THE EFFECT OF AGE AND PROXIMITY TO DEATH ON HEALTH CARE COSTS

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Abstract

Health policy makers have expressed concern over the pressures that increased numbers of elderly will exert on rising health care costs. However, numerous studies have demonstrated that in fact, health care costs tend to be concentrated on patients in their last year of life. Thus, the key event driving health care costs may be proximity to death rather than age per se. Two recent studies have examined the independent influences of age and proximity to death on health care expenditures using longitudinal data. However, they only examine costs in the last two years of life, and thus fail to address the effect of age on health care expenditures when further from death, where more age-related chronic illnesses may play a role. Additionally, they model cost observations in a cross-sectional manner, without linking cost observations of the same patient together to control for individual patient-level influences on expenditures. Using data from the Oxford Record Linkage Study (ORLS), this study first repeats the methodology of previous studies, modifying their models to address potential weaknesses. We find that age plays an insignificant role in hospital costs, once accounting for patients' time to death. Instead, there is a large increase in costs in the last quarter of life. In further work, panel data analyses will be used to determine if findings on the effects of age and proximity to death on health care expenditures hold when controlling for patient-level effects. The panel data analysis will be performed for a much longer time period, to include the possible effects of chronic disease on health care expenditures.

Introduction

Health policy makers have expressed concern over the pressures that increased numbers of elderly will exert on rising health care costs. However, previous studies have demonstrated that in fact, health care costs tend to be concentrated on patients in their last year of life. In the US, studies from 1978 to 1988 consistently found that the Medicare recipients who died in a given year, while comprising only 6% of the total Medicare population, accounted for 28% of Medicare expenditures. (Lubitz and Prihoda, 1984; Lubitz and Riley, 1993; Riley et al. 1987) Indeed, descriptive studies on the costs of patients in their last year of life have shown that older patients tend to have similar or reduced hospital utilisation and costs compared to younger patients, although the costs for nursing home care may be higher (Lubitz and Prihoda, 1984; Henderson et al. 1990; Brameld et al. 1998; Scitovsky, 1988; Spillman and Lubitz, 2000; Temkin-Greener et al. 1992; Roos et al. 1987; McGrail et al. 2000; Levinsky et al. 2001) If this is the case, then the key event driving health care costs may be proximity to death rather than age per se; the rise in health care costs observed with increasing age may actually be a function of increasing probability of death. If true, this would suggest that projections of the effect of increasing life expectancy and aging populations on health care expenditures are not reliable, since they do not account for the fact that additional years of life may actually be lived in health rather than illness, with morbidity and health service use occurring only at the very end of life.

Two recent studies have examined the independent influences of age and proximity to death on health care expenditures using longitudinal data, and have in fact found proximity to death, and not age, to play a significant role in health care costs. (Zweifel et al. 1999; O'Neill et al. 2000) However, these studies only examine costs in the last two to five years of life, and thus fail to assess if age-neutrality of health expenditures holds when further from death, where more age-related chronic illnesses may play a role. Additionally, they model health care expenditures in a cross-sectional manner, without linking cost observations of the same patient together to control for individual patient-level influences on expenditures. Using data from the

Oxford Record Linkage Study (ORLS), which follows hospital usage of patients from 1970 to the present, this paper first reiterates the model used in the Zweifel et al study, to see if their results hold with the ORLS data. We alter their model to address some potential weaknesses in their analyses. In another work, we provide a longer-term analysis further from death, moving into panel data analysis to control for individual-patient effects on health care expenditures.

Data

The Oxford Record Linkage Study began in 1963, collecting statistical abstracts for all hospital inpatient and day case care, birth certificates, and death certificates in a defined geographical area. The only non-inpatient records collected are for psychiatry (outpatients, day patients, and domiciliary and ward visits). Data items covered in ORLS for each hospital episode include patient's date of birth, age, sex, district of residence code, date of admission, date of discharge, specialty on admission, diagnoses, and operations/operative procedures. For all death records, information is also available on date of death, diagnosis of death, and place of death. What is unique about the ORLS is the linkage of successive records of the same person to enable individual patient-level analyses. (Gill et al. 1993) The dataset is derived from linkable Hospital Activity Analysis (HAA), Hospital Inpatient Enquiry (HIPE), and Hospital Episodes Statistics (HES) records.

As Table 1 shows, the populations of counties in the ORLS area are representative of England as a whole, though they tend to be slightly younger than England and Wales on average, with a higher percentage of people aged 1 to 44 and a lower percentage of people aged 65 and over. (Lee and Goldacre, 2000) The ORLS regions also have a slightly higher proportion of males than England.

We selected those elderly patients who were aged 65 and over as of 1970, and tracked their general and psychiatric hospital and death records to 1999, the end of the dataset. This provided 29 years of data for analysis. We chose to include only those patients in the older ages to avoid problems of right censoring. Patients at younger ages would be less likely to have passed away by the end of the data period, and hence would not have a death record. Without a certain record of a patient's death, it

would be difficult to categorise that patient as close to death or far from death; indeed, the patient could have passed away the day after the end of the data period, and we would not know this information to categorise him/her appropriately. Only tracking patients who were 65 years or older in 1970 ensured that the problem of right censoring of survivors would not be noticeable, as mortality data from 1999 English life tables estimate that 99.4% of patients who are 65 years old die within 30 years. (ONS, 2001) Since the patients in our dataset were often older than 65 in 1970, the death rate over the 29 years of analysis should have been even higher than this 99%, effectively eliminating any censoring bias and ensuring that almost all patients had a death record to be properly categorised by time of death.

During our time period of analysis, the coverage of the dataset by region changed. From 1970 to 1974, only Oxfordshire and West Berkshire were included, while many other regions were added on in 1975. Hence, we only included patients who had District Health Authority of residence in Oxfordshire or West Berkshire for each of their hospital episodes and for their death record, to ensure that all of their hospital episodes and death record were included in the dataset.

