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Socio-Economic Status, Health Shocks, Life Satisfaction and Mortality: Evidence from an Increasing Mixed Proportional Hazard Model

Paul Frijters*, John Haisken-DeNew and Michael A. Shields*****

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*Research School of Social Sciences, Australian National University, Canberra, Australia, **RWI, Essen, Germany, ***Department of Economics, University of Melbourne, Melbourne, Australia

ABSTRACT

The socio-economic gradient in health remains a controversial topic in economics and other social sciences. In this paper we develop a new duration model that allows for unobserved persistent individual-specific health shocks and provides new evidence on the roles of socio-economic characteristics in determining length of life using 19-years of high-quality panel data from the German Socio-Economic Panel. We also contribute to the rapidly growing literature on life satisfaction by testing if more satisfied people live longer. Our results clearly confirm the importance of income, education and marriage as important factors in determining longevity. For example, a one-log point increase in real household monthly income leads to a 12% decline in the probability of death. We find a large role of unobserved health shocks, with 5-years of shocks explaining the same amount of the variation in length of life as all the other observed individual and socio-economic characteristics (with the exception of age) combined. Individuals with a high level of life satisfaction when initially interviewed live significantly longer, but this effect is completely due to the fact that less satisfied individuals are typically less healthy. We are also able to confirm the findings of previous studies that self-assessed health status has significant explanatory power in predicting future mortality and is therefore a useful measure of morbidity. Finally, we suggest that the duration model developed in this paper is a useful tool when analysing a wide-range of single-spell durations where individual-specific shocks are likely to be important.

Keywords: income, education, marriage, life satisfaction, shocks, mortality, duration analysis

JEL Classification: I1, C23

1. Introduction

The relationship between socio-economic characteristics and health, and the causal pathways underlying such a relationship, continues to be a widely debated topic by economists and other social scientists (see Adda et al., 2003; Adler et al., 1994; Benzeval and Judge, 2001; Case, 2001; Ettner, 1996; Smith, 1999; van Doorslaer et al., 1997). As noted by Deaton and Paxson (1998), "There is a well-documented but poorly understood gradient linking socio-economic status to a wide range of health outcomes". Economists have recently contributed to the untangling of the gradient by using large household panel data sets, exogenous variations in income and/or dynamic econometric techniques to attempt to more firmly establish if income changes do causally affect adult morbidity. Importantly, all the evidence so far suggests that any such causal effect is weak and quantitatively small in magnitude (see, for example, Adams et al., 2003, and Meer et al., 2003, for US evidence; Contoyannis et al., 2004, for the UK; Frijters et al., 2005, for Germany; and Lindahl, 2005, for Sweden). This is despite it being reasonable to think that higher income could be used to 'buy' a better lifestyle through greater leisure opportunities and improved nutritional intake, fewer financial worries, better access to medical services and an improved living environment through better housing and the ability to move to more prosperous neighbourhoods.

A second strand of the literature has focused on the role of socio-economic characteristics in determining length of life. Two of the pioneering studies on this topic were the first and second Whitehall studies of Marmot et al. (1984, 1991), which found that men working in the lowest grades of the British civil service were observed to have death rates significantly higher than those in the highest grades. In this paper, we aim to shed further light on this important issue by developing and estimating a duration model that accounts for individual-specific health shocks, which we apply to high-quality household panel data. So far the studies that have used such data have found mixed results. For example, while Gerdtham and Johannesson (2004) found an important role for income in explaining variations in longevity in Sweden using a Proportional Hazard (PH) model, Gardner and Oswald (2004) found no such role when estimating a binary probit model of mortality with lagged income using data from the British Household Panel Survey. However, both studies confirmed previous findings of a positive relationship between marriage and longevity, and between education and longevity. A detailed review of the earlier literature can be found in Gardner and Oswald (2004), but it appears that there is still little consensus about the quantitative importance of socio-economic characteristics in explaining mortality.

In addition to investigating the roles of income, education and marriage, conditioning on initial health status and measures of wealth, we provide new evidence on the importance of individual-specific health shocks in determining length of life. We also provide what we believe is a novel contribution to the rapidly growing literature on life satisfaction and happiness (see Oswald, 1997; Frey and Stutzer, 2002; Frijters et al., 2004, for reviews), by testing if individuals with higher life satisfaction live longer independent of their socio-economic status. This question also indirectly relates to the small recent medical literature that finds that more optimistic people have a better survival rate following certain chronic illness such as cancer (see, for example, Allison et al., 2003). However, the evidence on this issue is mixed (see Schofield et al., 2004). We are also able to contribute to the debate about the usefulness of self-assessed measures of morbidity, by testing whether or not such measures are strong predictors of future mortality (see Idler and Angel, 1990; Idler and Benysmini, 1997; van Doorslaer and Gerdtham, 2003).

We address these issues using 19 waves of high-quality panel data on around 26,000 individuals followed in the German Socio-Economic Panel (GSOEP) over the period 1984 to 2002. Important for our analysis, is the fact that when individuals drop-out of the GSOEP panel, information is collected on the reason, which allows us to identify around 2,400 individuals who died in this period. We introduce a new duration model that we call the "Increasingly Mixed Proportional Hazard Model" (IMPH), which allows for unobserved heterogeneity that increases over time due to unobserved persistent health-related shocks. We argue that the assumptions underlying the IMPH model are superior to the often used Mixed Proportional Hazard Model (MPH) in the context of modelling length of life, and find strong evidence that health shocks explain a large part of the variation in longevity. We also suggest that the IMPH model is a useful tool for modelling a wide range of single spell duration applications in economics and the social sciences where individual-specific persistent shocks are likely to be important e.g. duration of unemployment or duration to bankruptcy.

In Section 2 we describe our data, define the main variables used in the analysis and provide some preliminary statistics. We introduce our modelling framework in Section 3, and the corresponding results are discussed in Section 4. Conclusions are drawn in Section 5.

2. Data and Sample Properties

To provide new evidence on the roles of socio-economic characteristics and life satisfaction on the duration of life we use high-quality data drawn from 19 waves of the German Socio-Economic Panel (GSOEP) between 1984 and 2002. The GSOEP is a nationally representative household panel that follows a large sample of adults (living in some 7,000 households) each year since 1984. In 1990, the year of German reunification, the panel was extended to include residents of the former East Germany. As with any panel survey, the GSOEP suffers from attrition with individuals dropping out of the panel for a variety of reasons. In order to maintain the nationally representative nature of the data, each year new individuals enter the panel for the first time. For those individuals that move home, the GSOEP is very successful in following them up. Importantly, in the context of this study, information is collected from other household members if an individual has died in the past year, and if this is not possible, this information is obtained from neighbours or from the official death register.

In this paper, we use the full sample of adults in East and West Germany observed in all the currently available waves of the GSOEP. This comprises 26,401 individuals age over 15, for which we have 223,723 observations. The average number of years in the panel is 8.47. The average age of the sample is 44.5 years, 48.8% of respondents are male, 79.9% reside in West Germany and the average real monthly pre-tax household income is 3,949DM. Household income has been deflated by the OECD main economic indicators consumer price index (base year 1995).

Of the 26,401 individuals we observe, 2,400 died over this period implying a mortality rate of 9.1%. Unfortunately, data is not collected on cause of death. The youngest death we observe is at age 19 and the oldest death at age 105, with an average age of death of 73 (71 for males, 76 for females). Figure 1 shows the hazard of death by age. The likelihood of mortality is very small in Germany up until the age of about 45, then increases gradually between ages 45 and 75, followed by a steep gradient thereafter. However, the raw data clearly suggests that income plays an important role in determining survival rates. This is highlighted in Figure 2, where separate hazard of death by age are shown for individuals with an initially observed real pre-tax monthly household income above and below the sample mean value. While there is little difference in the death hazard by income for individuals aged less than 60, individuals initially observed with below mean income have a higher chance of death between ages

Figure 1:
Death Hazard by Age

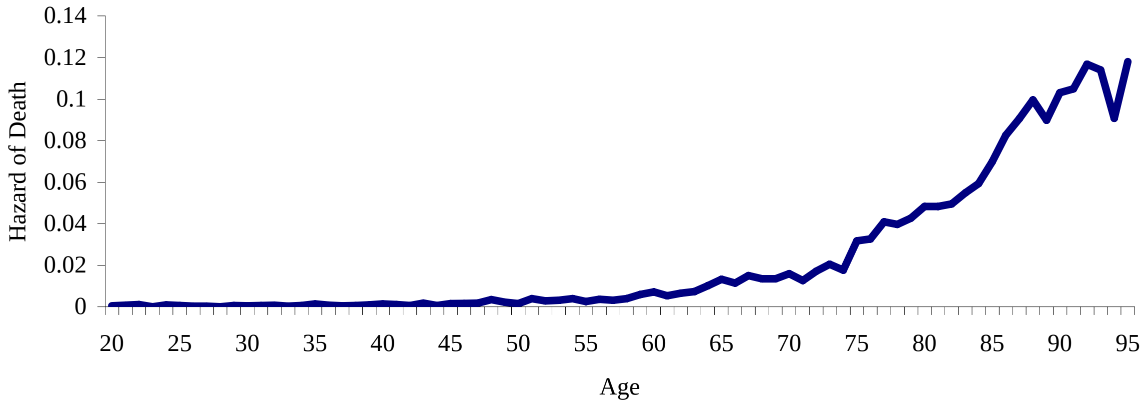

Figure 2:
Death Hazard by Age and Initial Income
(Smoothed 3-year moving average)

