-0.00053**
	(0.00004)	(0.00002)	(0.00001)	(0.00001)	(0.00004)	(0.00013)
Semi-elasticity	-0.0129	0.0557	-0.0510	-0.00196	-0.0240	-0.0103
Observations	125,779,446	28,743,182	11,756,775	34,762,288	28,682,222	21,834,979
			Males			
Unemployment rate	-0.00024**	0.00003	-0.00008**	-0.00002	-0.00019*	-0.00127**
	(0.00008)	(0.00002)	(0.00002)	(0.00002)	(0.00008)	(0.00030)
Semi-elasticity	-0.0220	0.0446	-0.0727	-0.0157	-0.0248	-0.0216
Observations	62,174,045	14,779,844	6,030,930	17,743,257	14,365,242	9,254,772
			Females			
Unemployment rate	-0.00010*	0.00003+	-0.00000	0.00002	-0.00013**	-0.00025+
	(0.00004)	(0.00002)	(0.00001)	(0.00001)	(0.00004)	(0.00013)
Semi-elasticity	-0.00951	0.0720	-0.00878	0.0252	-0.0315	-0.00539
Observations	63,605,401	13,963,338	5,725,845	17,019,031	14,316,980	12,580,207

Estimation results from OLS regression models (like model 6, Table 3) on individual-level data for the association between regional unemployment rates and mortality. Estimated separately within each age and sex subsample. Estimates presented as marginal effects with implied semi-elasticities and adjusted for a rich set of dummies for region, calendar year, age and sex (if estimated together). Standard errors clustered on region. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by **, * and +, respectively.

semi-elasticity is between 3 and 5 percent. These results are similar for men and women (separate results for men and women are not reported).

Deaths from accidents, falls and poisoning are also pro-cyclical, although only statistically significant for men (not reported). Again, the pro-cyclical semi-elasticity is high for those aged 45-65 (and significantly so for men), although here it is also high (but insignificant) for children. For children we also find pro-cyclicality in deaths from respiratory diseases, which could be related to more pollution during economic upturns (Heutel and Ruhm, 2013).

Suicide is also pro-cyclical in our data. The pro-cyclicality is particularly pronounced for the age group 18-24 (with a semi-elasticity of about 1.3), and similar in magnitude for men and women. Previous studies have not found consistent results for suicide (counter-cyclical in, e.g., Ruhm (2000) and Stevens et al. (2011); pro-cyclical in, e.g., Neumayer (2004)), and Lindo (2013a) finds that the result depends on what level (regional, state or county) the macroeconomic conditions are measured.

We find deaths related to cancer to be pro-cyclical. While Ruhm (2013) and Stevens et al. (2011) find counter-cyclical patterns, Ruhm (2000), Gerdtham and Ruhm (2006) and Lindo (2013a) find non-significant pro- and counter-cyclical patterns. Ruhm (2000) argued that cancer can be unrelated to business cycles since it is not likely to respond rapidly to changes in lifestyle, environmental factors or medical intervention. Recently, he has pointed out that if the success of cancer treatment depends on financial resources, economic upturns may reduce deaths from cancer if a better financial situations in good times enables patients to afford better treatment (Ruhm, 2013). Given the high quality of the universally available public health-care system in Norway, with virtually no high-quality private alternative in treatment for mortal cancer, this mechanism appears irrelevant in our data. For the young and younger adults, we also find counter-cyclical results for cancer. However, for the mature adults and the elderly, we find that deaths due to cancer correlates positively with the business cycles.

There are no clear findings for deaths related to mental illnesses, but we note that it is particularly counter-cyclical for those aged 25-44. This might be picking up detrimental effects of job loss on affected workers' health that can be associated with hospitalizations related to consumption of alcohol and drugs (Eliason and Storrie, 2009b).[23] We also find counter-cyclical

[23]There are also some signs of pro-cyclical mortality related to mental disorders for children (0-17), with similar semi-elasticities for males and females (although significant for females only). But we should recall that there are very few deaths in this age group; cf. Table 2.

Table 5: Pro-cyclical mortality by causes of death

	All ages	0-17	18-24	25-44	45-64	65+
			Cardiovascular			
Unemployment rate	-0.00013*	0.00000	-0.00001*	-0.00001+	-0.00010**	-0.00047**
	(0.00005)	(0.00000)	(0.00000)	(0.00000)	(0.00003)	(0.00013)
Semi-elasticity	-0.0264	0.0812	-0.242	-0.0523	-0.0516	-0.0189
			Accidents, falls, poisoning			
Unemployment rate	-0.00001	-0.00000	0.00001	0.00001	-0.00001+	-0.00005
	(0.00001)	(0.00000)	(0.00000)	(0.00001)	(0.00000)	(0.00003)
Semi-elasticity	-0.0449	-0.118	0.154	0.128	-0.0605	-0.0495
			Respiratory			
Unemployment rate	-0.00001	-0.00000**	-0.00000	0.00000	-0.00000	-0.00001
	(0.00002)	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00007)
Semi-elasticity	-0.00617	-0.288	-0.00438	0.0104	-0.0175	-0.00185
			Suicide			
Unemployment rate	-0.00001+	-0.00000	-0.00002**	-0.00001	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00000)
Semi-elasticity	-0.0504	-0.120	-0.131	-0.0729	-0.0172	-0.00201