Data on hospital use in the ORLS are provided in the form of number of patient days, counting day cases as one patient day. However, for this analysis, a conversion to costs was needed. We used cost data from the various Trusts in England, obtained from Trust Financial Returns to the Department of Health (TFR2), which provides total number of patient days and total expenditures in the different specialties for each Trust by financial year. We obtained a weighted average cost per inpatient day for England by summing total expenditure across the trusts and dividing by total patient days. In order to eliminate any random fluctuation in the data, we averaged cost data from financial years 1997/98 and 1998/99 to get an average for the two-year time period 1997/99. All costs are expressed in constant 1998-99£ using Hospital and Community Health price deflators provided by the UK Department of Health. We then matched the specialty codes from the Trust expenditure data with the specialty codes from ORLS for general hospital records. For the hospital records with an unknown or incorrect specialty code (4.6% of all records), the average medical or surgical cost was used, depending on the approximate code range. No subspecialty coding was available for psychiatric hospitalisations, so average psychiatric costs per

day were used. Multiplying each patient's number of days in the hospital for a given specialty by that specialty cost provided an approximate cost for that hospital stay.

The initial data extraction provided hospital and/or death records for 104,179 patients. Of these, 657 patients had an incorrect age and 446 patients had an unknown age, and were removed from analyses. An additional 1214 patients had an unknown discharge date for at least one hospitalisation. This would make calculation of cost of a hospital episode impossible, and hence these patients were removed from analysis. 5034 patients (4.8% of the sample) had no death record and were excluded from further analysis, since we could not be sure if these patients had survived the time period of analysis (which was unlikely), or had migrated out of the ORLS regions, so that their death records would not have been captured by the dataset. This left us with 96,828 patients for analysis: 38,807 males and 58,021 females.

Patient age, sex, diagnosis, cause of death, source of admission, place of discharge, marital status, and social class were all considered in analysis (Table 2). Average number of days in hospital until death was 57.2 (± 194.8) days, at a cost of £9464,62 (± £28,374.00). Average age at death was 83.4 (±7.4) years. Females tended to be heavier users of hospital care than males, with slightly greater number of days in hospital and hospital costs before death. (Table 3) 46.2% of patients (44,739) did not have any hospitalisations from 1970 to death. Of the remaining patients who did have at least one hospitalisation, the majority eventually died in hospital, comprising 53.0% of all patient deaths. Place of death varied slightly by patient age group, with older patients having a larger proportion of deaths in nursing home than younger patients. However, hospital deaths still accounted for the largest percentage of deaths in all age groups. The proportion of patients who died in hospital or nursing home versus private address corroborated with available mortality statistics collected by the Office of National Statistics for the UK, when accounting for slight differences in category definitions. {ONS 2001 ID: ONS2001}

The Analytical Model

THE TEMPLATE OF ZWEIFEL ET AL

The quest to untangle the independent effects of age and proximity to death on health care costs was initiated in a paper by Zweifel et al, 1999 (Zweifel et al. 1999). Using health insurance data on patients who had died between 1981 and 1992, they recorded health care expenditures for each quarter prior to death, first for quarters up to two years prior to death, and then quarters from two to five years prior to death. The quarterly cost observations were analysed in a cross-sectional manner, without linking the cost observations of the same patient in any way as the patient approached death over time. Eighteen percent of patients did not incur any costs in the time period of analysis, leading to a non-normal distribution in the cost variable of the data. Hence, separate models were run, first on the likelihood of incurring a cost, and then on the level of cost among those observations with a positive cost value. Zweifel et al point out that excluding zero cost observations in the second part of the model could result in selection bias, since it could lead to an overrepresentation of sick patients. The truncation of the cost distribution by excluding zeroes in the second part of the model could shift the data, such that the regression coefficients would not be representative of the population as a whole. Thus, a two-step Heckman sample selection estimation method was used in analysis. (Heckman, 1976; Heckman, 1979) In the first step, a probit model was run, examining the likelihood of a positive quarterly cost observation as opposed to zero cost, with the following equation:

$$\Pr(HCE > 0) = \alpha + \beta_1 A + \beta_2 A^2 + \beta_3 S + \beta_4 A * S + \beta_5 INS + \sum_{q=1}^{7} \gamma_q Q_q + \sum_{t=1982}^{1992} \delta_t Y_t \quad (1)$$

where A = patient age
S = dummy variable for sex (with male = 0, female = 1)
INS = dummy variable for insurance status (with no insurance = 0, insurance = 1)
Q = quarter prior to death (with baseline of 8 quarters from death)
Y = calendar year (with baseline of 1981)

From this probit model, the inverse mills ratio, λ, was calculated using maximum likelihood estimation. The second part of the model examined the level of health care costs among the quarterly observations with positive costs. The same

regressors from the first part were used in an OLS regression, that looked at how patient age, sex, insurance status, and quarter from death affected health care costs (controlling for calendar year). The λ was inserted as a regressor to control for the potential bias caused by excluding observations with zero cost. There was skew in the dependent variable of quarterly health care costs, and so the dependent variable was log transformed to make a more normal distribution. Thus, the second step of the model was set up as follows:

$$\ln(HCE) = \alpha + \beta_1 A + \beta_2 A^2 + \beta_3 S + \beta_4 A * S + \beta_5 INS + \beta_6 \lambda + \sum_{q=1}^{7} \gamma_q Q_q + \sum_{t=1982}^{1992} \delta_t Y_t \quad (2)$$

A significant coefficient for λ indicates a significant selection bias, meaning that the first probit equation and second OLS equation are not independent of one another, as would be the assumption for a two-part model. By including λ in the second regression, Zweifel et al sought to control for this effect, thereby providing regressor coefficients that were robust for the effects of selection bias and generalisable to the population as a whole.