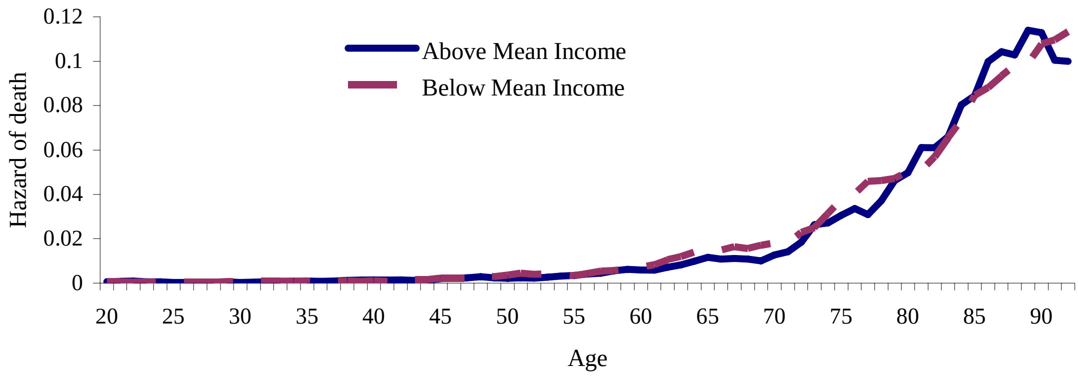

Figure 3:
Death Hazard by Age and Initial Life Satisfaction
(Smoothed 3-year moving average)

60 and 80. Interestingly, the converse is the case for those with low incomes who survive until at least 85, although the sample sizes for the most elderly are small.

Finally, Figure 3 shows the relationship between initially observed life satisfaction and the hazard of death. Although there appears to be no difference across high and low satisfaction up until the age of about 74, individuals who report low life satisfaction (i.e. <8 on a 0-10 scale) have a higher likelihood of death at each age above 74. Therefore there is some evidence from the raw data that more satisfied individuals live longer.

3. Empirical Models

In this section we outline our empirical strategy by first describing one of the most widely used duration analysis models by economists, namely, the Mixed Proportional Hazard Model (MPH). We then introduce a new extension to this model, which we have called the "Increasing Mixed Proportional Hazard Model" (IMPH), and then contrast the underlying assumptions of the two models. We suggest that the IMPH model is a useful new tool for modelling a wide-range of single-spell durations in economics when cumulative individual unobserved shocks are likely to be important and/or when the researcher observes a lot of information about respondents in the initial interview but little thereafter.

(i) The MPH Model

In the literature on single-spell duration hazard models to date, the Proportional Hazard (PH) model, and its extension to allow for unobservable heterogeneity, the Mixed Proportional Hazard (MPH) model, have been by far the most popular. The MPH takes the form:

$$\theta(t \mid \lambda, x) = \lambda z'(t)\phi(x) \tag{0.1}$$

where x is a set of observable characteristics, θ is the hazard rate at duration t, $z'(t)$ is a continuous baseline function, and $\lambda > 0$ is a fixed unobservable characteristic. Van den Berg (2001) provides an extensive survey of the various applications of this model, for which the durations under scrutiny not only include the length of life, but also include the length of unemployment, the length of business solvency, the length of wars, the length of time until first child and the length of time until a stock market crash. This model is identified under a certain set of assumptions, including the assumptions that λ and x are independent and that $E(\lambda)$ is finite (see Elbers and Ridder, 1982; Heckman and Singer, 1984; Ridder, 1990; and Heckman, 1991). Various recent extensions deal with the cases where there are multiple durations (Honoré, 1993; Frijters, 2002), and a combination of multiple and competing durations (Abbring and Van den Berg, 2003). However, the basic building block of any individual hazard remains the same i.e. multiplicativity in the various components of the hazard and some observed characteristics (time varying or not) that are not related to λ.

The treatment of unobservables in this model is unusual for a time-series model. The MPH model essentially includes the presence of three unobservable components. The first unobservable component is the fixed individual one (λ). The second component stems from the fact that even conditional on observables and λ, the model does not specify an observed event, but only a hazard rate of an event occurring which implicitly means that other time-varying unobservables (whose distribution is constant) determine whether a transition is made or not. One can call these 'incidence unobservables'. The third and more hidden unobservable component is the baseline function $z'(t)$: duration itself is not a directly meaningful variable and merely proxies for other time-varying variables. When researchers discuss the hazard to first-time unemployment for instance, the baseline function is sometimes interpreted as picking up discouragement, stigma and time-varying benefit entitlements (see Van den Berg, 2001). When researchers discuss the hazard to death, where the baseline depends on age, the baseline function is interpreted as picking up health deterioration. The baseline function should therefore more properly be understood as a common time-varying unobservable.

However, having only common time-varying unobservables is clearly implausible in most practical applications in economics. In time-series analyses it is normal to have cumulative unobserved shocks over time. In the case of wage changes for instance, an unobserved promotion leading to a wage increase is not usually reversed the next period, but is a permanent wage change. In the case of first-time unemployment also, some time-varying unobservables (such as benefit entitlements or motivation) are subject to individual-specific persistent shocks. In the case of the hazard to death, unobserved time-varying cumulative health deterioration occurs but is not the same for all individuals. We thus argue that it is more natural to assume that time-varying unobservables have a distribution over the population and are cumulative, leading to an individual-specific path in the time-varying unobservables rather than a common path.

(ii) The Increasingly Mixed Proportional Hazard Model (IMPH)

The main limitation of the MPH model in the context of modelling longevity is that it places an unduly large emphasis on unobserved health differences at some starting point, whilst paying no attention to the potentially much greater issue of unobserved cumulative individual health deteriorations.

We therefore propose the following model to deal with this limitation:

$$\begin{gathered} \theta(t \mid \lambda_t, x) = f(\lambda_t) z'(t) \phi(x) \\ \lambda_t \sim N(0, t) \end{gathered} \tag{0.2}$$

which has both common time-varying unobservables (in $z'(t)$) and an individual time-varying unobservable, λ_t. This unobservable is defined to have expectation 0 over the whole population (surviving and not-surviving) at any time, and follows a Wiener process, also known as a random walk or a unit root process. It can be understood as the accumulation of smaller iid shocks over time and captures the permanent health shocks that are such a pervasive aspect of real life.[1] In our empirical application we will only consider the function $f(\lambda_t) = e^{\sigma\lambda_t}$ but will discuss identification for the more general case where f(.) is a positive monotonically increasing function. However, the problem of identification arises in this model because individuals, who are hit by particularly severe health shocks that increase their hazard rate of dying, are also more likely to leave the stock of the living over time leaving a selective stock of individuals. Therefore, even though for the entire population that starts at *t*=0, $\mathrm{E}(\lambda_t) = 0$ at any age *t*, for those that survive until *t*, $\mathrm{E}(\lambda_t) < 0$. In the Appendix we show that the model with discrete jumps in time (our application) is identified under weak assumptions. We also provide a discussion of the conditions needed for identification of a continuous version of this model.