Continued on next page

Table 5: continued from previous page

	All ages	0-17	18-24	25-44	45-64	65+
			Cancer			
Unemployment rate	-0.00004**	0.00000	0.00000	0.00000	-0.00005*	-0.00017**
	(0.00001)	(0.00000)	(0.00000)	0.00000)	(0.00002)	(0.00006)
Semi-elasticity	-0.0164	0.0635	0.00718	0.00667	-0.0230	-0.0153
			Mental and behavioral			
Unemployment rate	0.00000	-0.00000*	-0.00000	0.00002*	-0.00000	-0.00003
	(0.00001)	(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00003)
Semi-elasticity	0.00151	-0.647	-0.0683	0.206	-0.0146	-0.0261
			Dermatological			
Unemployment rate	0.00000*	0.00000	-0.00000	0.00000	0.00000	0.00001*
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Semi-elasticity	0.143	1.819	-1.932	0.361	0.362	0.133
Observations	125,779,446	28,743,182	11,756,775	34,762,288	28,682,222	21,834,979

Estimation results from OLS regression models (like model 6, Table 3) on individual-level data for the association between regional unemployment rates and given cause of death. Estimated separately within cause and age subsample. Estimates presented as marginal effects with implied semi-elasticities and adjusted for a rich set of dummies for region, calendar year, age and sex. Standard errors clustered on region. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by **, * and +, respectively. See Appendix A for details on diagnoses included in the cause of death categories.

associations between unemployment and deaths related to dermatological diseases, especially for old women (results not reported).

5.4 The disabled and the non-employed

We now draw further on our individual-level panel data to explore the relationship between mortality and the business cycle. In Section 2 we stressed that death rates could be dominated by groups outside of or in the fringes of the labor market. Here we explore if pro-cyclicality varies for the disabled versus the non-disabled and for the employed versus the non-employed. For example, if the opportunity cost of time or more hazardous working conditions were the main mechanisms explaining the pro-cyclical death rates, we would expect death rates to be more pro-cyclical for the employed population than for the non-employed.[24] Moreover, if pro-cyclicality is related to the quality of health-care, we would expect mortality to be more pro-cyclical for those more dependent on the health-care system. We explore this by checking if mortality is more pro-cyclical for the disabled than for the non-disabled.

In Table 6 we present results for individuals drawing and not drawing a disability pension . We recall from Table 4 that mortality is pro-cyclical for all age groups for whom disability pensions are relevant (age group 24-64).[25] The results in model 1 confirm that those drawing a disability pension have more pro-cyclical mortality rates than those not drawing a disability pension, but the difference is not statistically significant. Since there are relatively few deaths for those below 65, we also take another approach in identifying a group that is particularly dependent on the quality of health care. In model 2 we check whether those above age 65 who had drawn on a disability pension in the past have more pro-cyclical mortality than those living to age 65 who were never on a disability pension. This reveals the same main findings—the mortality of those on disability pension is more pro-cyclical than the mortality of those never on disability, but not significantly so. Overall, these results suggest that the mortality of those

[24] Stevens et al. (2011) found that semi-elasticities were close to zero and not statistically different from zero for individuals in their prime working age. But, as we argued above, this is presumably the age group for which recessions tend to result in job losses that are detrimental to health (Sullivan and von Wachter, 2009; Rege et al., 2009; Eliason and Storrie, 2009a). Thus, given that mortality is pro-cyclical for those who remain employed through the recession (and possibly also for those outside of the labor market), such detrimental effects for those who lose their job will attenuate the association on the overall population, particularly in this age group.

[25] We only look at individuals older than 24 and younger than 65, as only a very small proportion of the younger individuals draw disability pensions, and disabled individuals are automatically transferred to elderly pension at age 67.

Table 6: Pro-cyclical mortality of the disabled and employed

	(1) 25-64	(2) 66+	(3) 19-24	(4) 25-44	(5) 45-64	(6) All given ages
Unemployment rate (UR)	-0.0000564*	-0.000320*	-0.00003	-0.00001	-0.00006+	-0.00018**
	(0.0000228)	(0.000160)	(0.00002)	(0.00001)	(0.00003)	(0.00005)
Disabled*UR	-0.000225	-0.000105				
	(0.000148)	(0.000223)				
Non-employed*UR			-0.00003	0.00010*	-0.00023*	
			(0.00003)	(0.00004)	(0.00009)	
Semi-elasticity reference group	-0.0178	-0.0089	-0.0405	-0.0049	-0.0055	-0.0169
Semi-elasticity disabled/non-employed	-0.0820	-0.0089	-0.0836	0.1211	-0.0792	
Observations	63,444,510	14,929,227	9,742,686	33,753,518	27,775,378	125,779,446

Estimation results from OLS regression models (like model 6, Table 3) on individual level data for the association between regional unemployment rates and mortality for given age groups. Models 1-5 include interactions between unemployment rate and disabled or non-employed (measured in t-1). No interactions in model 6, but a dummy for employment status (in t-1) included. Estimates presented as marginal effects with implied semi-elasticities, and adjusted for a rich set of dummies for region, calendar year, age and sex in all models. Standard errors clustered on region. **, * and + indicate significance (two-sided test) at the 1, 5 and 10 percent level.

more dependent on the health-care system is not significantly more pro-cyclical than the mortality of the less dependent.