ZWEIFEL ET AL RESULTS

First, Zweifel ran the above selection model with data for two years prior to patient death. Full results are not presented in their paper for the probit part of the model, apart from describing a significant positive effect of the age variable on the likelihood of a positive cost observation, that was countered by a negative effect for the age squared variable. Moving to the second OLS part of the model, dummy variables for proximity to death had significant coefficients for up to 6 quarters prior to death. (Table 4) The positive coefficients indicate that quarters closer to death exhibited higher costs than quarters farther from death. (Figure 2) The coefficient for age was not significant, and hovered around zero; similarly, age squared was not significant. Sex was significant, indicating that females had higher health care costs than males, and year was significant, indicating that technological and other policy changes may have led to increases in health care costs in later years. A significant coefficient for λ indicated that indeed there had been selection bias in the sample truncation for the OLS part of the model. (Table 4)

Zweifel then repeated this analysis with data further from death, from 2 to 5 years prior to death, to see if the age-neutrality held with patients who are not as close to dying. (Table 4) Now none of the proximity to death variables had a significant impact on health care costs, and neither did the age variables. It is still questioned, however, whether this age-neutrality holds as one gets further from death; unfortunately the limitations of Zweifel's data prevented such analyses.(Zweifel, 2000)

A REITERATION OF THE ZWEIFEL STUDY USING ORLS

Using data from the ORLS, we mirrored the analysis of Zweifel et al to provide a comparison with another country. First, we extracted a random sample of 7236 patients (7.5% of the dataset) for ease in computations. For this sample, we aggregated hospital costs for each quarter prior to patient death, into quarterly cost observations. The same two-step Heckman model was estimated using STATA 7.0, with the following probit and OLS models:

$$\Pr(HCE > 0) = \alpha + \beta_1 A + \beta_2 A^2 + \beta_3 S + \beta_4 A * S + \sum_{q=1}^{7} \gamma_q Q_q + \sum_{t=1971}^{1999} \delta_t Y_t \qquad (3)$$

$$\ln(HCE) = \alpha + \beta_1 A + \beta_2 A^2 + \beta_3 S + \beta_4 A * S + \beta_5 \lambda + \sum_{q=1}^{7} \gamma_q Q_q + \sum_{t=1971}^{1999} \delta_t Y_t \qquad (4)$$

The main differences are first the extent of health care cost inclusion, as Swiss insurance funds cover more than just hospital costs, while the ORLS covered only hospital costs. Second, the ORLS model did not have an insurance status variable, as that is particular to the health care insurance environment of Switzerland.

Our results were remarkably similar to that of Zweifel et al (Table 5). In the probit part of the model, we found increasing proximity to death to play a significant role in raising the likelihood of observing a positive quarterly cost. The age coefficients were both significant, and in the same pattern as with Zweifel. The dummy variable for sex was significantly positive, meaning that females were more

likely to have a hospitalisation than males. Also, later years of admission all showed significant and positive coefficients, demonstrating an increased likelihood of hospitalisation in later years of the dataset. This may reflect changes in technology or other changes in practice patterns.

Turning now to the OLS part of the model, one can see the similarity again with Zweifel's results. (Table 5) The coefficient for lambda was significant at the 5% significance level, indicating a bias due to sample selection, that has asymptotically been controlled for with the Heckman estimation. Coefficients for the proximity to death dummy variables for the first 5 quarters up to death were significant and positive, indicating higher costs as one approaches death (Figure 2). Age variables were insignificant, though the coefficients maintained the same signs as in the probit model. Sex was significant and positive, meaning that females have higher costs than males, and the year of admission was now significant and negative for later years, indicating that hospital costs tended to decrease in later years.

In interpreting these results, it is important to remember that the Heckman model seeks to correct for the effects of sample selection in deriving the final coefficients. The coefficients for regressors on health care costs are generalisable to the entire population because they take into account both the regressor's effect on the likelihood of a positive cost, and the level of that positive cost.

Like Zweifel et al, the ORLS data for 2 to 5 years from death demonstrated that the significance of any effect of proximity to death on health care costs dissipates as you get further from death, and age-neutrality is maintained. (Table 5) The probit part of the model still showed some significant effects on proximity to death influencing the likelihood of a positive cost observation, even at a time distance of 5 years. However, in the second part of the model, none of the variables were significant, although the equation as a whole still provided explanatory power, as demonstrated by a Wald test of the hypothesis that all of the coefficients were jointly zero. Furthermore, the insignificant coefficient for lamba indicates that there was not a selection bias; therefore, the determination of a positive cost observation was not related at all to the level of cost observation.

SOME CRITIQUES AND CHANGES TO THE ZWEIFEL MODEL

Method of Estimation

There are a few aspects of the Zweifel estimation of the Heckman two-step estimation model that call its results into question. First, there is the issue of the method of coefficient estimation. Zweifel et al used a two-step estimation approach, inserting an inverse Mills' ratio from the probit part into the second, OLS part. However, several sources agree that using a full information maximum likelihood estimation is less prone to errors than the two-step method, and hence should be used when possible (Leung and Yu, 1996; Puhani, 2000; STATA Corp, 1999) Additionally, both the probit and OLS parts of the Zweifel model demonstrated heteroscedasticity when run on the ORLS dataset. It is unclear in Zweifel's paper whether or not heteroscedasticity was controlled for in their Heckman estimation. Accounting for heteroscedasticity in the Heckman estimation could be important, since the Heckman model assumes that the covariance matrix of the errors of the first and second part of the model is constant across all observations. Thus, heteroscedasticity could lead to inconsistent estimation of the inverse Mill's ratio. (Donald, 1995) In STATA, it is possible to estimate the Heckman sample selection model as a maximum likelihood estimation, with White-corrected standard errors in the presence of heteroscedasticity. We repeated the same model as above with this different estimation method and compared our results (Table 6).