Importantly, the IMPH model inverts the usual assumption on unobserved heterogeneity: whilst the MPH assumes there to be heterogeneity at the start of the

[1] There are a number of potential extensions and generalizations of this model. One such generalization in a discrete environment is to have an additive process with an unknown distribution of shocks each period.

observation plan which reduces to zero over time because only those with low unobserved heterogeneity remain in the sample, our model assumes that there is zero unobserved heterogeneity at the start of the observation plan (i.e. perfect initial information on hazards) which increases over time due to unobserved persistent shocks. We take the following parameterisation:

$$\begin{aligned} &\phi(x) = e^{x'\beta} \\ &z'(t) = e^{\theta_a} \Longleftrightarrow s_{a-1} \le t < s_a \end{aligned} \tag{0.3}$$

which means β conveys the influence of the observables x; the baseline hazard $z'(t)$ is taken to be a non-parametric step-function of age where we need to estimate the parameters θ_a. We furthermore take age to be discrete (in years), we have as our information set for each individual i some individually-specific starting age t_{i0}, a set of characteristics denoted by X which are observed at some individual-specific calendar time τ_{i0}, and for the subset that has died before the end of our observation plan (ending at calendar time S), we observe age at death T_i. The likelihood of an individual i who still lives at the end of our observation plan (calendar time S) is therefore:

$$\int \prod_{t=t_{i0}}^{t=t_{i0}+S-\tau_{i0}} (1-e^{\lambda_t} e^{\sum \theta_a * (s_{a-1} \le t < s_a)} e^{X'\beta}) dG(\lambda_t, S-\tau_{i0}) \tag{0.4}$$

where we integrate over the distribution of all paths λ_t in the time-interval of length $S-\tau_{i0}$. It is also important to bear in mind that t here denotes age and not calendar time. A computational problem arises when we consider that $G(\lambda_t, S-\tau_{i0})$ is in principle of infinite dimension. If we reduce the dimensionality of λ_t to one where there are discrete shocks each year, then $G(\lambda_t, S-\tau_{i0})$ is still of dimension $S-\tau_{i0}$ and can thus be extremely large. To solve this, we use a simulation method whereby we draw a large number M of possible paths λ_t from the Wiener process and integrate over them. Denote each randomly drawn path j as $\lambda^j = \{\lambda_0^j, \lambda_1^j, .., \lambda_T^j\}$ where T denotes the maximum age

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However, in the continuous case any process with unknown additional shocks will closely resemble a Wiener process when aggregated to discrete time intervals.

observed in the sample. Then, our computed likelihood for someone who remains alive at S equals:

$$\frac{1}{M}\sum_{j=1}^{M}\{\prod_{t=t_{i0}}^{t=t_{i0}+S-\tau_{i0}} (1-e^{\lambda_t^j-\lambda_{t_{i0}}^j}e^{\sum\theta_a*(s_{a-1}\le t<s_a)}e^{X'\beta})\} \tag{0.5}$$

and the likelihood for someone who is observed to die at age T_i equals:

$$\frac{1}{M}\sum_{j=1}^{M}\{\prod_{t=t_{i0}}^{t=T_i-1} (1-e^{\lambda_t^j-\lambda_{t_{i0}}^j}e^{\sum\theta_a*(s_{a-1}\le t<s_a)}e^{X'\beta})*e^{\lambda_{T_i}^j-\lambda_{t_{i0}}^j}e^{\sum\theta_a*(s_{a-1}\le T_i<s_a)}e^{X'\beta})\} \tag{0.6}$$

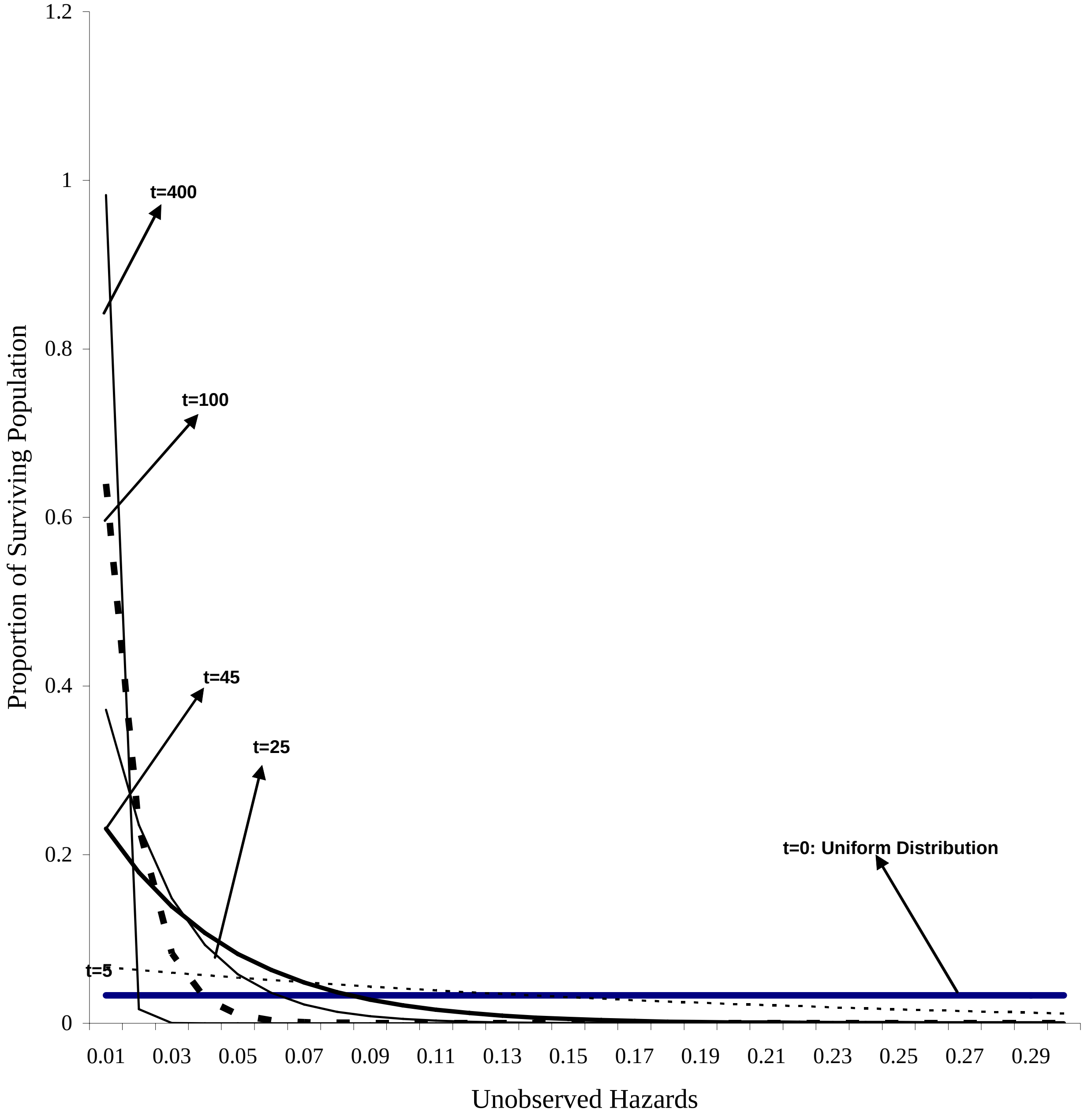
where $e^{\lambda_{T_i}^j-\lambda_{t_{i0}}^j}e^{\sum\theta_a*(s_{a-1}\le T_i<s_a)}e^{X'\beta}$ equals the probability of dying at age T_i. For large enough M, this simulated likelihood approaches the true one. The precision of the approximation can further be increased by reducing the time-interval. Given our data, where individuals are interviewed each year, the natural unit of time is years. In this application, we have found that taking smaller time intervals made only a negligible difference to the main parameters of interest. We undertook a specification search using M=1000, and in a final run used M=2000 and M=5000, neither of which changed the estimated coefficients noticeably or significantly, implying that M=1000 appears to be reasonable in practice.

(iii) Contrasting the MPH and IMPH Models

The basic idea of the IMPH model versus the MPH model can be clearly illustrated by showing how the two models work in a hypothetical case. To focus the discussion on the unobserved heterogeneity distribution, which is the sole item of difference between these two models, consider a case with no observed heterogeneity and no baseline hazard.