In models 3-5 we have similarly compared the pro-cyclicality between the employed and non-employed (by age groups 19-24, 25-44 and 45-64).[26] Mortality is generally more pro-cyclical for the non-employed than the employed. Above we reasoned that those being laid off in recessions are likely to have counter-cyclical mortality, which would contribute to lowering the pro-cyclicality in the overall population of employed and non-employed, maybe especially so for groups more likely to be displaced during recessions. In line with this, we note that for men aged 45-64 mortality is more pro-cyclical for the non-employed than for the employed. In model 6 we have taken an alternative approach in exploring whether it is the employed or the non-employed who are hit the most by the business cycles. Here we have estimated the association between mortality and business cycles by *controlling* for employment status (in t-1). Again, controlling for employment status enhances the pro-cyclicality somewhat (compare model 6 of Table 3 with model 6 of Table 6), especially for groups where employment is typically high.[27]

5.5 Pro-cyclical morbidity

Previous authors have suggested that pro-cyclical mortality is just a reflection of a more general pro-cyclicality in morbidity, as we would expect all of the mechanisms we discussed in Section 2 to also affect morbidity. However, there are very few studies on business cycles and morbidity. Ruhm (2013) notes that "[d]ue to limited data availability, few analyses examine how macroeconomic conditions affect morbidity" (p. 1).[28] It is thus important to document that previous findings on mortality carry over to less

[26] We measure employment status in t-1. One reason for this is that we measure employment status at the very end of each calendar year, preventing us from capturing employment status in the calendar year of death.

[27] Moreover, and as we might expect if the unhealthy are less likely to be employed, the estimate for the association between the dummy for the individual's own non-employment and mortality is positive (not reported).

[28] He mentions two exceptions (Ruhm, 2003; Charles and DeCicca, 2008), but later in the paper he concludes that an "important implication" of his analysis is that "findings of some recent investigations of macroeconomic variations in health outcomes or behaviors should be viewed with extreme caution because the analysis periods are too short to provide reliable estimates," and as one example of a study based on such short periods he mentions the analysis of Charles and DeCicca (2008) on male obesity using data from 1997-2001 (p. 17). Ruhm (2003) uses a sample of 217,471 person-year observations surveyed in 1972-1981 from the National Health Interview Survey (NHIS), and finds that respondents reported more medical problem and more "bed-days" when the economy was booming.

Table 7: Pro-cyclical disability by age and gender groups

	(1) All given ages	(2) 18-24	(3) 25-44	(4) 45-64
		Men and women		
Unemployment rate	-0.00053**	-0.00000	-0.00019+	-0.00120**
	(0.00017)	(0.00004)	(0.00010)	(0.00039)
Semi-elasticity	-0.0524	-0.00325	-0.0525	-0.0569
N	64,367,074	10,700,332	30,670,463	21,556,523
		Men		
Unemployment rate	-0.00038*	-0.00004	-0.00018+	-0.00085+
	(0.00017)	(0.00005)	(0.00011)	(0.00046)
Semi-elasticity	-0.0408	-0.0312	-0.0623	-0.0431
N	32,940,562	5,485,406	15,703,921	11,068,030
		Women		
Unemployment rate	-0.00070**	0.00003	-0.00020+	-0.00160**
	(0.00022)	(0.00004)	(0.00010)	(0.00046)
Semi-elasticity	-0.0646	0.0312	-0.0456	-0.0709
N	31,426,512	5,214,926	14,966,542	10,488,493

Estimation results from OLS regression models (like model 6, Table 3) on individual-level data for the association between regional unemployment rates and disability, including only individuals in age groups where disability pension is relevant. Estimated separately within each age and sex subsample. Estimates presented as marginal effects with implied semi-elasticities and adjusted for a rich set of dummies for region, calendar year, age and sex (if estimated together). Standard errors clustered on region. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by **, * and +, respectively.

definite measures of health. Our data allow us to check whether the pro-cyclicality is also present for becoming disabled, obese and being involved in traffic accidents.

Table 7 illustrates the results on the pro-cyclicality of disability pension entry. We have restricted our analysis to individuals in the age range from 18-65, since children (and elderly from age 67) are ineligible, and individuals above 65 can typically retire with other pensions. From model 1 we see that disability entry is pro-cyclical, with an implied semi-elasticity of about 0.5 percent. In contrast to the results for mortality (Table 4), the pro-cyclicality in morbidity increases monotonically with age. The overall results are similar for men and women, but they seem mostly driven by women aged 45-64. This result might be taken to provide some support for mechanisms related to increased workload in economic upturns.[29]

[29]As suggested by Rege et al. (2009), workers of old age respond most to downsizing events by entering a disability pension. Hence, a counteracting effect on disability pension entry rates for individuals experiencing job loss might be less pronounced for in-