While the patterns of coefficients remained similar for the probit part of the model, with the proximity to death, age, sex, and year variables demonstrating significant coefficients in the expected directions, the final coefficients changed slightly. There was an insignificant, negative coefficient for the first quarter prior to death, indicating that there is not a difference in the cost of a patient in the last quarter of life versus the 8^{th} quarter from death. Looking at the other quarters from death, there is still a trend towards more expensive care as one approaches death, but fewer of the coefficients are significant – most likely a result of estimating standard errors that are robust for heteroscedasticity. The insignificant coefficient for the quarter just prior to death could be explained by the large proportion of patients in our sample who died in hospital (53.0%), and thus may have had their last hospitalisation curtailed, compared to a patient who survived on for another time period. In fact,

across all the patients in the sample, average weekly hospital costs per patient in the last quarter of life demonstrated a noticeable decrease in the final weeks of life. (Figure 3) Hence, it is possible that while the last quarter to death can lead to an increased likelihood of hospitalisation (as indicated by the findings of the probit model), the curtailment of a hospital stay could lead to an overall insignificant change in hospital costs. It is interesting that the robust maximum likelihood estimation picked up this pattern of decreasing hospital costs in the last quarter of life, while the two-step OLS estimation did not.

Exclusion Restrictions and Collinearity of the Inverse Mill's Ratio: Critique

Another critique of Zweifel's Heckman model is that of the collinearity problem with the inverse Mill's ratio in the second part of the model. (Salas and Raftery, 2001) The vector of regressors from the selection part, $\mathbf{x}_1$, often have a large set of variables in common with the vector of regressors in the second part, $\mathbf{x}_2$. If the two vectors are identical, then the second step of the model is only identified if the inverse Mills ratio is nonlinear in its relationship to $\mathbf{x}_1$. However, it has been demonstrated that λ is in fact an approximately linear function over a wide range of its argument, which leads to issues of collinearity in the second step of the model. (Puhani, 2000) Therefore, for the Heckman model to work in practice, one needs regressors that are significant in selection, but not in the second part of the model, creating what is termed an "exclusion restriction." (Puhani, 2000) The collinearity of λ is further exacerbated when there is a high degree of censoring. Indeed, Monte Carlo simulations have shown that even when the "true" model is a selection model with $\mathbf{x}_1 = \mathbf{x}_2$, a two-part model (which uses independent probit and OLS steps without correcting for sample selection bias) outperforms both the Heckman limited information two-step estimation and the full information maximum likelihood estimation, if there are no exclusion restrictions and a 25% probability of selection. (Leung and Yu, 1996)

In the model derived by Zweifel et al, we have no exclusion restrictions, and our sample demonstrates a 10% probability of selection. Running an OLS regression of λ on $\mathbf{x}_2$ leads to an R^2 of 0.9992. Hence, the lack of identification of the model due to collinearity of λ is a definite problem. Such collinearity could perhaps explain why the ORLS model for 2 to 5 years prior to death had joint significance among all the

regressors, but no significance for individual regressor coefficients. Also, potential problems of collinearity are indicated when lambda has a negative coefficient, as it had for our 2 to 5 year model. (Heckman, 1976)

We sought to address the issue of collinearity by reexamining the regressor specification of the model. We included additional regressors for the first, probit part of the model, namely cause of death and social class. Having a cause of death of heart disease significantly lowered both the likelihood of a positive cost observation and the level of that cost. Being from a professional social class led to an increased likelihood of a positive cost observation, but did not change the subsequent level of that cost. This could be explained by the fact that social class may affect access to hospital care, but once admitted, patients are treated relatively equally regardless of their social class. Hence, social class became our exclusion restriction.

We next sought to add more regressors to $\mathbf{x}_2$ to further differentiate $\mathbf{x}_1$ from $\mathbf{x}_2$ and hopefully mitigate the collinearity problem. In addition to cause of death (which was significant for both parts of the model), we included diagnosis, source of admission, place of discharge, and marital status during the first hospitalisation in the particular quarter of observation. A comparison of OLS regressions on ln(cost) using $\mathbf{x}_2$ from the Zweifel approach and $\mathbf{x}_2$ from this approach further indicated that the addition of new regressors improved the goodness-of-fit, from an adjusted R^2 of 0.051 to 0.208. A Cook-Weisberg test for heteroscedasticity found significant heteroscedasticity in the second part of the model, and so Heckman maximum likelihood estimation with robust standard errors was used for analysis. This left us with the following model:

$$\Pr(HCE>0)=\alpha+\beta_1 A+\beta_2 A^2+\beta_3 S+\beta_4 A*S+\sum_{q=1}^{7}\gamma_q Q_q+\sum_{t=1971}^{1999}\delta_t Y_t+\sum_{c=2}^{5}\chi_c C_c+\sum_{s=2}^{5}\zeta_s Soc_s \quad (5)$$

$$\ln(HCE)=\alpha+\beta_1 A+\beta_2 A^2+\beta_3 S+\beta_4 A*S+\beta_5\lambda+\sum_{q=1}^{7}\gamma_q Q_q+\sum_{t=1971}^{1999}\delta_t Y_t+\sum_{c=2}^{5}\chi_c C_c+\sum_{a=2}^{7}\phi_a Adm_a+\sum_{d=2}^{7}\pi_d Dis_d+\sum_{m=2}^{4}\mu_m M_m+\sum_{x=2}^{5}\sigma_x Dx_x \quad (6)$$

where M = patient marital status (baseline married)

Adm = source of admission (baseline transfer from another hospital)
Dis = place of discharge (baseline transfer to another hospital)
Dx = diagnosis (baseline heart disease)
C = cause of death (baseline heart disease)
Soc = patient social class (baseline social classes 1 and 2, non-manual/professional)

The results followed the pattern found with equations 3 and 4, with proximity to death and sex significantly increasing cost while age had no significant effect. The coefficient for the first quarter before death was still insignificant, but now showed a positive sign. (Table 7) Being married led to lower hospital costs, as did having heart disease as the cause of death. Being transferred from another hospital increased the cost of the current hospitalisation, and similarly being transferred out at the end of the hospitalisation was more expensive than being discharged to home or long term care. Diagnoses of "cancer" and "other" were both significantly more expensive than a diagnosis of heart disease for a given hospitalisation.