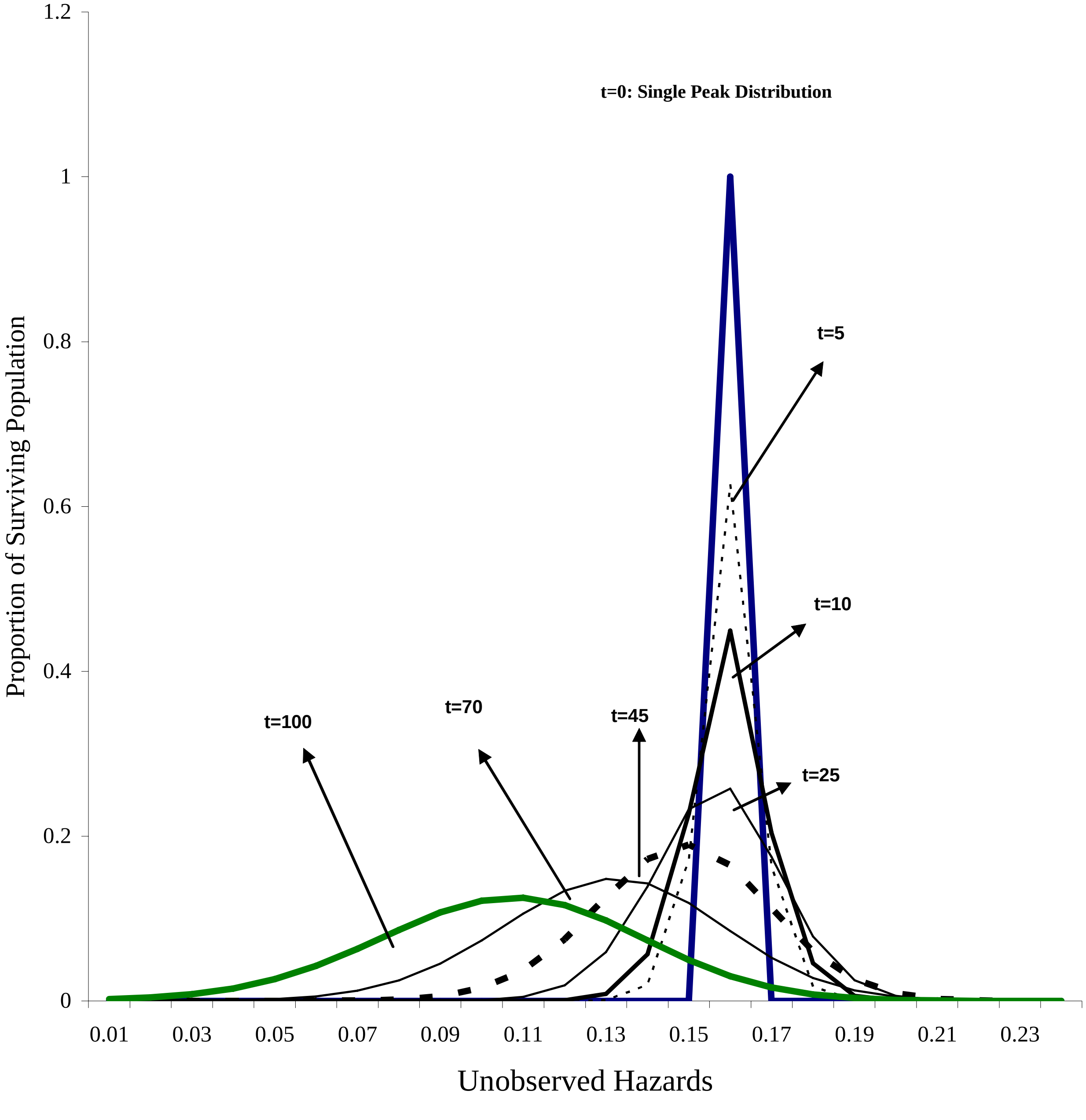
In Figure 4 we have taken a very simple MPH model, where there is only unobserved heterogeneity which at *t*=0 follows a uniform distribution on the points {0.01,0.02,..,0.3}. We can see that at *t*=0 the unobserved heterogeneity distribution is uniform, but over time the distribution becomes more and more tilted to the low hazard rates, until after 400 periods, nearly all individuals surviving in the sample are those with the lowest unobserved hazard rates (i.e. hazards equal to 0.01). This shows a well-known trait of the MPH model, which is that all the ‘high-risks’ (i.e. high unobserved hazards) sort themselves out of the surviving population, leaving only low-risk individuals in the surviving population.

Figure 4:
The Distribution of Unobserved Heterogeneity over Time in the MPH model



Contrast this with the IMPH model. In Figure 5, we take each individual to start with the same hazard rate in the mid-point of the [0.01,0.3] range, but a Wiener process operates on this distribution such that at each point in time, the unobserved heterogeneity

Figure 5:
The Distribution of Unobserved Heterogeneity over Time in the IMPH Model



has an equal chance of going up as well as down.[2] We can see that at *t*=0, the distribution has a single spike and that as time passes, the distribution flattens, until finally, after 100 periods, the unobserved heterogeneity distribution of the survivors follows a bell-type

[2] Our specific assumptions here are that the entire population starts at a hazard rate of 0.16, and that every individual at each point in time has a probability of 90% to keep the same hazard rate, a 5% probability of increasing the hazard rate by 0.01, and a 5% probability of decreasing the hazard rate by 0.01 (except at 0.01 itself).

shape. However, the bell is not perfect with the left tail being thicker than the right tail. This relates to the fact that the mean of the distribution gradually shifts downwards i.e. it is individuals with shocks that make them less likely to leave that survive. The survival of the low-risk groups shown in Figures 4 and 5, which results in a shift in the distribution to the left, is therefore a feature of both the MPH and IMPH models.

One major difference between the MPH and the IMPH models is that the MPH model presumes to know very little about the population at the start of the sampling frame (t=0), but that over time one ‘learns’ more and more about the population in the sense that there is less and less variation in the unobservables and the remaining population is therefore more and more homogeneous. In contrast, the IMPH presumes to know a lot about the population at the start of the sampling frame, but ‘loses touch’ with the population in the sense that there is more and more variation in the unobservables in the surviving population. We argue that for our application the latter presumption is more sensible since the GSOEP asks a whole host of question to respondents, but those who die are often not observed having responded to questions for several years. In fact, for around 40% of those we observe dying, no questionnaires are responded to in any of the five years before death. In such a situation, where one knows a lot about a population at some fixed point in time, but little after that other than who has left the state of interest (in our case, life), we suggest the IMPH model as the logical model to use rather than the MPH model.

The situation where the researcher observes a great deal of information about a population at some point in time, but observes far less afterwards, other than whether some particular event took place, arises often in economics. For example, the unemployed and the disabled are in many data sets asked many questions at the time that they become unemployed or disabled. However, after such an ‘intake-interview’, it is often the case that little is known about the respondent other than whether they leave unemployment or disability. It is very likely that persistent shocks are unobserved for these people e.g. whether they marry, whether they have followed training, whether they have moved house and whether they have been active in voluntary work. The IMPH model is also more appropriate for such situations.

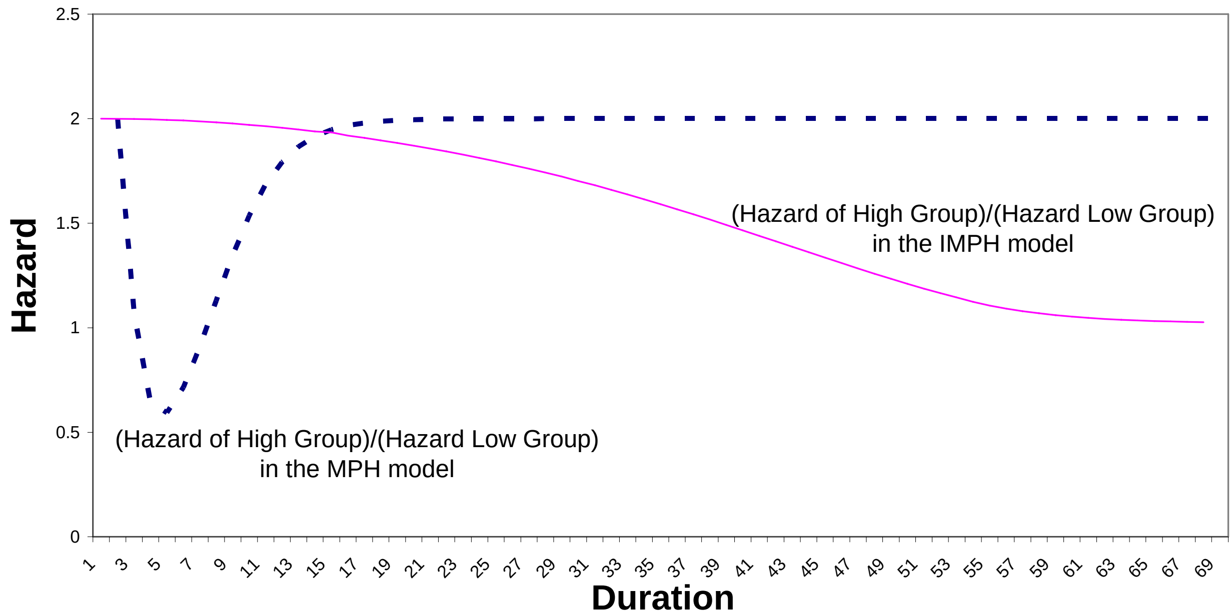
The IMPH model also has other advantages over the MPH model. In particular, the origin of ‘unobserved heterogeneity’ is left unspecified in the MPH model. Unknown factors are presumed to be present before t=0 which have left permanent differences between individuals. These unknown factors are often interpreted in labour market context as upbringing or peer influences. However, once observed in the sample such processes are presumed to have stopped completely i.e. there is nothing that affects individually-varying unobserved factors once the duration of interest begins. Upbringing and peer influences essentially 'stop'. This aspect of the MPH model is often unappealing. If there are unobserved processes at work creating unobserved differences between individuals, then it would seem unlikely that these would happen to stop just because individuals were interviewed or recorded in some other way.