In Table 8 we show results on the pro-cyclicality of weight-related indicators of morbidity.[30] Here we only have data on young males at age 18. The results show a consistent pattern of pro-cyclicality of weight, BMI, overweight and obesity. A 1 percentage point increase in the local unemployment rate reduces the BMI by 0.4 percent. This reduction in BMI is similar to the estimates found by Ruhm (2000) for a sample of the U.S. adult population.[31] Moreover, the association between these measures of weight and business cycles is larger for the measures capturing the upper and more morbid tail of the distribution: The semi-elasticity is larger for obesity (0.9 percent) than for overweight (0.5 percent). This is consistent with previous results finding that more unhealthy behavior in upturns is largely due to movements at the intensive, rather than the extensive, margin: Those who already drink or smoke a lot, drink and smoke even more in upturns (Ruhm and Black, 2002; Ruhm, 2005b). Similarly, it might be that those who are already on an unhealthy diet gain even more weight during upturns.[32]

dividuals aged 25-44 than that expected for their mortality rates. Observing pro-cyclical disability pension rates could also reflect a "discipline effect" from the expected cost of being absent from work (Nordberg and Roed, 2009), as the path from employment to disability typically starts with a period of sick leave.

[30]The table also includes two other outcomes. In model 6 we present the association between IQ scores and the business cycle. We see that higher unemployment rates are associated with higher IQ scores, and it is tempting to speculate that this is related to young men putting in more effort in taking the test when unemployment is high. However, the estimated effect is only marginally statistically significant and very small in magnitude. Height cannot be similarly affected by effort, and it is thus reassuring for our applied method that the association between unemployment rates and height is virtually zero and not statistically significant at any conventional levels (model 7).

[31]Using micro-data from the Behavioral Risk Factor Surveillance System, Ruhm (2000) shows that a 1 percentage point increase in the local unemployment rate leads to a 0.6 percent decrease in the BMI for a sample of U.S. adults. Using a sample of working-aged men living in the 58 largest metropolitan areas in the U.S.,Charles and DeCicca (2008) find that weight is counter-cyclical for African-Americans and less-educated males as well as for individuals with low predicted employment probabilities. For the full sample of individuals, they see no relationship between weight and the local unemployment rate.

[32]Obviously, we are not suggesting that the pro-cyclicality in mortality that we observe for young men (see Table 4) is directly explainable by our findings of pro-cyclical obesity. It does reflect, however, that aside from mortality, other and less definite measures of health are affected by business cycles. But to the extent that our findings of pro-cyclicality in excess weight for men at age 18 carries over to other parts of the population (as indicated by the findings of Ruhm (2000)), weight gained in upturns can affect mortality. Stevens et al. (1998) show that excess body weight increases the risk of death from cardiovascular diseases and other diseases for individuals aged 30-74.

Table 8: Pro-cyclical obesity

	(1) Ln(Weight)	(2) Ln(BMI)	(3) Underweight	(4) Overweight	(5) Obesity	(6) Ln(IQ)	(7) Ln(Height)
Unemployment rate	-0.00440**	-0.00417**	0.00260*	-0.00865*	-0.00313+	0.00492+	-0.00011
	(0.00152)	(0.00152)	(0.00100)	(0.00348)	(0.00163)	(0.00284)	(0.00017)
Semi-elasticity			0.0433	-0.0541	-0.0894		
Mean	72.51	22.40	0.06	0.16	0.035	5.13	179.81
Standard deviation	12.08	3.37	0.24	0.37	0.185	1.77	6.49
Observations	824,831	824,831	824,831	824,831	824,831	798,740	824,831

Estimation results from OLS regression models (like model 6, Table 3) on individual-level data for the association between regional unemployment rates and given measures of weight (in kg), BMI (weight in kg divided by squared height in meters), underweight (BMI<18.5), overweight (BMI>25), obesity (BMI>30), IQ (Stanine) and height (meters). Data only available for men at age 18. Estimates presented as marginal effects with implied semi-elasticities and adjusted for a rich set of dummies for region, calendar year and age. Standard errors clustered on region. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by **, * and +, respectively.

5.6 Pro-cyclical traffic accidents

More traffic is a typical sign of a booming economy. This implies that more people are on the road, with an associated rise in the population at risk of being involved in a traffic accident. More traffic would also result in more congestion in areas with heavy traffic, and congestion may by itself raise the risk of accidents. Alternatively, higher income during economic upturns could increase drinking and drunk driving (Ruhm, 1995). Along these lines, there has been a consistent finding across several previous studies that traffic-related mortality is pro-cyclical. Most previous studies, however, have only looked at fatalities, while we, along with Ruhm (2013), also have data for analyzing non-fatal traffic accidents. Moreover, our data allow us to investigate whether the accident happened in a densely or non-densely populated area. If traffic accidents are pro-cyclical because of more congested roads, then we should expect that this is most pronounced for accidents accruing in densely populated areas.

From the upper panel of Table 9 we see that traffic accidents are pro-cyclical for adults in densely populated areas. Results are generally similar for men and women, although typically somewhat more pro-cyclical for men than for women (separate results for men and women are not reported). The semi-elasticity is particularly large for those aged 18-24, where it is 8 percent.[33] In non-densely populated areas, however, there is no pro-cyclicality in traffic accidents (second panel of Table 9), and for some age groups there are even signs that it is counter-cyclical. Again, results are similar for men and women (results are not reported).[34]

These differences between densely and non-densely populated areas suggest that it is not necessarily just the increase in the population at risk of being involved in traffic accidents that co-varies with the business cycles, but the congestion that more traffic involves in areas where the traffic is always heavy that result in more accidents.