We next regressed the inverse Mill's ratio from this new model on $\mathbf{x}_2$, to see if the problem of collinearity had been alleviated. Unfortunately, the R^2 only decreased slightly, from 0.999 to 0.994. Hence, collinearity of λ still presents a real problem for the sample selection model. In fact, several simulation studies assert that when there is a small probability of selection in the dataset and a lack of differentiation between the regressors from the first and second part of the model, the two-part model may be preferable. (Puhani, 2000). In addition, one may argue that a sample selection model is really only necessary when the selection is unobserved; otherwise, two-part models or hurdle models should be used. (Jones, 2000)

Two-Part Model

Table 7 presents a two-part model, with separate probit and OLS estimates. We modelled the probit part as a heteroscedastic probit, since maximum likelihood estimators are inconsistent for probit models that suffer from heteroscedasticity, as ours did. (Greene, 2000) For the OLS part of the model, we used White-corrected standard errors to correct for heteroscedasticity that had been found in preliminary regressions.

The probit part of the model showed the same patterns described previously, with increasing likelihood of cost occurrence with closer proximity to death and opposing effects of the age and age-squared variables. Females were more likely to have a cost observation, and the later years also led to a higher likelihood of hospitalisation. Having heart disease as cause of death was associated with a decreased likelihood of hospitalisation compared to the other causes of death. The main difference between the heterscedastic probit model and regular probit model came with the social class variables, where there was no longer a difference between the non-manual and manual classes in terms of likelihood of positive costs.

Turning to the OLS part of the model, the coefficient of the dummy variable for the first quarter prior to death was significantly negative, meaning that among those patients that were hospitalised, costs tended to be lower just before death (perhaps due to the curtailment of hospital length of stay discussed earlier). The other quarters did demonstrate increasing costs approaching death, but only quarters 2 and 3 had costs significantly different than quarter 8. The year of admission variables indicate that later years had lower hospital costs. The effects of sex, cause of death, marital status, diagnosis of hospitalisation, source of admission, and place of discharge also followed the patterns previously described.

Predicted Costs with the Two-Part Model

We next estimated average costs at given ages and given time from death – controlling the other covariates – to see what effect these factors actually have. The two-part model enables predictions of the probability of hospitalisation in a quarter (from the probit step), and the quarterly cost among those patients that use hospital care in a quarter (from the second step). Multiplying the two predictions provides an estimation of the average hospital cost per quarter across the whole population. (Blough et al. 1999) Given the skewed nature of the cost variable, we used a generalised linear model of the form

$$\ln(E(y)) = \mathbf{x}\boldsymbol{\beta},\ y \sim \text{Gamma}$$

to estimate cost levels in the second part of the model. (Manning and Mullahy, 2001) 95% confidence intervals were derived using bootstrapping. Preliminary results are presented in Table 8.

The last quarter from death had significantly higher costs than the other quarters prior to death. This increase is due to the large rise in the likelihood of hospitalisation in the last quarter of life, as has consistently been shown in all the models used herein. Even though the cost once hospitalised may decrease, the larger proportion of hospitalised patients drives up the average cost across the population. The remaining quarters prior to death, however, all had similar average costs with greatly overlapping confidence intervals. These findings from the two-part model contrast the insignificant change in costs for the last quarter of life that was derived from the MLE Heckman model. We next predicted costs in the last quarter of life for various ages. For both males and females, average costs decreased with increasing age. Such findings provide further support for the hypothesis that proximity to death, rather than age, is the driver of health care costs.

Conclusions

The above models demonstrate the stability of the finding of age-neutrality of health expenditures in the last two years of life. Despite changes in the models and in the vectors of regressors used, the age variables were consistently insignificant in their effects on hospital costs. The proximity to death variables, however, changed slightly in their influence on health care costs, as alterations in the estimation method complicated the previously neat relationship between quarter from death and health care cost as shown using the two-step model from Zweifel et al (1999). Instead of a consistently progressive and significant increase in health care costs when approaching death, the newer models show that the quarter just prior to death may actually exhibit lower costs among hospitalised patients. Such a finding could be due to curtailment of the final hospital episode with patient death. However, the large rise in the likelihood of hospitalisation overrides this cost decrease, leading average hospital costs in the population to surge in the quarter prior to death, while costs for the other quarters prior to death all tend to hover in the same range.

The analyses described thus far have approached the data as a cross-section of independent quarterly cost observations. However, such analyses do not control for underlying patient-specific effects that may affect health care expenditures, and thus

may not fully describe the relationship of expenditures to age and proximity to death. Indeed, including more regressors in Zweifel's model still left us with the problem of omitted variables, when performing a RESET test on an OLS regression of ln(cost) on our expanded $\mathbf{x}_2$. The omitted variable problem would lead to bias in our point estimates of the coefficients of the regression, and thereby limit our ability to assess the marginal effects of the regressors on health care costs. It is quite possible that these "omitted variables" are the individual patient-specific effects, that would be accounted for in a more rigorous analysis that linked cost observations stemming from the same patient. Such panel data analyses could provide useful further research.

Some Points for Discussion Regarding Panel Data Analyses:

- I have been working with a fixed effects model (as I was unable to correctly specify a random-effects model, that had individual effects uncorrelated with the available regressors). I have an unbalanced panel (some patients died after 3 quarters in the dataset, while others lasted for at least 8 quarters). This leads to differences in each patient's variance of hospital cost, i.e. groupwise heteroscedasticity. What effect, if any, will groupwise heteroscedasticity have on fixed effects models? How could I correct for that?
- Like the analyses presented above, I approached the panel data analysis with a two-part model. Due to skew in the cost variable, I ran a fixed effects regression on ln(cost). However I am not sure of the best way to transform back to the raw-scale cost, to compute predicted costs and marginal effects. For the cross-sectional data, I had used a GLM model, but I don't know if this is possible with fixed-effects panel data. The GLM equivalent for panel data in STATA 7.0 as far as I could find, xtgee, only does random-effects modelling.

