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Waiting Times and Socioeconomic Status: Evidence from England

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ABSTRACT

Waiting times for elective surgery are often referred to as an equitable rationing mechanism in publicly-funded healthcare systems providing access to care not on the basis on willingness to pay or socioeconomic status. This study uses patient level administrative data from the Hospital Episode Statistics database in England to investigate whether patients with higher socioeconomic status (as measured by small area level income and education deprivation) wait less than other patients. The analysis focuses on the time waited for an elective hip replacement in 2001. Overall, it provides evidence of inequity in waiting times favouring more educated individuals and, to a lesser extent, richer individuals. The results from log-linear regression models and duration analysis bring evidence that inequalities occur within hospital providers and over large part of the waiting time distribution. Controlling for hospital heterogeneity reduces bias in the measurement of inequality experienced by the lowest income groups.

Keywords: Waiting times, socioeconomic status, duration analysis.
JEL: I11; I18.

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1 Introduction

Waiting times are a major health policy issue in many OECD countries. Average waiting times can reach several months for common procedures like cataract and hip and knee replacement (Siciliani and Hurst, 2004; 2005). They tend to generate dissatisfaction for patients and the general public. Waiting times postpone and therefore reduce patients' benefits. Moreover, waiting may deteriorate the health status of the patient, prolong suffering, and generate loss of utility and uncertainty.

It has been argued that, in the absence of other rationing mechanisms, waiting times help to bring into equilibrium the demand for and the supply of health care by deterring patients with small benefit from asking for treatment (Lindsay and Feigenbaum, 1984, Martin and Smith, 1999, Cullis et al., 2000). Other rationing mechanisms also exist. For example, economists often argue that co-payments might be a suitable alternative to contain moral hazard (Zweifel et al., 2009, Chapter 6). However, co-payments are often perceived as inequitable in the healthcare sector as patients with low income may be deterred from seeking care. In contrast, waiting times are perceived as more equitable, as the cost or disutility to the patient generated by waiting does not depend on their ability to pay (while the loss of utility generated by co-payments does depend on the ability to pay).

The present study investigates whether patients with high socioeconomic status (as measured by small area level income and skill deprivation) experience shorter waiting times than other patients for elective hip replacements. We use patient level administrative data from the Hospital Episodes Statistics database, which includes all patients treated by the publicly funded National Health Service in England. We find evidence that waiting times differ among NHS patients by socioeconomic status, favouring patients with higher status. Therefore, waiting times might be less equitable than previously thought.

Patients' socioeconomic status is proxied using the income and education deprivation score of their area of residence. The results from linear regression suggest that patients in the second education-deprived quintile wait 9% longer (about 22 days) than patients in the first quintile (with least deprivation in education). Patients in the third-to-fifth education-deprived quintile wait about 14% longer (about 32 days). Moreover, patients in the fourth and fifth most income-deprived quintiles wait about 7% longer (about 18 days) than patients in the least deprived quintile. The results from the extended Cox regression model suggest that patients deprived in the education domain experience from 13% to 20% lower hazard of being treated than least deprived, although this difference is decreasing over the time waited. Patients in the most deprived quintile of the income domain have 9% lower hazard of receiving treatment than lest deprived. Overall, the regression analysis provides evidences that most of the inequalities occur within hospitals rather than across hospitals. Failure in controlling for hospital heterogeneity might result in substantial underestimation of the difference between the top and the bottom income-deprived group. Finally, Kaplan-Meier survival curves and estimated hazard functions show that the inequality between better educated patients and other patients occurs over large part of the waiting time distribution: for any given point in the first 80% of the waiting time distribution, the probability of leaving the waiting list for patients from the least education-deprived quintile is always higher than for other patients.

1.1 Related literature

Siciliani and Verzulli (2009) investigate whether patients with higher socioeconomic status have lower waiting times for specialist consultation and non-emergency surgery using data from the Survey of Health, Ageing and Retirement in Europe (SHARE) from nine European countries (Austria, Denmark, France, Germany, Greece, Italy, the Netherlands, Spain and Sweden). They find that for specialist consultation, individuals with high education experience a reduction in waiting times of 68% in Spain, 67% in Italy and 34% in France. Individuals with intermediate education report a waiting-time reduction of 74% in Greece.

For non-emergency surgery, they find evidence of a negative and significant association between education and waiting times in Denmark, the Netherlands and Sweden. High education reduces waits by 66, 32 and 48%, respectively. They also find the presence of income effects, although generally modest. An increase in income of 10’000 Euro reduces waiting times for specialist consultation by 8% in Germany and waiting times for non-emergency surgery by 26% in Greece. Surprisingly, an increase in income of 10’000 Euro increases waits by 11% in Sweden.

Siciliani and Verzulli (2009) make use of survey data, which has the advantage that (household) income and educational attainment are measured at individual level. However, sample size tends to be generally small especially at individual procedure level (like cataract surgery, hip replacement, and so on), and waiting times are measured in weeks or months and are therefore approximated. Moreover, waiting time information (as well as other information like health status) is self reported.

In this paper we make use instead of an administrative database covering the whole of the publicly-funded English National Health Service, which records individual patients’ waiting times in days. The large sample size allows us to test for the socioeconomic gradient more accurately. Moreover, as well as age and gender, the database also includes the number and type of diagnoses of each patient which helps to control for patient severity of illness. On the other hand, in our analysis socioeconomic status is proxied through information on the socioeconomic deprivation score of their area of residence, using 32,000 Lower Super Output Areas (LSOAs) in England with average population 1,500. More precisely we use the income deprivation domain and skills sub-domain of the English Indices of Multiple Deprivation (Noble et al., 2004), which makes use (among others) of variables collected during the census in year 2001.

Cooper, McGuire, Jones and Le Grand (2009) investigate whether there was any change in waiting time inequality in some elective procedures (like hip and knee replacement, and cataract surgery) during the period of Labour government from 1997 to 2007 in the English National Health Service. They find that waiting times rose initially and then fell steadily over time. In 1997 waiting times and deprivation tended to be positively related. By 2007 the relation between deprivation and waiting time was less pronounced. They conclude that recent reforms like patient choice, provider competition, and higher capacity did not come at the cost of have an effect on equity.