[33] This might be related to a positive association between income and the propensity to undertake risky behavior, like drunk driving (Ruhm, 1995). If this propensity is negatively correlated with education level, we would expect the pro-cyclicality to be larger for those with low education. We have investigated this and find a small and insignificant association between unemployment rates and traffic accidents for the young (age 19-24) who have completed high school (2 percent). For high-school dropouts, however, the pro-cyclicality is significantly larger (5 percent).

[34] In general, these results are reflected in additional analyses (results are not reported) on traffic fatalities, but for fatalities there are very few observations in some groups. In densely populated areas fatalities are pro-cyclical, especially so for young adults (18-24). In non-densely populated areas, fatalities tend to be counter-cyclical, especially for children and women.

Table 9: Pro-cyclical traffic accidents by population density of area

	(1)	(2)	(3)	(4)	(5)	(6)
	All Ages	0-17	18-24	25-44	45-64	65+
Densely populated areas						
Unemployment rate	-0.00006*	0.00001	-0.00028**	-0.00009+	-0.00005**	-0.00003*
	(0.00003)	(0.00001)	(0.00009)	(0.00005)	(0.00002)	(0.00001)
Semi-elasticity	-0.0504	0.0136	-0.0795	-0.0568	-0.0458	-0.0453
Observations	121,965,127	27,769,182	11,368,711	33,785,871	27,822,105	21,219,258
Non-densely populated areas						
Unemployment rate	0.00004	0.00004+	-0.00005	0.00001	0.00006+	0.00006**
	(0.00003)	(0.00003)	(0.00013)	(0.00005)	(0.00003)	(0.00002)
Semi-elasticity	0.0206	0.0589	-0.00870	0.00417	0.0330	0.0548
Observations	121,965,127	27,769,182	11,368,711	33,785,871	27,822,105	21,219,258

Estimation results from OLS regression models (like model 6, Table 3) on individual-level data for the association between regional unemployment rates and traffic accidents in densely and non-densely areas. Estimates presented as marginal effects with implied semi-elasticities and adjusted for a rich set of dummies for region, calendar year, age and sex. Data on traffic accidents in 1979 were missing. Standard errors clustered on region. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by **, * and +, respectively.

5.7 Migration and earnings

As mentioned in Section 2, associations of pro-cyclical mortality could be affected by the business cycle's effect on migration if the mortality of migrants differ from that of non-migrants. Using individual-level data we can explore if migration is affected by the business cycle. Results on the association between unemployment rates and migration between municipalities are presented in Table 10. Although there are some signs of pro-cyclical migration for young adults, the association between unemployment rates and migration is generally weak. Thus, it appears unlikely that health-related migration flows are an important factor behind the pro-cyclical mortality observed in regional data.

Ruhm (2000) shows that controlling for the mean income of the state has little impact on the estimated pro-cyclicality of almost all causes of death. On the other hand, he shows that there is a strong, positive relationship between income and homicides and motor vehicle fatalities. Since income is likely to be pro-cyclical, especially among young adults, and if higher income is associated with more risky behavior, again particularly for young adults, this might help explain why mortality rates are particularly pro-cyclical for them. In Table 11 we confirm that earnings are pro-cyclical, and especially so for young men.

5.8 Pro-cyclical mortality across socioeconomic groups

Who are hit by pro-cyclical mortality? Investigating differences across socioeconomic groups in pro-cyclical mortality is interesting for at least two reasons. First, it can provide knowledge on how various socioeconomic groups are affected by the business cycle, and especially whose health is more detrimentally affected. Such knowledge can help identify groups with individuals at risk of dying in economic upturns and downturns. Second, it might shed some light on the mechanisms underlying the effects of macroeconomic conditions on morbidity and mortality. Edwards (2008) investigates such distributional effects by using individual-level data from the U.S. National Longitudinal Mortality Study. He finds scant evidence that disadvantaged groups, such as African-Americans, the unemployed and the disabled, are hit more significantly by pro-cyclical mortality than more advantaged groups. Indeed, he finds strong evidence that those with higher education are hit more strongly by pro-cyclical mortality than those with very low eduction, and in fact, the relation is counter-cyclical for those with very low education. His results thus suggest, if anything, that the

Table 10: Pro-cyclical migration

	(1) All Ages	(2) 0-17	(3) 18-24	(4) 25-44	(5) 45-64	(6) 65+
			All			
Unemployment rate	0.00016	-0.00054	0.00140	-0.00021	0.00008	0.00007
	(0.00019)	(0.00063)	(0.00098)	(0.00037)	(0.00017)	(0.00009)
Semi-elasticity	0.00581	-0.0154	0.0238	-0.00510	0.00790	0.0157
Observations	112,349,047	26,086,446	10,743,137	31,502,039	25,292,207	18,725,218
			Men			
Unemployment rate	0.00004	-0.00050	0.00110	-0.00030	0.00007	0.00001
	(0.00022)	(0.00062)	(0.00070)	(0.00052)	(0.00016)	(0.00009)
Semi-elasticity	0.00158	-0.0146	0.0246	-0.00704	0.00638	0.00284
Observations	55,483,978	13,415,295	5,509,503	16,072,466	12,628,860	7,857,854
			Women			
Unemployment rate	0.00031+	-0.00057	0.00212+	-0.00013	0.00007	0.00012
	(0.00016)	(0.00064)	(0.00116)	(0.00025)	(0.00018)	(0.00010)
Semi-elasticity	0.0109	-0.0163	0.0288	-0.00334	0.00806	0.0275
Observations	56,865,069	12,671,151	5,233,634	15,429,573	12,663,347	10,867,364