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Table 1: Demographic Representativeness of ORLS Populations by Age Group and Sex

		% aged <45	% aged 45-64	% aged 65-74	% aged 75-84	% aged 85+	% of each sex in total pop
1973							
	ORLS	68.3	20.5	7.1	3.2	0.8	50.4%M, 49.6%F
	England and Wales	62.5	23.7	8.9	4.0	0.9	48.6%M, 51.4%F
1983							
	ORLS	66.2	21.2	7.4	4.2	1.0	49.7%M, 50.3%F
	England	62.6	22.3	8.9	5.1	1.2	48.7%M, 51.3%F
1997-98							
	ORLS	64.0	22.8	7.2	4.4	1.6	49.8%M, 50.2%F
	England	61.2	23.0	8.3	5.4	1.9	49.3%M, 50.7%F

Table 2: Description of Variables used in Analysis

Diagnosis/ Cause of Death	Marital Status	Social Class	Place of Death	Source of Admission	Place of Discharge
Heart disease	Single	Social Class 1 and 2	Private address	Waiting list	Home
Stroke	Married	Social Class 3	Hospital	Accident and Emergency	Self-discharge
Cancer	Widowed	Social Class 4	Nursing home	Booked admission	Death
Respiratory	Divorced or separated	Other	Brought to hospital dead	Transfer	Transfer
Other	Unknown		Other	Long term care	Long term care
				Other	Other

Table 3: Descriptive Statistics of Patients in the Extracted ORLS Dataset

Mean (± SD)	Males	Females	Both
Number of patients	38,807	58,021	96,828
Age at death	81.2 ± 7.2	84.8 ± 7.2	83.4 ± 7.4
Average number of hospitalisations from 1970 until death	1.9 ± 3.0	2.0 ± 3.7	2.0 ± 3.4
Average hospital days from 1970 until death	43.2 ± 145.3	66.5 ± 221.3	57.2 ± 194.8
Average hospital cost from 1970 until death	£7,473 ± £21,522	£10,796 ± £32,083	£9,464 ± £28,374

Table 4: Heckman two-step regression coefficient estimates for LN(real quarterly health care expenditures), Zweifel et al

Variable	0 to 2 Years from Death		2 to 5 Years from Death	
	Coefficient	Standard Error	Coefficient	Standard Error
N	3601	—	3186	—
Constant	5.314*	2.708	5.380*	2.634
A	-0.043	0.068	0.020	0.066
A^2	0.0002	0.0004	0.00004	0.0005
S	1.632*	0.740	-1.452**	0.590
A*S	-0.017	0.009	0.026**	0.008
INS	0.761**	0.212	0.712**	0.272
λ	2.424**	0.856	1.695*	0.841
Q1	1.415**	0.540	1.695*	0.841
Q2	1.849**	0.168	—	—
Q3	0.901**	0.142	—	—
Q4	0.626**	0.140	—	—
Q5	0.385**	0.127	—	—
Q6	0.459**	0.126	—	—
Q7	0.404**	0.125	—	—
Q8	—	—	—	—
Q9	—	—	0.043	0.119
Q10	—	—	-0.006	0.119
Q11	—	—	0.0146	0.121
Q12	—	—	0.012	0.123
Q13	—	—	-0.067	0.123
Q14	—	—	-0.048	0.123
Q15	—	—	0.002	0.124
Q16	—	—	-0.111	0.124
Q17	—	—	-0.045	0.125
Q18	—	—	-0.109	0.125
Q19	—	—	-0.035	0.126

** Significant at the 1% level
* Significant at the 5% level

Figure 2: The Effect of Quarter to Death on Health Care Costs

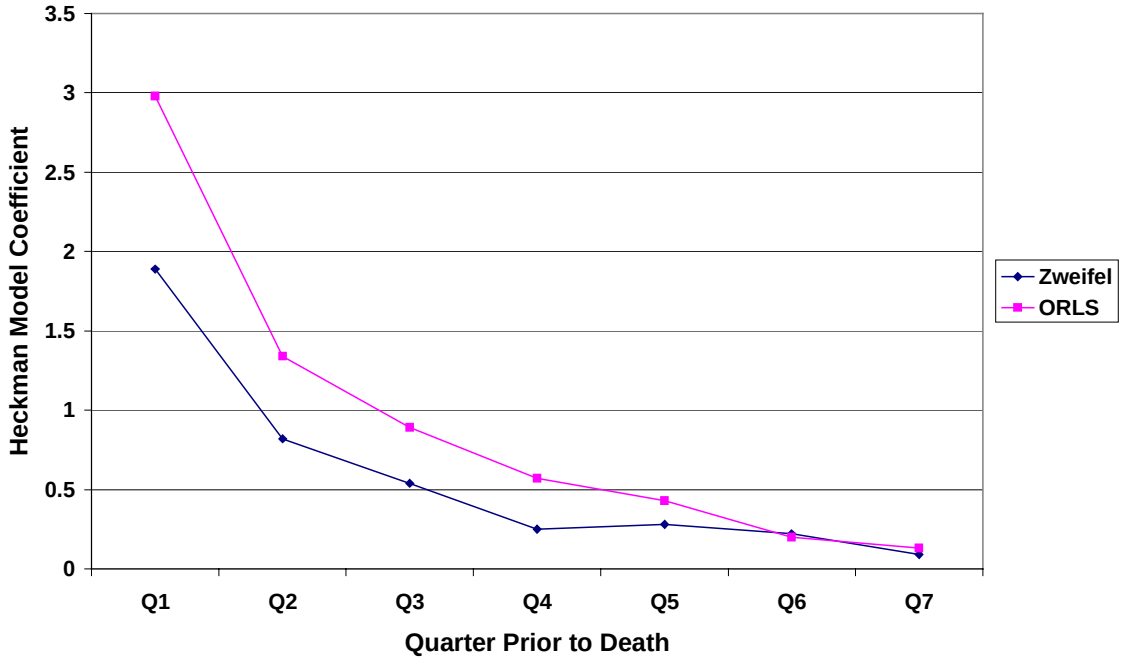

Table 5: Heckman two-step regression coefficient estimates for ln(real quarterly health care expenditures), ORLS data with Zweifel Model