Our model effectively presumes that the outcome of 'unobserved processes' are revealed as specific variables at the start of a sampling period, but that these unobserved processes continue unabated after that and therefore lead to an increase in unobserved heterogeneity.

A legitimate question is to ask 'so what', in the sense of whether there is any good reason to suppose that the MPH model and the IMPH model are in general going to yield different results. We show in this study that they do in terms of the quantitative effect of socio-economic characteristics on mortality. However, the key issue we want to raise in this respect is the identification of the unobserved heterogeneity distribution in the MPH model applied to single spell data. As noted by Elbers and Ridder (1982), the unobserved heterogeneity distribution is identified from the change in the relative hazard between a high-risk group and a low-risk group. To illustrate this, Figure 6 shows a typical profile of the observed relative hazards in a hypothetical environment (again, without any baseline hazard). In this figure we have supposed that there is a group with an observed difference whose true effect on the hazard rate is to double it. Both groups start out with the same unobserved heterogeneity distribution.

The broken line shows the observed relative hazard for the MPH model and the straight line shows the same statistic for the IMPH model. For the MPH model, the relative hazard of the two observed groups (high and low) at the start reveals what the true relative effect is. This is an important observation in the identification of the MPH model, because it is a feature that holds for all possible MPH models. Over time, however, the relative hazard of the high group first declines (possibly even below 1) and then returns again to its initial level. This decline is due to sorting, with those in the high risk group that have high unobserved heterogeneity leaving quickest. This means that within the high-risk group the unobserved heterogeneity distribution changes faster than for the low-risk group. In essence, within the high-risk group, those with low unobserved heterogeneity are very quickly the only individuals remaining, whilst within the low-risk group, this sorting is much slower. This is the reason why the relative hazard drops even though the true effect on the hazard of being in the high-risk group remains 2 over the entire period. The observed relative hazard in the MPH model can even drop below 1, which means that if we do not observe individuals from the start of the period we could easily draw misleading conclusions. Consequently, when the start of the spell is not observed for the entire sample, there is an initial-conditions problem with the MPH model.

Figure 6: How Relative Hazards for Observed Groups Change in the MPH and the IMPH model



For the MPH model this relative hazard profile is not just due to our choice of parameters. Rather, the general profile holds for all MPH models, regardless of the baseline hazard, the observed heterogeneity or the unobserved heterogeneity distribution. There is always a dip followed by a recovery in the relative hazards between the high and low risk groups. However, the exact shape of the profile is of a particular form: it is unique to a particular unobserved heterogeneity distribution and hence identifies the unobserved heterogeneity distribution. Such profiles in empirical practice are therefore used in this way. Baker and Melino (2001) showed that this source of identification is very weak with finite data and that the MPH model for single spells is extremely sensitive to the parameterization of the baseline hazards.

The relative hazards in the IMPH model also start out being correct. However, the profile of the relative hazard is very different to the case of the MPH model. There is still a clear decline in the relative hazard, but it accelerates over time rather than reduces over time. However, as the duration goes to infinity, the relative hazard should always tend to 1, since the relative importance of the initial heterogeneity versus the unobserved cumulative shocks becomes less and less. Therefore, if the IMPH model is correct, the relative hazard of the high risk and the low risk groups has a very different profile from what the MPH model 'uses' to identify parameters and would in general mean that different parameter estimates can be obtained.

We can now look for the empirical equivalent of the relative hazards in Figure 6, by plotting the relative hazards for four key socio-economic variables that we will use in the empirical analyses. These are shown in Figure 7, where we have used 10-year-smoothed hazards to reduce the importance of small numbers of deaths at various ages. This figure shows the ratio of the hazard for groups divided up on the basis of the main observed socio-economic characteristics. These are initial real household monthly income, initial life satisfaction, initial marital status and initial years of schooling. Although it is no more than a casual ocular test, these ratios do appear to tend to 1 as age increases. All the 'action' in the relative hazards is in the age range 35-65, whilst at very high ages, when most initial fixed unobserved heterogeneity should have been sorted out, relative hazard ratios become very close to 1. This provides some tacit support for the IMPH model, which predicts that relative hazards for any variable should tend to 1, in contrast to the MPH model, which predicts relative hazards at high durations to be further from 1 than at intermediary durations.

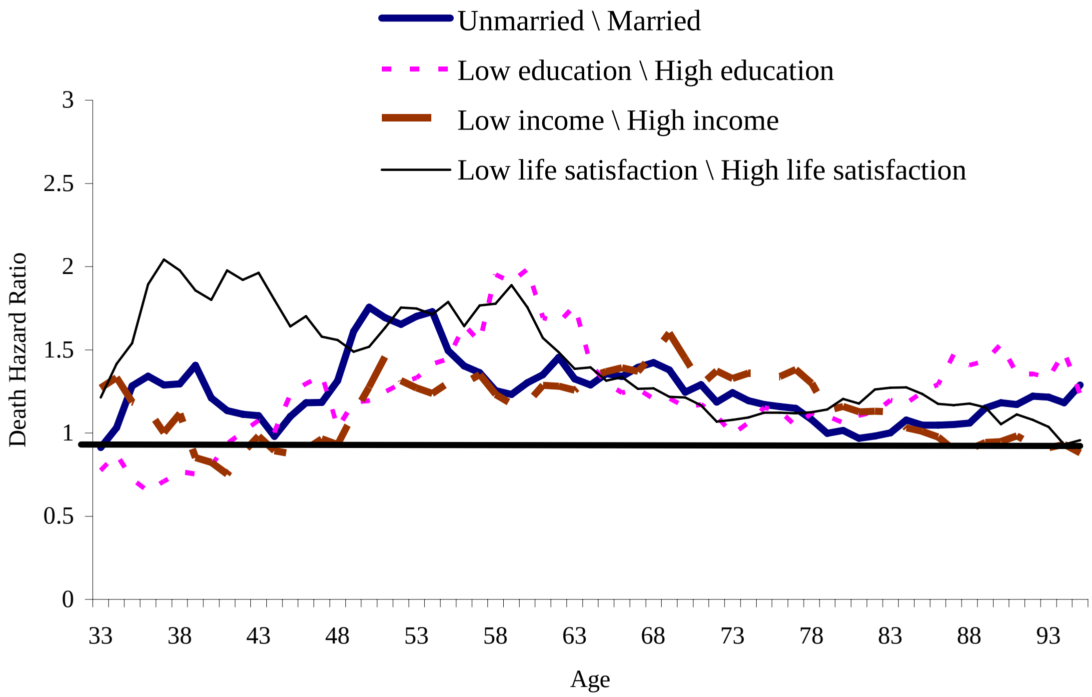
(iv) Relation to biometric hazard models

In the biometric literature, there have also been some attempts at incorporating unobserved Wiener processes into a hazard framework. Yashin and Maton (1997) review that literature and discuss the main type of model that has been implemented empirically:

$$\begin{aligned} &\theta(t \mid Y_t, x) = z'(t) + Y_t^* Q(t) Y_t \\ &\qquad dY_t = f(Y,t)dt + b(t)dW_t \end{aligned} \tag{0.7}$$

where W_t is a Wiener process vector, Y_t^* is the transpose of Y_t which is a vector, and the matrix $Q(t)$ and the function $f(Y,t)$ satisfy some regularity conditions. This model is richer in some dimensions and more restrictive in other dimensions than the IMPH model. It is richer in the sense that it deals with multiple Wiener processes in stead of one. It is more restrictive in the sense that its identification and estimation relies on the additive quadratic formulation of the term $Y_t^* Q(t) Y_t$. In applications, authors presume to be able to (infrequently) measure Y_t, unlike our application where we (apart from the initial condition) presume never to measure Y_t. It's the quadratic form in (0.7) that allows explicit analytic computation of conditional means and variances. The applications which Yashin and Maton (1997) review consist of fitting population-age-mortality profiles where $Q(t)$ is a simple function of age.