Similarly to Cooper at al. (2009) we make use of data from the Hospital Episodes Statistics. Our analysis differs from theirs in several respects. First, they measure patient's socioeconomic status using the Carstairs index of deprivation, which offers an appropriate measure of material deprivation but does not capture any aspect of deprivation in the education domain (Carstairs, 2000). Instead we measure patient's socioeconomic status using two distinct indices explicitly designed to capture the dimension of deprivation in income and education separately. We use the skills sub-domain and income domain from the Indices of Multiple Deprivation 2004. Our analysis in section 4 shows that education deprivation and income deprivation have distinct effects on waiting time. Specifically, the former seems to have a stronger and more robust effect than the latter in all the model specifications used in the present analysis. The data used in our study refer to the census year 2001 in order to minimize measurement error in the socioeconomic variables, since information on educational attainment and income is collected from the census year 2001.

Second, we provide accurate controls for patients' heterogeneity in health status using the type and the number of diagnoses as a proxy of severity (in addition to age and gender). Patients are typically prioritised on the waiting list, with more severe patients waiting less (Gravelle and Siciliani, 2008a, 2008b), and severity being correlated with deprivation. The lack of adequate controls on severity might then generate biased results.

Third, we control for supply using hospital level fixed effects. Waiting times may vary considerably between hospital organisations, due to variations in capacity, practice style, efficiency and other local supply factors that are not directly related to the socioeconomic status of patients. If hospitals with short waiting times tend to be located in urban areas where income-deprived people are more concentrated, omitting hospital effect might result in underestimating the social gradient in waiting time.

Fourth, we investigate inequalities in patients' waiting time using duration analysis models in addition to linear regressions. Although the latter provide easy to read results in terms of average differences, the former are more appropriate tools for the comparison of duration of states, i.e. the time waited before the admission by different socioeconomic groups. Duration analysis allows us to investigate differences in waiting times over the whole distribution of the time waited enlarging the scope of our inequality analysis. Moreover, duration analysis allows for modelling non-normally distributed dependent variables relaxing some of the parametric assumptions of the linear regression models.

Scholder, Van Doorslaer, Geurts and Frenken (2003) investigate whether the probability of reporting 'problematic' waiting times differs across individuals with different socioeconomic status in the Dutch healthcare system. Using the CBS-Health Interview Survey, they find no evidence of variations in hospital waiting times and in waiting times for specialist consultation across individuals with different socioeconomic status.

Dimakou, Parkin, Devlin and Appleby (2009) employ duration analysis to identify the effect of government targets on the distribution of waiting times in the English NHS. They show that the hazard rate increases as time approaches the target. However, they do not control for socioeconomic status, which is our main focus.

Our analysis is also related to the broader literature of measuring equity in healthcare utilisation (Van Doorslaer and Wagstaff, 2000), which tests whether individuals with higher socioeconomic status have higher utilisation of healthcare, controlling for need, within a publicly-funded health system. The level of healthcare utilisation is typically measured by the number of visits to a specialist or a family doctor, and need is measured by self-reported health. The evidence often suggests the presence of pro-rich inequity for physician visits. However, if physician visits are split between specialist visits and family-doctor consultations, then the evidence suggests pro-rich inequity for specialist visits and of pro-poor inequity for family-doctor consultations (van Doorslaer et al., 2004).

The study is organized as follows. Section 2 provides the econometric specification. Section 3 describes the data. Section 4 discusses the results. Section 5 concludes.

2 Econometric specification

The purpose of this paper is to investigate the relationship between socioeconomic status and waiting times. Define w as the waiting time between the time the patient is added to the waiting list and the time the patient is admitted for treatment. Our linear regression model is defined by:

$$\ln(\mathrm{w}_{\mathrm{ij}}) = \alpha_{\mathrm{j}} + \boldsymbol{\beta}_1'\mathbf{y}_{\mathbf{ij}} + \boldsymbol{\beta}_2'\mathbf{e}_{\mathbf{ij}} + \boldsymbol{\beta}_3'\mathbf{s}_{\mathbf{ij}} + \mathrm{u}_{\mathrm{ij}} \qquad (1)$$

where w_{ij} is the waiting time of patient i in hospital j; $\mathbf{y}_{\mathbf{ij}}$ and $\mathbf{e}_{\mathbf{ij}}$ are two vectors of dummy variables that take value equals 1 if patients come from the bottom four quintiles of the income and education distribution respectively (the top quintile of income and education are assumed as baseline); $\mathbf{s}_{\mathbf{ij}}$ is a vector of dummies capturing severity of patients' health condition; α_{j} is a hospital-specific fixed effect and u_{it} is the idiosyncratic error. There are socioeconomic inequalities in waiting times if the vector $\boldsymbol{\beta}_1 \neq 0$ or $\boldsymbol{\beta}_2 \neq 0$. Specifically, if $\boldsymbol{\beta}_1 > 0$, then wealthier patients (the baseline) wait less than other patients; if $\boldsymbol{\beta}_2 > 0$, then better educated individuals wait less. In publicly-funded healthcare systems (like the National Health Service in England), access to care should be based on "need" and not on "ability to pay" or socioeconomic status. We investigate whether this is case for patients waiting for elective hip replacements.

We use a log transformation of the dependent variable in order to reduce the skew to the right that characterize the distribution of waiting time and estimate Equation 1 using OLS. The assumption of asymptotic normality of the OLS is likely to be violated when the dependent variable is substantially skewed invalidating inference analysis. The log transformation reduces the skew of the waiting time distribution, although it might not be sufficient to ensure asymptotic normality. Also, this transformation provides a convenient interpretation of the estimated coefficients in terms of proportional changes in the average waiting times.

Equation (1) offers controls for the severity of patients' health condition $\mathbf{s}_{ij}$. Typically, doctors give to patients different priorities on the waiting list according to their health condition and capacity to benefit from the treatment (Gravelle and Siciliani, 2008a). Patients in poor health might be at greater risk of a negative outcome from surgical operation if kept waiting for too long or might experience greater disability and pain during their wait. Thus, we expect some of the coefficients in $\boldsymbol{\beta}_3$ to be negative for patients with most severe conditions. Moreover, it may be argued that patients with higher socioeconomic status have generally better health. Therefore, severe health conditions might be correlated (negatively) both with waiting times and socioeconomic status. Failure in providing appropriate control for severity might generate biased results.