Estimation results from OLS regression models (like model 6, Table 3) on individual-level data for the association between regional unemployment rates and migration. Estimates presented as marginal effects with implied semi-elasticities and adjusted for a rich set of dummies for region, calendar year, age and sex (if estimated together). Data on migration only available for the years 1977-2005. Standard errors clustered on region. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by **, * and +, respectively.

Table 11: Pro-cyclical earnings

	(1) All given ages	(2) 18-24	(3) 25-44	(4) 45-64
All				
Unemployment rate	-1692+	-7626**	-1307	-2070**
	(876)	(1590)	(1123)	(544)
Semi-elasticity	-0.00636	-0.0520	-0.00404	-0.00703
Observations	82,175,948	11,756,775	34,762,288	28,682,222
Men				
Unemployment rate	-3218**	-8805**	-2881	-3601**
	(944)	(1583)	(1769)	(789)
Semi-elasticity	-0.00943	-0.0517	-0.00700	-0.00930
Observations	41,594,416	6,030,930	17,743,257	14,365,242
Women				
Unemployment rate	-789	-6984**	-369	-1238*
	(566)	(1954)	(494)	(593)
Semi-elasticity	-0.00418	-0.0573	-0.00159	-0.00615
Observations	40,581,532	5,725,845	17,019,031	14,316,980

Estimation results from OLS regression models (like model 6, Table 3) on individual-level data for the association between regional unemployment rates and earnings. Data on earnings only available for individuals above 18 years for the full analytic period. Estimates presented as marginal effects with implied semi-elasticities and adjusted for a rich set of dummies for region, calendar year, age and sex (if estimated together). Standard errors clustered on region. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by **, * and +, respectively.

more advantaged are hit more strongly by pro-cyclical mortality than the disadvantaged.

But, as carefully acknowledged by Edwards (2008) himself, his data source entails a couple of disadvantages. Aside from not being entirely representative of the overall adult U.S. population, the socioeconomic variables are only measured once for each individual (and at a different ages across individuals). On this background, he restricts his measures of socioeconomic status to variables with little variation over the adult life cycle (birth date, sex, race and education). We have annual data on the entire Norwegian population, enabling us to look at differences in pro-cyclical mortality across socioeconomic groups defined according to age, sex, education, earnings and wealth.[35]

In Table 12 we report results for the differences in the association between unemployment rates and mortality across individuals who have and have not completed high school. When estimated on the overall sample of both men and women in all age groups above 19, we see thatmortality tends to be pro-cyclical for both groups, but in general not significantly so for the high-school dropouts. It is, however, significantly more pro-cyclical for the well-educated group. For the youngest group included (19-24), the results are in the other direction but not statistically significant, which might be related to the fact that a number of those not completing high school at this young age could be finishing it soon (and thus actually be in high school at the time). Mortality for men and women who have completed high school tends to be more pro-cyclical (results by gender are not reported), although having completed high school raises the pro-cyclicality more among men than women.

Turning to Table 13 we report results for the differences in the association between unemployment rates and mortality across individuals who had high and low earnings over the last three years.[36] When estimated on the overall sample of both men and women in all age groups for which we have earnings (20-65), we see that mortality tends to be pro-cyclical for the low earners. It is, however, significantly less pro-cyclical for the high earners. This differential effect across high and low earners is more pronounced for men than for women (not reported).

Table 14 illustrates results for the differences in the association between

[35] Also, recall that in Section 5.4 we looked at differences in pro-cyclical mortality according to employment and disability status.

[36] We split at earnings above/below two "basic amounts"; see Section 4.1. We also tried splitting at median earnings, and these results echo the estimates shown in Table 13.

Table 12: Pro-cyclical mortality across educational groups

	(1)	(2)	(3)	(4)	(5)
	All given ages	19-24	25-44	45-64	65+
	Men and women				
Unemployment rate (UR)	-0.00004	-0.00007*	0.00009+	-0.00003	-0.00032+
	(0.00005)	(0.00003)	(0.00005)	(0.00005)	(0.00016)
Completed high school*UR	-0.00017*	0.00005	-0.00011*	-0.00009	-0.00041*
	(0.00007)	(0.00003)	(0.00005)	(0.00006)	(0.00020)
Mean of mortality, completed high school	0.00581	0.000381	0.000696	0.00417	0.0417
Mean of mortality, not completed high school	0.0202	0.00111	0.00143	0.00673	0.0535
Observations	94,149,566	9,915,228	34,215,913	28,361,906	21,656,519

Estimation results from OLS regression models (like model 6, Table 3) on individual-level data for the association between regional unemployment rates and mortality, with interactions for high-school completion. Data on education missing for a few individuals in a few years, in which case observations are excluded from the analyses. Estimates presented as marginal effects and adjusted for a rich set of dummies for region, calendar year, age and sex. Standard errors clustered on region. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by **, * and +, respectively.