Variable	0 to 2 Years Prior to Death				2 to 5 Years Prior to Death			
	Probit		OLS		Probit		OLS	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
N	55,002				71,612			
Constant	-4.169**	0.898	-6.722	6.602	-1.936	1.118	58.597	437.528
A	0.072**	0.022	0.220	0.113	0.006	0.028	0.047	1.224
A^2	-0.0005**	0.0001	-0.001	0.001	-0.0001	0.0002	0.001	0.019
S	0.432*	0.192	2.371**	0.831	-0.468*	0.239	11.200	78.073
A*S	-0.005*	0.002	-0.027**	0.010	0.006*	0.003	-0.137	0.988
λ	3.115*	1.431	3.115*	1.431	-25.242	190.503	-25.242	190.503
Q1	1.334**	0.031	2.980*	1.515	—	—	—	—
Q2	0.412**	0.034	1.339**	0.509	—	—	—	—
Q3	0.267**	0.035	0.890**	0.346	—	—	—	—
Q4	0.173**	0.036	0.568*	0.246	—	—	—	—
Q5	0.096**	0.036	0.430*	0.176	—	—	—	—
Q6	0.050	0.037	0.195	0.147	—	—	—	—
Q7	0.038	0.037	0.125	0.143	—	—	—	—
Q8	—	—	—	—	—	—	—	—
Q9	—	—	—	—	0.246**	0.047	-5.419	41.040
Q10	—	—	—	—	0.246**	0.047	-5.473	41.075
Q11	—	—	—	—	0.214**	0.047	-4.565	35.721
Q12	—	—	—	—	.0161**	0.048	-3.407	26.872
Q13	—	—	—	—	0.191**	0.048	-4.152	31.991
Q14	—	—	—	—	0.116*	0.049	-2.545	19.433
Q15	—	—	—	—	0.132**	0.049	-2.791	22.271
Q16	—	—	—	—	0.078	0.050	-1.813	13.298
Q17	—	—	—	—	0.109*	0.050	-2.463	18.380
Q18	—	—	—	—	0.042	0.051	-0.965	7.222
Q19	—	—	—	—	0.027	0.052	-0.570	4.799

** Significant at the 1% level
*Significant at the 5% level

Table 6: Heckman robust MLE regression coefficient estimates for ln(real quarterly health care expenditures), 0 to 2 years from death, ORLS data with Zweifel Model

Variable	Probit		Ln(Cost)	
	Coeff	SE	Coeff	SE
N	55,002			
Constant	-4.172**	0.877	5.135**	1.864
A	0.073**	0.022	0.055	0.046
A^2	-0.0005**	0.0001	-0.0002	0.0002
S	0.431*	0.189	1.370**	0.375
A*S	-0.005*	0.002	-0.015**	0.005
Q1	1.334**	0.031	-0.150	0.084
Q2	0.412**	0.033	0.312**	0.081
Q3	0.267**	0.034	0.220**	0.086
Q4	0.173**	0.036	0.133	0.088
Q5	0.096**	0.036	0.188*	0.090
Q6	0.050	0.037	0.074	0.094
Q7	0.037	0.037	0.034	0.092
Wald test of indep eqns $\chi^2(1) = 10.82$; Prob > $\chi^2 = 0.001$				

** Significant at the 1% level
* Significant at the 5% level

Figure 3: Average Weekly Hospital Costs per Patient in the Last Quarter of Life

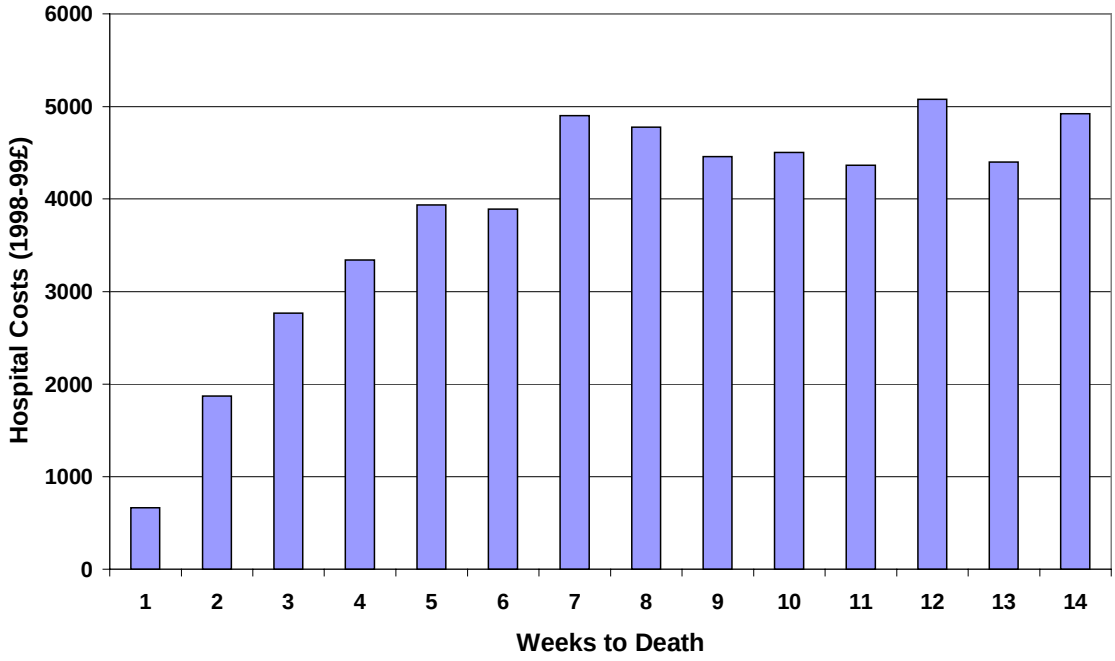

Table 7: Heckman robust MLE regression versus Two-part model, 0 to 2 years from death, ORLS data with extended model