Figure 7:
Death Hazard Ratios by Socio-Economic Characteristics and Age



(v) Explanatory Variables

Following the recent studies that have focused on the role of socio-economic characteristics in determining length of life (e.g. Gerdtham and Johannesson, 2003, 2004; Gardner and Oswald, 2004), we control for a wide-range of initial socio-economic and demographic individual characteristics in our models that a priori would be expected to influence longevity. In addition to the powerful mortality predictors of age and gender, it is important for the IMPH model that we comprehensively capture initial differences in health status. We do this in three ways. Firstly, we include a variable indicating the extent of disability (which is reported in terms of percentage disabled in the GSOEP). Secondly, we include a self-assessed measure of general health status which is the level of health satisfaction reported by the individual that is captured on a 0 (very unsatisfied) to 10 (very satisfied) scale. There is some evidence that self-assessed health measures are a powerful predictor of mortality, and a significant predictor of future changes in functioning among the elderly (see, for example, Idler and Angel, 1990; Idler and Kasl, 1995; Grant et al., 1995; and Idler and Benyamini, 1997). Self-reported health satisfaction has also been found to be a good predictor of future health care usage (van Doorslaer et al., 2000). In this paper we are able to test if self-assessed health is also a good predictor of mortality in Germany. Thirdly, we also control for the presence of an invalid in the household (usually a spouse or parent) as we expect that such caring responsibility would be directly detrimental to the health of the carer.

Turning to the economic variables, we control for initial income and wealth, as well as the prosperity of the region of residence. The income measure we include is the log of real pre-tax total monthly household income in 1995 prices. We control for wealth in two ways. Firstly, we control for whether or not the household owns outright or has a mortgage on their home, and conditional on home ownership, an imputed monthly rentable value of the home. Secondly, we control for the amount of asset income the household receives per month.

Importantly, we also include controls for marital status, years of schooling and employment status, all of which we expect, given the results of previous studies, to be significant predictors of mortality. We also control for number of children in the household and whether or not the individual was born outside of Germany. In an attempt to contribute to the recent literature that focused on the potential importance of income inequality on health outcomes (see Gravelle et al., 2001, for a discussion), following Gerdtham and Johannesson (2004) we include a measure of average income by geographical area (region in our case) that is time-varying across our 19-year sample period.

Finally, in order to test whether individuals with high life satisfaction live longer, we control for initial life satisfaction, which in the GSOEP is reported on the familiar 0 (very unsatisfied) to 10 (very satisfied) scale.

4. Empirical Results

Table 1 presents the parameter estimates from PH models using the entire sample, and then separately for East and West Germans. The corresponding results from the MPH and IMPH models using the entire sample are then shown in Table 2.[3] The estimates from the PH models are shown in order to allow for a direct comparison with the results of Gerdtham and Johannesson (2004) for Sweden. Moreover, for our purposes the PH model, which does not control for unobserved heterogeneity, also acts as a useful comparison for the MPH and IMPH models. In this respect, the PH model is nested in the IMPH model since when the variance of λ_t goes to 0, the model reverts to a PH model. This comparison also leads to a natural test of the validity of the IMPH model, namely the Likelihood Ratio Test of the additional value of the extra heterogeneity parameter versus the PH model. The additional Likelihood between the IMPH and the PH model is 91.6 (for the model using the whole sample), which means the *p*-value of the IMPH being statistically 'better' than the PH is in the order of 0.99999. The significance of the increasing heterogeneity can also be deduced from the *t*-value of 12.35 on the log of the standard deviation of λ_t.

In contrast, the MPH model is not nested in the IMPH model, and can therefore not be directly compared by looking at the log likelihood, although we do note that the IMPH has a higher likelihood. Rather, the fit of the MPH model compared to the IMPH model can be based on the Akaike information criterion, which equals $A(k)=-2*L+2k$, where L is the log-likelihood and k is the number of parameters in the models. The lower the score, the better the model fits the data. We can see that according to this criterion the IMPH performs statistically best of all three models (the score of the PH model for the

[3] The MPH model we have estimated specifies the mixing distribution to have mass-points. The results presented in Table 2 allow for 2 mass-points, although we have also estimated this model using more mass-points to test for robustness of the main results (see later text). The assumption on mixing is that the mixing occurs at the moment of entering the panel, which is consistent with the assumption that the fixed unobservables are measurement errors in the initial observed characteristics. A natural alternative to ask is whether it would have made sense to estimate a MPH model where the mixing occurs at birth and would thus denote a fixed unobserved health characteristic? The MPH would then, however, be inappropriate as an empirical comparison to the IMPH for this data, mainly because of the initial conditions problem. That is, under the assumptions of the MPH model, the actual sample when mixing occurs at birth is selective because only the 'good risks' have survived long enough to make it into the sample. To deal with this, one (explicitly or implicitly) has to make assumptions about the entire life history of all sample participants from birth until entry into the sample. This would entail making detailed assumptions about their marriage, health and employment histories, and all other variables that change over time but are not observed before the start of the sample. Comparing the outcome of such an exercise with the outcomes of the IMPH would be meaningless because of these auxiliary assumptions, which is why we have opted to take the PH as an additional empirical benchmark by which to compare the IMPH model. This is also why we only estimate the MPH under the assumption that the unobservables are measurement errors.

whole sample was 21228.3). As a robustness check on the correct number of points of support for the MPH model, we re-estimated the MPH model with three points of support instead of two. This actually led to a lower Akaike information score i.e. the likelihood with three points of support was -10572.34, which comes at the cost of two extra variables.

TABLE 1:

Proportional Hazard Model Estimates of Mortality

	PH					
	All		West		East	
	Coeff.	**|t|-stat**	**Coeff.**	**|t|-stat**	**Coeff.**	**|t|-stat**
Age < 50	-4.121	38.71	-4.173	36.32	-3.717	12.70
49<age<65	-2.511	29.48	-2.575	27.35	-2.103	10.03
64<age<75	-1.601	22.56	-1.581	20.32	-1.702	9.36
74 < age< 85	-0.690	11.62	-0.685	10.65	-0.745	4.71
Male	0.618	12.42	0.610	11.14	0.651	5.16
Married	-0.170	3.34	-0.169	3.05	-0.131	0.93
Number of children	-0.001	0.03	0.012	0.29	0.001	0.01
Foreign-born	-0.708	8.20	-0.716	7.87	0.005	0.02
Years of schooling	-0.040	3.37	-0.036	2.79	-0.076	2.41
% Disabled	0.005	6.21	0.005	6.17	0.003	1.20
Health satisfaction	-0.091	10.46	-0.083	8.89	-0.145	5.71
Invalid in household	0.170	2.37	0.076	0.95	0.529	3.38
Employed	-0.063	0.65	-0.026	0.24	-0.278	1.28
Non-participant	0.194	2.13	0.207	2.00	0.241	1.18
Life satisfaction	0.016	0.52	-0.002	0.07	0.244	1.59
House owner	-0.003	0.53	0.054	0.82	-0.437	2.36
House owner * Imputed rent / 1000	0.001	0.04	-0.001	0.47	0.074	1.12
Asset income / 10000	0.031	0.96	0.028	0.86	0.059	0.20
Log household income	-0.095	2.16	-0.099	2.11	-0.100	0.76
Log Average area income	-0.139	3.25	-0.153	3.41	-0.079	0.64
West Germany	-0.073	1.14				
Sample in observed years	338717		289077		49640	
Number of individuals	25772		20376		5396	
Number of deaths	2236		1878		358	
Mean Log Likelihood per year	-0.031		-0.031		-0.034	

Notes: Absolute t-statistic in parentheses. Omitted categories are female, not married, born in Germany, no invalid in household, unemployed, renter, living in West Germany.

TABLE 2:

Mixed Proportional Hazard and Increasing Mixed Proportional Hazard Model Estimates of Mortality

	MPH		IMPH	
	All		All	
	Coeff.	**|t|-stat**	**Coeff.**	**|t|-stat**
Age < 50	-3.248	37.05	-4.346	34.75
49 <age< 65	-2.671	28.40	-2.777	25.21
64 <age <75	-1.781	21.80	-1.881	18.99
74 < age< 85	-0.867	10.95	-0.899	11.26
Male	0.657	11.97	0.697	12.12
Married	-0.177	3.19	-0.164	2.85
Number of children	-0.006	0.16	-0.022	0.52
Foreign-born	-0.747	8.46	-0.786	8.56
Years of schooling	-0.039	3.15	-0.037	2.90
% Disabled	0.005	6.28	0.005	6.40
Health satisfaction	-0.105	10.95	-0.105	10.37
Invalid in household	0.260	3.35	0.239	3.04
Employed	-0.068	0.70	-0.089	0.87
Non-participant	0.202	2.14	0.241	2.44
Life satisfaction	0.063	1.92	-0.025	0.71
House owner	-0.054	0.80	-0.053	0.75
House owner * Imputed rent / 1000	0.004	0.24	0.001	0.49
Asset income / 10000	0.035	1.05	0.037	1.06
Log household income	-0.121	2.45	-0.130	2.51
Log average area income	-0.546	2.01	-0.105	2.10
West Germany	-0.065	0.66	-0.075	1.07
Log Standard Deviation of Lambda	-		-1.301	12.35
First point of support	1	-	-	
Second point of support	42.45	1.79	-	
Probability of first point	0.128	-	-	
Probability of second point	0.872	5.95	-	
Sample in observed years	338717		338717	
Number of individuals	25772		25772	
Number of deaths	2236		2236	
Total likelihood	-10573.1		-10501.5	
Akaike information criterion	21192.18		21047.05	

Notes: Absolute t-statistic in parentheses. Omitted categories are female, not married, born in Germany, no invalid in household, unemployed, renter, living in West Germany.