Table 13: Pro-cyclical mortality across groups with high and low earnings

All	(1)	(2)	(3)	(4)
	All Given Ages	19-24	25-44	45-64
Unemployment rate (UR)	-0.00009**	-0.00005*	0.00009*	-0.00025**
	(0.00004)	(0.00002)	(0.00004)	(0.00008)
High Earnings*UR	0.00007+	-0.00002	-0.00010*	0.00019*
	(0.00004)	(0.00004)	(0.00004)	(0.00007)
Mean of mortality, high earnings	0.00212	0.000718	0.000786	0.00402
Mean of mortality, low earnings	0.00476	0.000724	0.00186	0.0105
Observations	71,869,853	8,425,343	34,762,288	28,682,222

Estimation results from OLS regression models (like model 6, Table 3) on individual-level data for the association between regional unemployment rates and mortality, with interaction for individuals' earnings. High earnings is an indicator variable for having mean earnings exceeding two "basic amounts" (see Section 4.1) over the period ($t-1$, $t-2$, $t-3$). Estimates presented as marginal effects and adjusted for a rich set of dummies for region, calendar year, age and sex. Standard errors clustered on region. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by **, * and +, respectively.

Table 14: Pro-cyclical mortality across groups with high and low wealth

	(1)	(2)	(3)	(4)	(5)
	All Given Ages	19-24	25-44	45-64	65+
	Men and women				
Unemployment rate (UR)	-0.00023**	-0.00005*	-0.00000	-0.00020**	0.00000
	(0.00004)	(0.00002)	(0.00001)	(0.00007)	(0.00030)
High wealth*UR	0.00020*	0.00003	-0.00000	0.00021+	-0.00004
	(0.00009)	(0.00004)	(0.00003)	(0.00011)	(0.00024)
Mean of mortality, high wealth	0.0201	0.000599	0.000960	0.00513	0.0479
Mean of mortality, low wealth	0.0106	0.000753	0.00106	0.00639	0.0562
Observations	93,704,832	8,425,343	34,762,288	28,682,222	21,834,979

Estimation results from OLS regression models (like model 6, Table 3) on individual-level data for the association between regional unemployment rates and mortality, with interaction for individuals' wealth. High wealth is an indicator variable for having strictly positive mean wealth in the time period $t-1$, $t-2$ and $t-3$. Estimates presented as marginal effects and adjusted for a rich set of dummies for region, calendar year, age and sex. Standard errors clustered on region. Significance (two-sided test) at the 1, 5 and 10 percent levels are indicated by **, * and +, respectively.

unemployment rates and mortality across wealthy and non-wealthy individuals (split at strictly positive net wealth over the last three years).When estimated on the overall sample of both men and women above age 20 (for which we have wealth data), we see that mortality tends to be pro-cyclical for those with low wealth, while there is no clear association for the wealthy individuals. The difference is statistically significant. The differential effect in pro-cyclicality between the wealthy and the non-wealthy is especially pronounced for men above the age of 45 (results not reported).

In line with Edwards (2008) we find that socioeconomically vulnerable groups, such as those with low earnings and wealth, have more pro-cyclical mortality rates than the less vulnerable. As for level of education, we find more pro-cyclical mortality rates for the well-educated. This might reflect the fact that the socioeconomically vulnerable groups, as measured by earnings and wealth, have poorer health, while there is no similar health selection for education. Alternatively, it might be an issue of reverse causality if those of poor health earn less and thus obtain less wealth. We take this to suggest that mechanisms behind the association diverge for the well educated on the one hand and those of low earnings and wealth on the other.

6 Conclusions

The main contributions of our analysis are as follows: First, we provide clear evidence of pro-cyclical mortality for a country with one of the world's most generous welfare systems. This is interesting since it casts doubt on previous arguments that a strong welfare regime can moderate the business cycles' impact on mortality (Gerdtham and Ruhm, 2006).

Second, we follow previous methods on regional data and perform individual-level analyses on the exact same population. Importantly, we find that the estimated pro-cyclicality is highly sensitive to the aggregation of the typically included demographic controls. Indeed, our estimated semi-elasticity more than doubles when we substitute the traditional regional-level controls for demographic co-variates with a rich set of dummies. While several previous authors have been arguing for including demographic controls flexibly (e.g. Ruhm 2013), our finding suggests that this is critical.

Third, we are able to document that not only mortality, but also less definite measures of health deterioration, are pro-cyclical. Previous authors have suggested that pro-cyclical mortality is just a reflection of a more general pro-cyclicality in morbidity, as we would expect all of the mechanisms we discussed in Section 2 to also affect morbidity. However, there are very few studies on business cycles and morbidity (Ruhm, 2013). We look at the associations between unemployment rates and disability, obesity and traffic accidents, and it is reassuring that we find pro-cyclical patterns for these measures of morbidity too.