We also introduce hospital fixed effects to investigate whether socioeconomic inequalities in waiting times are explained by differences in average waiting time across hospitals. For instance, wealthier and better educated patients might be more likely to be treated in hospitals with low average waiting times, since they travel longer distance than other patients for elective admissions (Propper et al., 2007). Under such a hypothesis, differences in waiting times between the top socioeconomic group (the baseline) and all the other groups should decrease after controlling for hospital effect. In contrast, if inequalities occur mainly within hospitals we would expect the social gradient to remain substantially unchanged after controlling for hospital effect. Moreover, hospital characteristics might be correlated with the socioeconomic characteristics of the patients' area of residence. For example, hospitals with high supply of elective treatments are likely to be located in urban areas where low income patients are more concentrated. Therefore, omitting hospital effect might result in underestimating inequalities for this group of patients.

Duration analysis is used to investigate differences between socioeconomic groups over the whole distribution of the time waited. First, we adopt two non-parametric models: the Kaplan-Meier survival functions (Cameron and Trivedi, 2005, Chapter 17.5.1, Jones, 2007, Chapter 6.6) and estimated hazard functions by socioeconomic groups. The survival function $S(t)$ measures the probability of still being on the waiting list after t periods, namely the proportion of patients still in the waiting list after t times. $S(t)$ is estimated for each socioeconomic group using the non-parametric maximum likelihood estimator (Kalbfleisch and Prentice, 2002, Chapter 15):

$$\hat{S}(t) = \prod_{z|t_z \le t} \left(\frac{n_z - d_z}{n_z}\right) \tag{2}$$

Where t_z, z = 1,..., is the time at which patients exit the waiting lists, n_z is the number of patients still in the waiting list just before time t_z , and d_z is the number of patients who leave the waiting list at time t_z.

The hazard rate, $h(t)$, measures the instantaneous probability of leaving the waiting list (i.e. of being treated) at time t conditional on having been on the list until time t. Hazard functions, $\hat{h}(t)$, are estimated from the baseline hazard, $\hat{h}_0(t_z)$, obtained from a Cox regression model fitted without covariates. Then, a weighted kernel-density function, K(.), is adopted to smooth the estimated hazard contribution, $\Delta\hat{h}_0(t_z) = \hat{h}_0(t_z) - \hat{h}_0(t_{z-1})$ (Klein and Moeschberger, 2003, pages 167-168):

$$\hat{h}(t) = b^{-1} \sum_{z=1}^{D} K\left(\frac{t - t_z}{b}\right) \Delta\hat{h}_0(t_z) \tag{3}$$

Where b is the bandwidth of the kernel and the summation is over the D time waited (i.e., number of days waited) at which the patient exits the waiting list.

Second, we employ the Cox regression model to estimate the effect of socioeconomic status on the probability of leaving the waiting list conditioning on the set of control variables described in the next Section. This model is characterized by a semiparametric specification since it does not require assumptions over the distribution of the time waited, namely the baseline hazard, $h_0(t)$, remains unspecified. The Cox model identifies the effect of each covariate on waiting time in terms of hazard ratios, i.e. the model estimates the ratio between the hazard rates of two different groups of patients. The standard Cox model assumes proportional hazards across different groups meaning that their hazard ratios remain constant over the time waited after controlling for covariates (Cameron and Trivedi, 2005, Chapter 17.8, see Dimakou et al., 2009, Appleby et al., 2005, for an application of duration analysis to waiting times) [4]. The standard Cox model calculates the conditional hazard rate of leaving the waiting list, $h(t;\ x)$, as:

$$h(t;\ x) = h_0(t)\exp(\textstyle\sum_k \beta_k x_k) \tag{4}$$

Where $x_k = \mathbf{y}', \mathbf{e}', \mathbf{s}'$ are variables measuring patient's income, education and severity. The proportional hazards assumption is satisfied if the hazard ratio between two groups of patients, j and j', is constant over time:

$$\exp\left[\textstyle\sum_k \hat{\beta}_k \left(x_j - x_{j'}\right)_k\right] \tag{5}$$

If the proportional hazards assumption is violated, then the stratified Cox model and the extended Cox model are more appropriate instruments of analysis. The former introduces group specific baseline hazards, $h_{0j}(t)$, for each of the J groups of patients with non proportional hazard keeping the same β coefficients for each stratum:

$$h(t;\ x) = h_{0j}(t)\exp(\textstyle\sum_k \beta_k x_k) \tag{6}$$

[4] Using data from the Hospital Episodes Statistics in the English NHS, Dimakou, Parkin, Devlin and Appleby (2008) show that the hazard rate (the probability of exiting the waiting list, i.e. of being treated) increases when the waiting time is closer to the maximum waiting-time target, and decreases when it is above the target. Dixon and Siciliani (2009) show that the hazard function can be used to create a link between the distribution of the waiting time of the patients on the list at a point in time, and the distribution of the waiting time of patients treated in a given time interval (for example one year, as typically in the Hospital Episodes Statistics).

The main advantage of the stratified Cox model is that it allows for different baseline hazards, $h_{0j}(t)$, for each of the J stratified groups. This produces a more flexible model relaxing the common baseline hazard specification that characterizes the standard Cox regression model. The main disadvantage is that hazard ratios between the stratified groups cannot be identified.

The extended Cox model introduces time dependency by interacting the covariates with a function of the time waited, $g_k(t)$, (Pettitt and Daud, 1990, Fisher and Lin, 1999):

$$h\big(t;\ x(t)\big) = h_0(\mathrm{t})\exp\left[\sum_k \beta_k\, x_k + \sum_k \delta_k\, x_k g_k(t)\right] \qquad (7)$$

Where $\delta_k$are the coefficients of the interactions of the covariates with the time waited. Now the hazard ratio between two groups of patients, j and j', is a function of the time waited:

$$\exp\left[\sum_k \beta_k \left(x_j - x_{j'}\right)_k + \sum_k \delta_k \left(x_j - x_{j'}\right)_k g_k(t)\right] \qquad (8)$$

In the extended Cox regression model the critical decision is the functional form of $g_k(t)$ that should be based on the data generating process (Therneau and Grambsch, 2000, Chapter 6.5). Some of the most common specifications are:

(i) $g_k(t) = t$

(ii) $g_k(t) = ln(t)$

(iii) $g_k(t)$ is a step function with constant hazard ratios within different intervals

Ignoring time dependency in the Cox regression model can result in biased standard errors and coefficients for time-dependent covariates (Schemper, 1992). Specifically, the power of the test for covariates defining groups of patients with non-constant hazard ratios decreases because suboptimal weights are used in combining the information provided by such groups. Moreover, the coefficients of covariates with hazard ratios converging[5] over the time waited are underestimated (Schemper, 1992).