Variable	Heckman Selection Model				Two-Part Model			
	Probit		Ln(Cost)		Probit		Ln(Cost)	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
N	55,002				55,002			
Constant	-4.481**	0.819	6.059**	1.766				
A	0.077**	0.020	0.055	0.043	0.108**	0.035	0.040	0.043
A^2	-0.0006**	0.0001	-0.0003	0.0002	-0.0008**	0.0002	-0.0002	0.0002
S	0.0258	0.176	0.999**	0.357	1.331**	0.432	0.917*	0.354
A*S	-0.003	0.002	-0.011*	0.004	-0.017**	0.005	-0.010*	0.004
Q1	1.335**	0.029	0.133	0.102	1.581	0.214	-0.206**	0.069
Q2	0.407**	0.033	0.310**	0.077	0.629	0.154	0.196**	0.071
Q3	0.264**	0.034	0.218**	0.049	0.213	0.184	0.165	0.076
Q4	0.170**	0.035	0.124	0.080	0.363	0.165	0.076	0.079
Q5	0.094**	0.035	0.180*	0.082	0.172	0.189	0.152	0.081
Q6	0.049	0.036	0.075	0.084	-0.002	0.218	0.063	0.084
Q7	0.035	0.036	0.003	0.083	0.131	0.196	-0.014	0.082
C stroke	0.146**	0.022	0.224**	0.051	0.374	0.122	0.187**	0.050
C cancer	0.327**	0.021	0.222**	0.054	0.736	0.172	0.136**	0.051
C resp	0.179**	0.022	0.313**	0.045	0.336	0.111	0.027**	0.043
C other	0.137**	0.022	0.195**	0.046	0.567	0.143	0.160**	0.045
M single	—	—	0.142*	0.059	—	—	0.139*	0.057
M wid	—	—	0.094*	0.041	—	—	0.095*	0.041
M div	—	—	0.139*	0.064	—	—	0.144*	0.064
M other	—	—	0.040	0.046	—	—	0.039	0.045
Soc 3	-0.043*	0.020	—	—	-0.047	0.054	—	—
Soc 4-5	-0.071**	0.023	—	—	-0.0005	0.053	—	—
Soc Other	-0.138**	0.024	—	—	-0.257**	0.095	—	—
Dx stroke	—	—	0.122	0.073	—	—	0.127	0.073
Dx cancer	—	—	0.239**	0.064	—	—	0.243**	0.063
Dx resp	—	—	0.092	0.062	—	—	0.094	0.062
Dx other	—	—	0.178**	0.042	—	—	0.184	0.043
Adm Wait	—	—	-0.832**	0.075	—	—	-0.832**	0.075
Adm A&E	—	—	-0.684**	0.054	—	—	-0.685**	0.054
Adm Bkd	—	—	-0.737**	0.061	—	—	-0.736**	0.062
Adm LTC	—	—	0.204	0.43	—	—	0.197	0.429
Dis Home	—	—	-0.986**	0.037	—	—	-0.981**	0.037
Dis Self	—	—	-1.700**	0.450	—	—	-1.682**	0.450
Dis Death	—	—	-1.098**	0.052	—	—	-1.101**	0.052
Dis LTC	—	—	-0.660**	0.126	—	—	-0.654**	0.124
	Wald test of indep eqns Prob > χ^2 = 0.000							

** Significant at the 1% level

* Significant at the 5% level

Table 8: Preliminary Predictions from the Two-Part Model (with 95% Confidence Intervals)

Quarter from Death	Probability of being a User	Quarterly Cost among Users (£)	Average Cost per Quarter	**Age (females)**	Probability of being a User	Quarterly Cost among Users	Average Cost in Last Quarter	**Age (males)**	Probability of being a User	Quarterly Cost among Users	Average Cost in Last Quarter
Q1	15.63% (5.6, 24.6)	3426.38 (2862, 4134)	535.66 (190, 898)	**65**	28.44 (17.0, 36.8)	3242.97 (2574, 4194)	922.57 (521, 1326)	**65**	23.09 (14.1, 30.1)	2624.85 (2036, 3369)	605.99 (334, 879)
Q2	3.27% (0.5, 8.6)	5412.41 (4480, 6533)	177.23 (24, 489)	**70**	25.68 (14.5, 33.7)	3336.79 (2745, 4010)	856.79 (451, 1219)	**70**	22.91 (13.6, 29.9)	2808.71 (2257, 3430)	643.46 (352, 904)
Q3	1.28% (0.1, 5.2)	6033.29 (4923, 7253)	77.26 (6, 322)	**75**	22.01 (10.8, 30.4)	3398.29 (2870, 4090)	747.87 (355, 1095)	**75**	21.70 (11.5, 29.3)	2974.79 (2441, 3567)	645.39 (330, 921)
Q4	1.65% (0.1, 4.7)	6103.78 (4803, 7536)	100.87 (7, 387)	**80**	17.74 (7.2, 26.6)	3425.62 (2882, 4118)	607.61 (240, 966)	**80**	19.54 (8.9, 27.9)	3118.55 (2589, 3737)	609.44 (276, 917)
Q5	1.11% (0.06, 4.7)	6328.63 (5053, 7796)	70.19 (4, 304)	**85**	13.26 (4.0, 22.5)	3417.93 (2846, 4118)	453.53 (136, 815)	**85**	16.64 (6.2, 25.9)	3235.89 (2712, 3888)	538.45 (198, 879)
Q6	0.63% (0.02, 3.0)	5959.08 (4698, 7439)	37.35 (1, 185)	**90**	9.06 (1.8, 18.5)	3375.46 (2780, 4109)	305.88 (62, 646)	**90**	13.26 (3.5, 23.0)	3323.39 (2737, 4064)	440.98 (120, 815)
Q7	0.84% (0.04, 3.9)	5306.03 (4226, 6601)	44.78 (2, 205)	**95**	5.54 (0.6, 14.1)	3299.51 (2689, 4112)	182.65 (22, 482)	**95**	9.79 (1.7, 20.1)	3378.43 (2692, 4259)	330.58 (59, 723)
Q8	0.75% (0.05, 3.0)	5813.54 (4449, 7335)	43.80 (3, 174)	**100**	2.95 (0.2, 10.4)	3192.36 (2472, 4162)	94.24 (6, 328)	**100**	6.57 (0.6, 16.6)	3399.34 (2542, 4530)	223.22 (22, 611)