(i) Individual-specific health shocks (the IMPH model)

As to the size of the unobserved heterogeneity shocks identified by the IMPH model, the coefficient on the log of the standard deviation of λ_t translates into yearly random shocks that increase or decrease the hazard rate to death by about 27% (=$e^{-1.3}$) per standard deviation. This is a large effect: the difference between the death hazard for an individual aged 40 compared to an 80 year old is about 0.03:1 i.e. an individual aged 80 is per year about 31 times more likely to die than a similar person aged 40. This is equivalent to about 12.6 standard deviations of the unobserved shocks, implying that increasing age from 40 to 80 is the same as experiencing 5 or 6 particularly bad unobserved shocks (slightly above 2 standard deviations). Another way of ascertaining the importance of the unobserved shocks is to reflect on the fact that the standard deviation of non-age effects, by which we mean the standard deviation of the total effect of all other observables on the log-hazard rate, is about 0.592. This is worth 2.2 standard deviations of the unobserved shocks. Importantly, the unobserved health shocks accumulate to have the same variance as all observed factors within 4.73 years. The IMPH model therefore finds strong support for the existence of large individual-specific unobserved shocks over time that impact on the hazard of death.

(ii) Socio-economic determinants of mortality

Despite the clear importance of health shocks in the IMPH model, and differences in the assumptions underlying the three models with regard to unobserved heterogeneity, we find a large degree of consistency in the parameter estimates of the socio-economic factors affecting mortality across the PH, MPH and IMPH models.

The findings for the baseline hazard are entirely as expected with the young having a far lower hazard to death than the old, which we attribute in our modelling framework to unobserved common deteriorations in health (often captured under the banner of ‘ageing’). Moreover, the estimates on the socio-economic characteristics to a large extent confirm our prior expectations, with there being consistent evidence that the death hazard (i.e. the probability of death at any point in time) significantly increases with being male, being disabled, having an invalid in the household and being a non-participant in the labour market, and significantly falls with being married, having more years of schooling, having high initial health satisfaction, having high real household income[4] and residing in

[4] The fact that the effect of household income on the death hazard is roughly the same across both East and

a more wealthy region of Germany (the latter two effects, however, are not significant in the PH model for East Germans). In contrast to income, our wealth indictors are not estimated to be significant predictors of mortality, with the exception of home ownership in East Germany, which is associated with a lower death hazard. This could be due to the limited nature of these measures, but if we take them at face value they would imply that accumulated assets simply ‘buy’ little life expectancy. We find no evidence that mortality is affected by number of children. Contrary to our expectation, being an immigrant in Germany is associated with longer life, but a higher probability of return migration for immigrants who experience health shocks might be driving this result.

Turning to the quantitative effects of the main socio-economic variables in explaining variations in mortality, Table 3 shows the estimated percentage change in the death hazard and the associated change in expected length of life due to increased household income, being married, having higher health satisfaction and having a great number of years of schooling. Here it is important to note that a reduction or increase in the death hazard of a certain percentage does not translate into the same percentage change in expected length of life. This is because a change in the hazard of death interacts with the baseline hazard. For example, having a 10% lower probability of dying when an individual is young, and therefore has an extremely low chance of dying anyway, is going to make very little difference, whereas a 10% higher probability of dying when an individual is very old, and has a high chance of dying per se, is only going to make a 10% difference *within that age range*.

Focusing on the results from the IMPH model, we find that a one-log point increase in real household monthly income leads to a fall in the death hazard of 12.21% and an increase in expected length of life of just under one year (at the gravity point). This important role that income has to play in determining longevity supports the result for Sweden by Gerdtham and Johannesson (2004), but is in contrast to that found by Gardner and Oswald (2004) who estimated a simple probit model of mortality using British data. However, while Gerdtham and Johannesson (2004) found no significant effect of

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West Germany, to some extent provides extra credibility to the income finding since, as we have argued in Frijters et al. (2005), incomes in East Germany can be considered mostly driven by exogenous (non-health related) factors in the years following reunification. Moreover, following Gerdtham and Johannesson (2004) we have tested the robustness of the income result to a number of functional forms and income definitions. For example, we have used household equivalent income adjusted for household size and composition. None of these additional tests changed the result of the significant income effect on mortality. These additional results are available on request.

community or area average income on mortality, we find a significantly positive effect with individual residing in higher income regions, conditional on their own household income, living longer. From the IMPH estimates, we calculate that residing in a geographical area with a one-log point higher average income is associated with a 10% decline in the death hazard, which correspondents to 0.75 years of life. However, the size of this effect is far higher in the MPH model, accounting for about 5 more years of life. The important role of area income could be capturing the direct role that income inequality might have on health, or the fact that richer areas might have better health or public amenities (e.g. such as road safety, less serious crime). It is certainly an important topic for future research.

TABLE 3:

Estimated Effects of Socio-Economic Characteristics of Mortality

	PH	**MPH**	**IMPH**
% Change in death hazard			
Income	9.08	11.38	12.21
Marriage	15.64	16.25	15.14
Health satisfaction	8.71	9.98	9.98
Years of schooling	3.94	3.81	3.66
Area average income	12.96	42.06	9.98
Additional years of life			
Income	1.00	1.12	0.93
Marriage	1.79	1.64	1.17
Health satisfaction	0.96	0.97	0.75
Years of schooling	0.42	0.36	0.27
Area average income	1.46	5.05	0.75
Total socio-economic variation in years of life			
Maximum expected years of life	95.62	96.13	93.61
Minimum expected years of life	44.47	38.53	43.14

Notes: The % change in the death hazard and additional years of life are computed for a one-log point increase in real household monthly income, being married relative to being single, a one-point increase on the 0-10 health satisfaction scale, a one-year increase in years of schooling and a one-log point increase in average area income, respectively (holding all else at the sample means). Total socio-economic variation in years of life shows the maximum expected and minimum expected years of life at the two extremes of the socioeconomic characteristics (calculated at the gravity point of the sample and holding age, gender and immigrant status constant).

Interestingly, the quantitative effect of being married has roughly the same effect as a one-log point increase in household income, being associated with a 15% reduction in the probability of death and living 1.17 more years. Self-assessed health, in the form of health satisfaction, is clearly a good predictor of mortality, with a one point increase on the 0-10 scale leading to a 10% decline in the death hazard. Moving from 5 to 10 on the scale would therefore be associated with a 50% decline in the probability of death and 3.75 more years of life. In fact, it is interesting to note that initial self-assessed health is a stronger predictor of mortality than initial levels of disability. This also provides some additional support to the validity of using self-assessed health measures as indicators of morbidity.

An important policy-related question to ask is what is the size of the estimated mortality differential at the two extremes of the socio-economic characteristics? Holding age, gender and immigrant status constant, we have calculated that an individual who is initially observed in the panel with the worst possible set of observable socio-economic characteristics is expected to live to only 43 years of age, in contrast to an individual with high initial health status, no disability, being married, highly educated, in the top decile of the income distribution and residing in the richest region etc., who would be expected to live to age 94. If we hold age, gender, immigrant status, and health satisfaction and disability constant, then the worst possible set of remaining socio-economic variables would give an expected 59 years of life, and the best set would give 92 years of life. These results clearly support the argument that socio-economic factors are very important in explaining variations in length of life across the population.

(iii) The role of life satisfaction

While the parameter estimate on life satisfaction in the IMPH model is negative, suggesting that individuals who were initially observed in the panel with high life satisfaction have a lower death hazard, it is not statistically significant. To explore the effect of initial life satisfaction on mortality further, we re-estimated the model excluding health satisfaction. When we did this the coefficient on life satisfaction was negative and significant at the 1% level (i.e. -0.041, *t*-stat = 4.13), with a one point increase in initial life satisfaction reducing the death hazard by 3.1%. This clearly implies that more satisfied individuals live longer. However, this is only the case because more satisfied individuals typically also have a better initial health status. The other parameter estimates were virtually unchanged.[5]

[5] The full results from these models are available on request.

We have also tested the robustness of this result by instrumenting life satisfaction using information on 'locus of control' collected in certain years of the GSOEP, which is an assessment of the extent to which an individual possesses internal or external reinforcement beliefs. It is widely used as a measure of personality traits by psychologists (see the *Journal of Personality and Social Psychology*, for a wide range of articles relating to locus of control and personality traits). Importantly, this experiment did not change the above life satisfaction result.