3 Data

We use anonymous individual hospital records for all patients admitted for elective hip replacement in English NHS Hospital Trusts in financial year 2001/2. We include all elective admissions involving primary total prosthetic replacement of the hip joint. Such admissions are identified under HRG H01, H02 and OPCS-4 codes W37.1, W38.1 and W39.1 as reported under the main operation of the first episode of care[6]. The OPCS-4 codes selected represent the three main variants of this procedure – "using cement", "not using cement", and "not elsewhere classified".

Patients coming for revisions or conversions of previous hip operations were excluded from the analysis. Patients requiring other types of hip replacement operation such as hybrid prosthetic replacements, resurfacings and prosthetic replacement of the neck of femur were also excluded. The waiting times for the former group might be affected by the outcome of previous hip operations, while the waiting times for the latter can be systematically different from the rest of the population of patients since they need different type of care.

We exclude from the analysis: i) 538 missing waiting time observations (i.e. 340 observations concentrated in two NHS Hospital Trusts not reporting any waiting time records); ii) 70 observations with a waiting time larger than three years; iii) four NHS Hospital Trusts with a volume of activity lower than 50 hip operations (i.e. 98 observations). The latter are likely to be hospitals that only occasionally supply extra capacity, since a regular orthopaedic speciality manages an average of 206 primary

[5] Here "converging" means that the hazard rates for two group of patients tends toward the same rate over the time waited.

[6] The first episode of care is the first episode that follows the patient admission to the hospital. An episode of care is defined as the time the patient spends under the care of a single consultant, e.g. an orthopaedic specialist. However, patients might need care from various types of consultants during their hospital stay, e.g. they can be transferred to a cardiology unit or intensive care unit if some complication occurs after their first treatment. In all these cases a subsequent episode of care is recorded.

hip operations in 2001/2. Our final sample includes 33,709 admissions divided in 163 NHS Hospital Trusts.

Waiting time is measured as the number of days elapsed from the date on which the specialist decides to add the patient to the waiting list and the date of the actual admission to the hospital for treatment[7]. The time elapsed from the date the general practitioner (family doctor) refers the patient to the specialist to the time the specialist visits the patient is not included. Also, if the patient does not attend or is unfit for surgery on the date of admission this time is not subtracted from the total waiting time.

The patients' health status is measured using dummies for her primary diagnosis and a variable counting the total number of diagnoses in the first episode of care. Patient's primary diagnosis identifies the main reason for the patient admission and is recorded using International Classification of Disease codes. We identify 15 most frequent primary diagnoses as described in Table 1 (therefore, note that there are different diagnoses for patients treated within the same HRG). Primary diagnoses mainly consist of different types of arthrosis: osteoarthrosis, coxarthrosis, and gonarthrosis. The number of diagnoses per patient reported in the HES dataset runs from 1 to a maximum of 7 in 2001/2. Using controls for number of patient's diagnoses provides a useful instrument for case-mix adjustment in studies using administrative data (Wray et al., 1997, Hamilton and Bramley-Harker, 1999). However, this indicator also includes diagnoses acquired during the hospital stay in the first episode of care, e.g. surgical complications or hospital-acquired infections. Therefore, this indicator might be affected by some degree of measurement error especially for those patients reporting a large number of diagnoses.

[7] One extra day was added to this measure of waiting time in order not to have any patient waiting zero days (i.e. when the date of referral equals the date of admission; 446 observations). This allows for using the log of waiting time without loosing observations. In sensitivity analysis we check that no difference occurs if no extra day is added and zero day waiters are dropped from the OLS regression.

The socioeconomic characteristics of the patients are proxied using the socioeconomic deprivation score of their area of residence. Specifically, patient's income and education are measured using the income domain and the skill sub-domain of the English Indices of Multiple Deprivation 2004 (Noble et al., 2004). The IMD indices measure deprivation over several dimensions at Lower Super Output Area (LSOA). There are 32,482 LSOAs in England with a mean population of 1,522 individuals, a range from 915 to 6,651 and standard deviation of 205. The IMD income domain score indicates the proportion of the LSOA population in 2001 who were living in low income households reliant on one or more means tested benefits, based on population census and benefit claims data (Noble et al., 2004).

The skills sub-domain of the index of multiple deprivation measures the proportions of working age adults (aged 25-54) in the area with no or low qualifications[8]. No qualification describes people without any academic, vocational or professional qualifications, while low qualifications define people with qualification equivalent to level 1 of the National Key Learning Targets (i.e., 1+ 'O' levels/CSE/GCSE any grade, National Vocational Qualifications level 1, General National Vocational Qualifications foundation certificate or equivalents; see Nicholls and Le Versha 2003 for a detailed description of these qualifications). The index is based on the adult qualification data collected in the Census 2001. The row score was then standardised using z-score, i.e. it was centred to its mean and divided by its standard deviation[9] (Noble et al., 2004).

[8] The index is designed to reflect the stock of educational disadvantage within a small area focusing on the working age population. Unfortunately, none of indices currently available measure the deprivation in education among retired workers specifically, who represent large part of the population of patients examined in this analysis. However, the index for the working age population also captures the deprivation in education among the elderly, since both populations cluster in the same areas. Ermisch and Jenkins (1999) find that only 3.3% of the British population moves house after retirement age in 1991-1995.