Fourth, with individual-level data we are also able to clearly define a number of subgroups, such as the disabled, for whom we expect some of the mechanisms to operate with greater strength. However, such subsample analyses make obvious the underlying problems involved in giving the associations between business cycles and mortality a causal interpretation (in an experimental sense, cf. e.g. Angrist and Pischke 2009). So, although our subsample analyses advances similar analyses in previous studies on regional data, we find it surprisingly unclear what we really learn from them. This might suggest that traditional micro-studies where the aim is to estimate causal effects are important in deepening our understanding of the mechanisms behind pro-cyclical mortality and morbidity. Several such studies have documented negative effects of job displacement on morbidity and mortality (Sullivan and von Wachter, 2009; Rege et al., 2009; Eliason and Storrie, 2009a). From the perspective of this micro-strand of the literature, however, the macro-level findings of pro-cyclicality should be a reminder that findings on subsamples for whom credible identification of causal effects are available may not at all be the subsample of most importance to society. For example, the results of our study, which line up with results of several influential previous studies, indicate that the negative effects of business cycles on displaced workers are not at all the whole story about health effects of economic fluctuations, and probably not even the most important one.

Finally, and related to the findings for the disabled and the non-employed, we study how pro-cyclical mortality hits socioeconomic groups differently. Knowing whose health is more correlated with macroeconomic conditions can help identify vulnerable groups, and it might also shed light on the relevance of suggested mechanisms. For data reasons, such heterogeneity in pro-cyclical mortality has been hard to investigate in previous studies.[37] We look at differences across education, earnings and wealth, and pro-cyclicality differs across these measures. For education, pro-cyclicality is more of a phenomenon among the advantaged than the disadvantaged, while for earnings and wealth, it is more of a phenomenon among disad-

[37]As discussed in Section 5.8, Edwards (2008) is a notable exception. He considers differences across educational groups.

vantaged than the advantaged. This result could simply be related to less health among those with low earnings and less wealth, while the relation between education and health is less clear.

Overall, our results underline a couple of areas for further exploration to better understand the association between health and macroeconomic conditions. The emerging evidence that pro-cyclicality is more pronounced among the well educated, along with some micro-studies showing that events associated with recessions have detrimental health effects on disadvantaged groups, may suggest that it is rather the excess prosperity of good times than the difficulties of recessions that result in the negative correlation between business cycles and health.[38] This might also be considered in line with previous findings that those who already consume a lot of alcohol, food and tobacco are hit most detrimentally by economic upturns (Ruhm, 2005b). Some of our findings point in the same direction: Pro-cyclicality is more pronounced for those who are obese than simply overweight; traffic accidents are pro-cyclical in areas where traffic is already heavy; and mortality of those dependent on health services are more pro-cyclical than for others. It thus seems like pro-cyclicality tends to occur for individuals who are already at risk of deteriorated healthy or in areas close to full capacity or congestion, in which a further pressure shows up as deterioration in health.

The propensity to undertake deviant or risky behavior may also vary with macroeconomic conditions. If such behaviors, like drunk driving, speeding and binge drinking, are positively associated with liquidity, this could also underlie the pro-cyclicality. As with Ruhm (2000) and Stevens et al. (2011), we also find that mortality is most pro-cyclical for young men (particularly for high-school dropouts), and we also find that young men's earnings are most responsive to the business cycle. To the extent that young men are more willing to undertake risky behaviors, analyses on the variation in the undertaking of risky behavior across the business cycle may help in understanding why pro-cyclicality is so large for this group. Overall, the observed associations between mortality and macroeconomic conditions seem to stem from a myriad of diverging mechanisms.

[38]Following the procedure of Mocan and Bali (2010), we did run a model allowing for different associations between mortality in economic upturns and downturns. We found, however, no significant differences.

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Appendix

A Aggregated Causes of Death

Based on the ICD10 Chapters, Statistics Norway uses the following aggregates. ICD10 codes in parenthesis.

Code = Short text

00 = Deaths from diseases (A00-R99)

01 = Infectious and parasitic diseases (A00-B99)

06 = Cancer (C00-D48)

25 = Hematological diseases, disorders in immune system (D50-D89)

26 = Endocrine, nutritional and metabolic diseases (E00-E90)

28 = Mental and behavioral disorders (F00-F99)

31 = Diseases in the nervous system and sense organs (G00-H95)

33 = Cardiovascular diseases (I00-I99)

37 = Diseases in the respiratory system (J00-J99)

42 = Diseases in the digestive system (K00-K93)

45 = Dermatological diseases. (L00-L99)

46 = Diseases in the musculoskeletal system/connective tissue (M00-M99)

48 = Diseases of the genitourinary system (N00-N99)

50 = Pregnancy, childbirth and the puerperium (O00-O99)

51 = Certain conditions originating in the perinatal period (P00-P96)

52 = Congenital malformations, deformations, chromosomal abnormalities (Q00-Q99)

55 = Symptoms, signs and abnormal clinical and laboratory findings(R00-R99)

58 = Accidents, falls and poisoning (i.e. external causes) (V01-Y89). We have used subcategories as defined by the European shortlist as follows:

......Accident fall and poisoning (European shortlist categories 61 and 62)

......Suicide (European shortlist category 63)

59 = Accidents (V01-X59, Y85-Y86)

59b = Other causes of external mortality (X60-Y84, Y87-Y89)

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