5. Conclusions

In this paper we have contributed to the debate about the importance of socio-economic factors in determining how long individuals live. We have done this in two main ways. Firstly, we have used 19 years of high-quality data on around 26,000 individuals from the German Socio-Economic Panel Study between 1990 and 2002, of which we observe 2,400 deaths. In this respect our analysis is most similar to that undertaken by Gerdtham and Johannesson (2004), who analysed a similar data set for Sweden. Secondly, as with the Swedish study, we have estimated a number of Proportional Hazard (PH) models of mortality, but we have also developed a new duration model, which we have called the Increasingly Mix Proportional Hazard Model (IMPH), that explicitly allows for unobservable individual-specific health shocks. This new model fits the data statistically better than the other main duration models (the Proportional Hazard Model and the Mixed Proportional Hazard Model (MPH)), and we find strong evidence that health shocks play a large role in determining longevity. However, despite the importance of heath shocks the parameter estimates of the various models in this application are remarkably consistent.

As expected, age, gender and initial health status are strong predictors of death. In addition, we have found a large role for socio-economic characteristics in determining how long an individual lives. In particular, we have been able to confirm the positive significant effects of being married and years of schooling on promoting longevity found for other countries, for both East and West Germans. With respect to the more contentious issue of the role that income plays in promoting longevity, we have found that having a higher level of real household income, when initially observed in the panel, is associated with living significantly longer. Moreover, this effect is considerably larger than found in the recent literature that has investigated the effect of income on morbidity using panel data. Specifically, a one-log point increase in household income leads to a 12% reduction in the probability of death. We have also found an important role for average regional income, with individuals residing in richer regions also living significantly longer. Further investigation might be able to unravel why this is the case. Importantly, we have calculated, holding age, gender and immigrant status constant, that an individual with the 'worst' socio-economic characteristics, including poor health and disability, is expected to live to only 43 years of age, compared to 94 years for an individual with the 'best' socio-economic characteristics. If we also hold health satisfaction and disability constant, then the worst possible set of remaining socio-economic variables would give an expected 59 years of life, and the best set would give 92 years of life. Together, we take these findings as strong support for the important role that socio-economic characteristics play in promoting longevity and explaining mortality variations across the population.

A new contribution in this paper has been to test whether individuals with high life satisfaction when initially interviewed in the panel live longer. The raw data and the results for duration models that do not control for initial self-assessed health status, clearly support this hypothesis. Importantly, however, once we control for health status this effect is no longer evident capturing the fact that less satisfied people typically have poorer health. The significant role that self-assessed health has in predicting future mortality confirms previous studies and supports the validity of such measures of morbidity.

Finally, we believe that the duration estimator that we have developed in this paper is a useful additional tool for econometricians. It can be applied to a wide-range of single-spell duration outcomes in economics where unobservable individual-specific persistent shocks are likely to be important and when little information is observed for individuals after the initial survey interview.

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Appendix

Take the model with the continuous hazard defined by:

$$\theta(t \mid \lambda_t, x) = f(\lambda_t) z'(t) \phi(x)$$
$$\lambda_t \sim N(0,t)$$

where durations are from a finite set of natural numbers, i.e. t=0,1, ..,T with T the end of the observation plan, and where the hazard is constant between intervals. What we thus have as observations are the survival functions at discrete points in time. We make the following additional assumptions, which closely follow the identification assumptions (and ideas) of Elbers and Ridder (1982) and Honore (1993):

Assumption 1: $\sum z'(t)dt = \infty$ (no defective distribution).

Assumption 2: $Ef(\lambda_t)$ is finite for any finite t.

Assumption 3: x has an open set of support X including x_0 and the function $\phi(x)$ is non-negative, non-constant, and differentiable on S.

We can then trivially choose a set of normalizations, and we take $\phi(x_0) = 1, f(0) = 1, z'(1) = 1.$ Proposition 1 shows identification.

Proposition 1: Under Assumptions 1, 2, and 3, the functions $z(.)$ and $\phi(x)$ and $f(\lambda_t)$ are non-parametrically identified as long as we observe more than 1 time period (T>0).

Proof. First, note that

$$S(0 \mid x_0) = e^{-z'(0)\phi(x_0)}, -\ln(S(0 \mid x_0)) = z'(0), \frac{-\ln(S(0 \mid x))}{-\ln(S(0 \mid x_0))} = \phi(x)$$

$$\frac{S(1 \mid x)}{S(0 \mid x)} = \frac{1}{\sqrt{2\pi}\sigma} \int e^{-\frac{\lambda^2}{2\sigma^2}} e^{-\phi_0 z'(1) f(\lambda)} d\lambda$$

The first line implies that we can trace $\phi(x)$ and $z'(0)$ from the survival functions $S(0 \mid x)$, which is one of the basic ideas of Elbers and Ridder (1982). Now, note that we can re-write the second line to be

$$\frac{S(1\mid x)}{S(0\mid x)} = \int e^{-\phi(x)z'(1)v} dG(v)$$
$$f(\lambda) = v, G(v) = \Phi(\lambda)$$

which means there is a one-to-one relation between the unknown distribution $G(v)$ and the combination of the unknown $f(\lambda_t)$ and the normal distribution. Because the relation between v and $f(\lambda_t)$ is monotonic and unique, we can identify $f(\lambda_t)$ by identifying $G(v)$. This inversion allows us to use the idea of Honore (1993): note that we observe $\frac{S(1\mid x)}{S(0\mid x)} = E[e^{-\phi(x)v}]$ for an open set X. Because $\frac{S(1\mid x)}{S(0\mid x)}$ is real analytic it can be extended to any value of $\phi(x)$. It is also the case that $\frac{S(1\mid x)}{S(0\mid x)}$ is the Laplace transform of G. From the uniqueness of the transform we can identify G, which in turn identifies $f(\lambda_t)$ for any λ_t because even at t=1, λ_t achieves the full support. Finally, we may not that we can then identify $z(.)$ for all periods after t=1 by the fact that $\frac{S(t\mid x)}{S(t-1\mid x)}$ is a monotonically increasing and continuous function of $z'(t)$ meaning we can trace $z'(t)$ forward uniquely from $\frac{S(t\mid x)}{S(t-1\mid x)}$.

Now, we can make some remarks as to the identification of the model if λ_t changes in continuous time rather than once at the start of every period and we observe hazards in continuous time.

Conjecture 1: Under Assumptions 1, 2, and 3, the functions $z(.)$, $\phi(x)$, and $f(\lambda_t)$ are non-parametrically identified.

Remark 1: $\phi(x)$ is identified by $\phi(x) = \lim_{t\downarrow 0} \frac{\theta(t|x)}{\theta(t|x_0)}$. Then, $z^{'}(0) = \theta(t=0\mid x_0)$ because $Ef(\lambda_t) = 1$ at $t = 0$. Intuitively one would think one could now replicate the basic idea above by looking at $\lim_{t\downarrow 0} d[\frac{S(t+\Delta\mid x)}{S(t\mid x)}]/d\Delta$. However, the difficulty is the non-intergrability of the underlying Wiener process.

Remark 2: Without variation in x, the model is not identified because any path $Ef(\lambda_t)$ can be compensated by $z(t)$ to leave an observationally equivalent model. Like the standard hazard model therefore, it is the interaction between x and t that identifies the model.

Remark 3: There is some information that is not yet used in this motivation which is useful in extending the model because the proof of proposition 1 does not use much of the information of the survival functions for high t.

Remark 4: A possible avenue is to use the analogy with differential equations. We can write the pdf $g\ [\lambda_t = y \,|\, T > t, z^{'}(t), \phi\ ]$ for t>0. It is known at time *t*=0. For time t+□, it can be written as: $\mathrm{g}[\lambda_{t+\square} = y \,|\, T \geq t + \square, z^{'}(t)\phi\ ] = \frac{\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\square}\sigma} e^{-\frac{(Y-y)^2}{2\square\sigma^2}} g_t(Y)(1-\square f(Y) z^{'}(t)\phi) dY}{\int\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\square}\sigma} e^{-\frac{(Y-s)^2}{2\square\sigma^2}} g_t(Y)(1-\square f(Y) z^{'}(t)\phi) dY ds}$. The numerator can be simplified as $1 - \square z^{'}(t)\phi Ef(\lambda_t)$. The difficulty now is finding the limit of this when □ goes to 0, and then to build an expression for $Ef(\lambda_t)$. If the characteristics of $Ef(\lambda_t)$ allow it to be invertible and smooth, then this, combined with the initial conditions and the differential equation for $z^{'}(t)$, would provide uniqueness.