[9] We have access only to the standardized index, thus we are not able to analyse the distribution of the deprivation in education in the patients' population (i.e. the standardized index has zero mean and unit standard deviation). However, standardized and raw index share the same ordinal properties, i.e. they produce identical ranks of patients by their deprivation in education. Therefore, quintiles of the standardized index used in our empirical analysis (section 4) identify exactly the same groups of patients as quintiles based on the original index. This makes the analysis of the impact of moving from

The income-deprivation scores of the general population (across all) LSOAs were divided into five quintiles. The deprivation mix among hip-replacement patients may therefore differ from the deprivation mix among the general population. More precisely, the quintiles across the general population are such that each quintile contains 20% of the individuals in the general population; instead, the proportion of patients which belong to each quintile can be above or below 20% (see Table 1 and more detailed description below). For our regression analysis, we therefore construct five dummy variables: each patient falls into one of the five dummies depending on their income deprivation relative to the cut-off deprivation points determined by the five quintiles.

The same procedure was applied to obtain the quintiles of the skill deprivation index. This makes the two indicators easy to interpret in regression analysis since both measure quintiles of national population of English LSOAs having an increasing proportion of deprived people.

Table 1 presents the descriptive statistics. Our sample covers 33,709 patients in need of hip replacement who received treatment in year 2001 in 163 different hospitals. The mean waiting time for hip replacement is 259 days (about 8 months and three weeks), and the median waiting time is 224 days. About 38% of patients are male. Patients are on average 69 years old. On average patients come from an area where about 12% of the residents lives in low-income households relying on means-tested income benefits. Differences across areas are substantial. At one end of the spectrum, some patients live in areas where 0% of the population is on benefits, while at the other end some patients live in areas where 96% are on income benefits (though the standard deviation is around 10%). Patients have on average 2.2 diagnoses with a minimum of 1, a maximum of 7 diagnoses, and a standard deviation of about 1.5. The most common diagnoses are "unspecified coxarthrosis" (45% of the patients) and "other primary coxarthrosis" (about 33%), followed by "bilater coxarthrosis" (6.3%).

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one quintile to the next in the distribution of the deprivation in education equivalent using any of the two versions of the index. The limit is that we cannot comment on the differences in the intensity of deprivation in education across quintiles since the standardized index has no cardinal meaning.

[Table 1 here]

Table 2 describes waiting times across different income groups. Patients who wait least are the least deprived – first quantile, ie the richest - (239 days). Patients in the second quintile wait 246 days, patients in the third and fourth quintile wait about 257 days, while patients in the most deprived (fifth quintile) wait 248 days. The observed relationship between income and waiting time is therefore non-monotonic with patients in the fifth quintile (the poorest) waiting about the same as those in the second quintile (the second richest).

[Table 2 here]

The lower part of Table 2 describes how waiting times vary across groups of patients living in areas with increasing deprivation in education. A similar picture emerges. Patients in the least deprived areas wait least (233 days). Patients in the second quintile wait 247 days, patients in the third and fourth quintile wait about 255 days, while patients in the most deprived (fifth quintile) wait 252 days. The observed relationship between education and waiting time is again non-monotonic.

Table 3 provides the distribution of patients across groups with different income and education. Although income and education are positively correlated, the amount of patients with low education and medium income, or high education and medium income is significant. For example among the least deprived on income about 16% patients have an education in third quintile. This allows us to identify the effect of deprivation in income and education separately in our regression analysis.

[Table 3 here]

4 Results

Table 4 reports the OLS estimates of the model described in Equation 1. Three different specifications of this model are estimated: Model 1a provides controls only for age and gender; Model 1b adds controls for type and number of diagnoses; fixed effects for the 163 hospital providers are introduced in Model 1c. The dependent variable is the log of waiting time, thus regression coefficients can be interpreted as proportional changes in the average time waited. All models are estimated using cluster robust standard errors by hospital providers. Since each hospital records the waiting times and clinical characteristics of its own patients, reported data are likely to be correlated within hospitals resulting in auto correlated error term. Failing in controlling for such autocorrelation can result in invalid standard error estimates.

[Figure 1 and Table 4 here]

Model 1a suggests that no significant differences exist in the average waiting times of patients by income, after controlling for age, gender and education. In contrast, patients from the top education quintile (i.e. the least deprived in education) wait on average 11.1% less than patients from the second quintile and 16.5% less than patients from the bottom three quintiles.

Results from Model 1b show no significant reduction in the socioeconomic gradient by education (about -1%) or income after introducing additional controls for the severity of patient's health, such as the primary diagnosis at the admission and number of other diagnoses. Therefore, we find no evidence that heterogeneity in the patients' health conditions explain the social gradient in waiting times, in other words patients from the bottom or top socioeconomic groups are not more likely to have health conditions that require priority in the waiting list for elective hip replacements. In contrast, introducing hospital fixed effects have a more extensive impact on our analysis (Model 1c). The difference between patients from the top and the bottom quintiles of the income domain rises from zero to 7.5% (p-value < 0.05), supporting the hypothesis that patients from areas most deprived in income are more likely to be treated in hospitals with short waiting times. This should not be surprising considering that large hospitals with better resources are generally located in urban areas where income-deprived people are more concentrated. Moreover, the education gradient remains substantially unchanged (about -2%) suggesting that large part of socioeconomic inequalities in waiting times operates within hospitals. Results from

Model 1c do not support the hypothesis that inequalities in waiting times are explained by the self-selection of wealthier and better educated patients in hospitals with short average waiting times. Under such a hypothesis, we would expect a substantial fall in the overall socioeconomic gradient after controlling for hospital effect. In contrast, the results suggest that patients from top socioeconomic groups obtain priority over other patients within hospitals.

As would be expected, patients admitted with a primary diagnosis of “rheumatoid arthritis” or “osteonecrosis” experience substantially shorter waiting times than other patients, i.e. 27% and 45-53% less than patients with “arthrosis” assumed as baseline. These two conditions are sensibly more severe and disabling than other diagnoses, thus are a legitimate source of inequality in waiting times. In particular, rheumatoid arthritis is a condition that might seriously impare the authonomy of individuals in their daily life and is most effectively treated if takled early in the course of the illness. Therefore, it is a good medical practice to give priority in the waiting lists to patients reporting such diagnosis (Sathi et al., 2003). A similar argument applies to the waiting times of patients aged 75 and over, who are more likely to experience greater disabilities for a given primary diagnosis than patent aged 45-54 (the baseline).

[Table 5 here]

Results from Cox regression models are reported in Table 5. Such models allow for the skew distribution of waiting time and relax some of the parametric assumptions of the OLS regression. Estimates from the standard Cox regression model described in Equation (4) are reported under Model 2a in the first column. In the second column, Model 2b provides controls for time-dependent hospital effects stratifying the sample by hospitals as describer in Equation (6). Finally, Model 2c reports the estimates of the extended Cox regression model introducing time-dependent covariates. This model specification is similar to that described in Equation (7), with the only difference given by the hospital stratification that is included in Model 2c.

Standard tests based on Schoenfeld residuals (Schoenfeld, 1982) and estimated hazard functions are used to examine potential time dependency on all the covariates described in Table 1 and the hospital fixed effects. The results show that the proportional hazards assumption is not satisfied across hospital providers, education, age, and some of the diagnostic covariates; namely the hazard ratios for this covariates is not constant over time. In the case of hospitals, this might reflects differences in managing patients' waiting lists across providers. Some hospitals might be less efficient than others in managing their waiting list and this might result in long queues that periodically need to be tackle increasing hospital activity over some part of the year. Other hospitals, instead, might be more efficient and ensure regular flows of patients out their waiting lists over time. In order to control for such a time-dependent provider effect, the Cox model is stratified by hospitals (Model 2b). The stratified model introduces a hospital specific baseline hazard, $h_{0j}(t)$, keeping the same β coefficients for each stratum, as described in Equation (6). Model stratification suits the objectives of our inequality analysis since we need to control for hospital heterogeneity, but we are not interested in identifying the hospital effects. In contrast, the time dependency of the other covariates is modelled introducing time interactions (Model 2c), since identifying the effect of such variables is one of the main objectives of this study.

Estimates from Model 2b show that controlling for hospital heterogeneity results in widening the hazard ratio between patients from the most and the least income-deprived quintiles with respect to Model 2a. Specifically, the hazard ratio[10] of leaving the waiting list changes from 0.96 to 0.91 in favour of the least income-deprived patients (the baseline). This means that the probability of leaving the waiting list for wealthier patients is 9% greater than for the poorer after controlling for hospital heterogeneity and only 4% greater if not controls are used. Moreover, this hazard

[10] The hazard ratio when the covariate is a dichotomy variable (i.e. the dummy variables in Models 2a-2b-2c) is known as *relative risk* and indicates presence of a characteristic. In our study, a patient characteristic, such as her/his hospital of treatment or her/his socioeconomic status, has no influence on the event of leaving the waiting list when its relative risk is 1.0, has a positive effect when greater than 1.0 and a negative effect when smaller than 1.0.

ratio becomes statistically significant in Model 2b (p-value < 0.01), while it is not in Model 2a. In contrast, the hazard ratios between second-to-fourth income quintiles and top quintile are not affected by substantial changes. Similar patterns are shown by the hazard ratios of the education quintiles: the difference in the probability of leaving the waiting list between the top and the bottom quintile increases from 2% to 6% in favour of the better educated patients; while the differences between the other quintiles remain substantially unchanged. However, these results are likely to be underestimated since the hazard ratios of the education quintiles decreases with the time waited (Figure 3). Results from Model 2b support OLS predictions suggesting that large part of socioeconomic inequalities in waiting times occur within hospitals. Moreover, omitting controls for heterogeneity in the hospitals' characteristics result in underestimating the difference in waiting times between top and bottom income groups as predicted by the OLS specification. Finally, most of the differences in waiting time across primary diagnosis vanish after controlling for hospital effect in Model 2b. This might be due to measurement error in reporting patient's primary diagnosis within hospital, i.e. some hospitals might be less accurate than others in identifying the correct patient's diagnosis in a basket of similar conditions (Wray et al., 1997).

As discussed in Section 2, ignoring time dependency might result in underestimated coefficients and large standard errors for time-dependent covariates, i.e. for education, age, and some of the diagnostic covariates. Then, including time interactions explicitly in the model can be an appropriate solution. However, it is necessary to specify a functional form for the time interactions, $g_k(t)$, as shown in Equation (7). In this study, we adopt a linear specification, $g_k(t) = t$, assuming that hazard ratios decrease (or increase) with a constant rate over the time waited. Our assumption is supported by the trends shown by the estimated hazard functions for the time-dependent covariates[11]. Figure 3 shows that the differences between the hazard rates of the education groups reduce with a constant rate over the time waited. Other functional forms do not seem supported by our data.

[11] Estimated hazard functions for age and diagnosis groups are available upon request from the authors.

The results from Model 2c provide similar evidence to the OLS estimates of Model 1c. Socioeconomic inequalities in waiting times are more intense by education rather than income. Patients from least deprived areas in the education domain (the baseline) experience a sensibly higher hazard of leaving the waiting list before other patients. In Model 2c the differences in waiting times by education groups are allowed to vary with the time waited, while are assumed to be constant in all the other model specifications. In other words, the differences in the probability of leaving the waiting list for patients who are still waiting at time t are allowed to change with the time waited. The hazard ratios shown under Model 2c in Table 5 refer to the hazard at the start of the patient's waiting time (i.e. t=0). In Figure 4, the hazard ratios of the education groups are plotted against the time waited in order to read clearly the inequality in waiting time measured by Model 2c. The values of the hazard ratios are obtained using Equation (8). At the start of the waiting time, the probability of leaving the waiting list for a patient from the least education-deprived quintile (the baseline) is 20% higher than for a patient from the most education-deprived quintile (i.e., 0.80 hazard ratio). This gap reduces with the time waited to 7% for those patients still waiting at the median waiting time (i.e. 0.80*1.0007*exp(224) = 0.93 hazard ratio). The probability of leaving the waiting list for these two groups becomes equal only for patients still in the waiting list after 322 days, namely the 34% of the patients. The hazard ratio for the fourth quintile of education shows a very similar pattern to the most deprived. The hazard ratio of patients in the third quintile of education has a similar starting level to the other two groups, but decreases with at a lower rate over the time waited (break even at 406 waiting days). Finally, the fourth quintile starts with at a difference of 13% in the probability of leaving the waiting list (i.e. 0.87 hazard ratio at t=0) and decreases its gap at the lowest rate over the time waited.

[Figures 2 and 3 here]

Figure 2 shows Kaplan-Meier survival curves by quintiles of education and income estimated using Equation (2). It describes the proportion of patients waiting for hospital admission at different points in time. The differences in the income domain are less marked, although survival curves are not conditioned by other covariates. In contrast, patients from areas least deprived in education wait sensibly less than other patients over large part of the distribution of waiting time. Differences in waiting times by education become less intense only for patients waiting more than 400 days, who represent 20% of the total population of patients. This aspect has important implications for our inequality analysis since can be interpreted as a fist order stochastic dominance relationship: for any given point in the first 80% of the waiting time distribution, the probability of leaving the waiting list for patients least deprived in education is always higher than for other patients.

5 Discussion

This study investigates socioeconomic inequalities in waiting times for elective hip replacement using administrative data reported by English public hospitals in 2001. The analysis identifies the effect on waiting time of two different indicators of the patient's socioeconomic status, income and education, and shows that both have a distinct effect on the inequality in waiting times. Overall, it provides evidence of inequity in waiting times favouring more educated individuals and, to a lesser extent, richer individuals. Linear regression analysis suggest that patients in the second quintile of education deprivation wait on average 9% (about 22 days) longer than patients in the first quintile (least deprived in education), and patients in the third-to-fifth quintile wait 13% longer (about 32 days). Moreover, patients in the fourth and fifth most income-deprived quintiles wait 6-7% (about 17 days) longer than patients in the least deprived quintile.

The results from the extended Cox regression model support the OLS predictions. Cox regression analysis adds some insights in the distribution of inequality in waiting time with the time waited, which the OLS regression is not able to capture. The differences in the probability of leaving the waiting list between patients from the most education-deprived quintile and patients from the least deprived quintile (the baseline) are largest at the start of the waiting time (+20% in favour of the least deprived). The gap remains substantial (+7%) for patients still in the waiting lists at the median waiting time (i.e. 224 days), and finally reduces to zero for patients still in the waiting lists after 322 days. Differences in waiting time with respect to other education quintiles follow similar paths.

Finally, Kaplan-Maier survival curves by education quintiles show that the probability of leaving the waiting list for patients in the least deprived quintiles is higher than for patients from other quintiles over large part of the distribution of waiting time. This inequality can be read in term of stochastic dominance: the waiting times experienced by least depraved patients dominate at first order waiting times of other patients in the first 80% of the distribution of waiting time. Knowing the distribution of the inequality in waiting times with respect to the time waitied might be useful information for the policy maker in defining appropriate measures to address this issue.

Our study highlights the importance of controlling for hospital heterogeneity in the analysis of socioeconomic inequalities in waiting times. Omitting the hospital effect might result in underestimating the inequality for patients with lowest income. This can be explained by the prevalence of hospitals with short waiting times in urban areas where income-deprived patients are more concentrated. Introducing controls for the hospital effect allows for distinguish inequality across hospitals and within hospitals. Our analysis brings evidence that socioeconomic inequalities in waiting times mainly occur within hospitals. This suggests that rich and better educated patients obtain some priority in the hospital waiting list over other patients.

There are different possible explanations for our results. First, individuals with higher socioeconomic status may have better social networks and lower opportunity cost in gathering information on waiting times, thus more likely to get treated before other patients. Second, they may be more active 'complainers' and engage more actively with the system exercising pressure as they experience delay in the treatment. Third, patients with lower socioeconomic status might have a lower probability to attend the day fixed for the hospital admission, increasing the duration of their waiting time. Finally the dynamic of hospitals' waiting lists might explain part of the observed inequality within hospitals. For instance, wealthier and better educated individuals might engage in research activities and identify the hospital with the shortest waiting time at a given time t within the year. Shortly, the waiting list of this hospital becomes full and another hospital becomes more convenient at time t+1. Instead, other patients are indifferent between the two hospitals since they do not know their waiting times and randomly select one of the two over the year. At the end of the year, the final result is that wealthier and better educated are treated before other patients within the two hospitals.

Future work might be devoted to understand which of these factors explain the relationship between waiting times and socioeconomic status highlighted in this study.

Table 1. Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Minimum	Maximum
Waiting time (days)	33709	248.145	173.698	0	1094
IMD* income domain score	33709	0.122	0.099	0	0.96
Least income-deprived quintile	33709	0.202	0.402	0	1
2nd	33709	0.280	0.449	0	1
3rd	33709	0.200	0.400	0	1
4th	33709	0.170	0.376	0	1
most income-deprived quintile	33709	0.147	0.354	0	1
IMD* skills sub-domain score	33709	0.027	0.898	-4.007	3.840
Least education-deprived quintile	33709	0.164	0.371	0	1
2nd	33709	0.218	0.413	0	1
3rd	33709	0.221	0.415	0	1
4th	33709	0.216	0.411	0	1
Most education-deprived quintile	33709	0.182	0.386	0	1
Age	33709	69.377	9.546	45	98
Proportion male	33709	0.382	0.486	0	1
Total diagnoses at admission	33709	2.204	1.476	1	7
1 diagnoses	33709	0.442	0.497	0	1
2 diagnoses	33709	0.236	0.424	0	1
3 diagnoses	33709	0.153	0.360	0	1
4 diagnoses	33709	0.081	0.273	0	1
5 diagnoses	33709	0.043	0.202	0	1
6 diagnoses	33709	0.025	0.155	0	1
7 diagnoses	33709	0.021	0.143	0	1
Type of primary diagnosis					
Rheumatoid arthritis, unspecified	33709	0.013	0.113	0	1
Arthritis, unspecified	33709	0.007	0.085	0	1
Primary generalized (osteo)arthrosis	33709	0.004	0.060	0	1
Polyarthrosis, unspecified	33709	0.008	0.088	0	1
Primary coxarthrosis, bilateral	33709	0.063	0.243	0	1
Other primary coxarthrosis	33709	0.328	0.470	0	1
Other secondary coxarthrosis	33709	0.012	0.110	0	1
Coxarthrosis, unspecified	33709	0.451	0.498	0	1
Other primary gonarthrosis	33709	0.009	0.093	0	1
Gonarthrosis, unspecified	33709	0.010	0.100	0	1
Other specified arthrosis	33709	0.003	0.058	0	1
Arthrosis, unspecified	33709	0.030	0.171	0	1
Pain in joint	33709	0.019	0.138	0	1
Joint disorder, unspecified	33709	0.003	0.054	0	1
Other osteonecrosis	33709	0.004	0.060	0	1
Osteonecrosis, unspecified	33709	0.004	0.064	0	1
other	33709	0.032	0.175	0	1

Notes : * Index of Multiple Deprivation 2004

Table 2. Indeces of Multiple Deprivation (IMD)

Quintiles of IMD income domain		Observations	mean(wt)
	least deprived	6,813	239.1
	2	9,438	246.1
	3	6,750	257.7
	4	5,745	257.1
	most deprived	4,963	247.9
Quintiles of IMD skills sub-domain			
	least deprived	5,539	233.0
	2	7,338	247.0
	3	7,445	254.9
	4	7,265	255.4
	most deprived	6,122	251.8

Table 3. Cross-tabulation of IMD* income domain and skills sub-domain quintiles

		Quintiles of IMD skills sub-domain					
		least deprived	2	3	4	most deprived	
Quintiles of IMD income domain	least deprived	2,964	2,450	1,095	301	3	6,813
	2	1,549	3,258	3,107	1,401	123	9,438
	3	557	1,022	2,049	2,527	595	6,750
	4	335	396	859	2,223	1,932	5,745
	most deprived	134	212	335	813	3,469	4,963
	Total	5,539	7,338	7,445	7,265	6,122	33,709

Table 4. OLS results. Dependent variable: log(waiting time)

	Model 1a	Model 1b	Model 1c
2nd income deprivation quintile	0.00292	0.00462	0.0188
3rd income deprivation quintile	0.0582	0.0622	0.0395
4th income deprivation quintile	0.0728	0.0729	0.0651**
most income-deprived quintile	-0.00414	0.00139	0.0745**
2nd skill deprivation quintile	0.111***	0.104***	0.0901***
3rd skill deprivation quintile	0.166***	0.156***	0.130***
4th skill deprivation quintile	0.165***	0.154***	0.128***
most skills deprived quintile	0.167***	0.157***	0.136***
age 55-64	0.00173	-0.0292	-0.0424
age 65-74	-0.0277	-0.0697**	-0.0768***
age 75-84	-0.126***	-0.177***	-0.171***
age 85 plus	-0.239***	-0.291***	-0.307***
male	0.0362***	0.0307**	0.0350***
2 diagnoses		0.0198	-0.0199
3 diagnoses		0.0427	-0.0157
4 diagnoses		0.0958**	0.0195
5 diagnoses		0.120**	0.0564
6 diagnoses		0.179***	0.0477
7 diagnoses		0.141**	-0.0193
Rheumatoid arthritis, unspecified		-0.184	-0.269***
Arthritis, unspecified		0.110	-0.0123
Primary generalized (osteo)arthrosis		0.0780	-0.0331
Polyarthrosis, unspecified		0.238	0.0558
Primary coxarthrosis, bilateral		0.128	-0.00740
Other primary coxarthrosis		0.0892	-0.0327
Other secondary coxarthrosis		0.270	0.0369
Coxarthrosis, unspecified		0.0747	0.00657
Other primary gonarthrosis		0.183	0.0155
Gonarthrosis, unspecified		0.221	0.158
Other specified arthrosis		-0.229	0.768
Pain in joint		0.114	-0.107
Joint disorder, unspecified		0.652*	-0.0964
Other osteonecrosis		-0.549***	-0.534***
Osteonecrosis, unspecified		-0.298	-0.448***
Others		-0.221	-0.328***
Constant	4.998***	4.942***	5.384***
Observations	33709	33709	33709
Hospital fixed effects included (163 hospitals)	No	No	Yes
R-squared	0.008	0.015	0.128

Note: *** p<0.01, ** p<0.05, * p<0.1

Cluster robust standard errors (163 hospital clusters)

Table 5. Cox proportional hazard models

	Model 2a	Model 2b	Model 2c	
Dependent variable: waiting time (days)	*hazard ratios*	*hazard ratios*	*hazard ratios*	*time interactions*
2nd income deprivation quintile	0.9780	0.9781	0.9788	-
3rd income deprivation quintile	0.9237***	0.9524**	0.9524**	-
4th income deprivation quintile	0.9342***	0.9519**	0.9513**	-
most income-deprived quintile	0.9640	0.9145***	0.9103***	-
2nd skill deprivation quintile	0.9625**	0.9408***	0.8690***	1.0003***
3rd skill deprivation quintile	0.9391***	0.9235***	0.8163***	1.0005***
4th skill deprivation quintile	0.9560**	0.9464**	0.8228***	1.0006***
most skills deprived quintile	0.9837	0.9374**	0.7981***	1.0007***
age 55-64	1.0049	1.0136	1.0790*	0.9997*
age 65-74	1.0506**	1.0794***	1.1384***	0.9998*
age 75-84	1.1399***	1.1722***	1.3451***	0.9994***
age 85 plus	1.2540***	1.2961***	1.5821***	0.9991***
male	0.9677***	0.9669***	0.9664***	-
2 diagnoses	0.9837	1.0096	1.0665**	0.9998***
3 diagnoses	0.9668**	0.9929	1.0708**	0.9997***
4 diagnoses	0.9165***	0.9538**	1.0215	0.9997**
5 diagnoses	0.9053***	0.9406**	0.9732	0.9998
6 diagnoses	0.8544***	0.9077**	1.0166	0.9995**
7 diagnoses	0.8465***	0.9563	1.0767	0.9995**
Rheumatoid arthritis, unspecified	1.0789	1.1937**	1.5366***	0.9989***
Arthritis, unspecified	0.8598**	0.9306	0.9285	-
Primary generalized (osteo)arthrosis	0.9472	1.0260	1.0200	-
Polyarthrosis, unspecified	0.6986***	0.8813	0.8727	-
Primary coxarthrosis, bilateral	0.8248***	0.9077*	0.9057*	-
Other primary coxarthrosis	0.8751***	0.9596	0.9596	-
Other secondary coxarthrosis	0.7474***	0.9083	0.8999	-
Coxarthrosis, unspecified	0.8809***	0.9092*	0.9102*	-
Other primary gonarthrosis	0.8715**	0.9813	0.9799	-
Gonarthrosis, unspecified	0.8600***	0.8389**	0.8379**	-
Other specified arthrosis	1.3925***	0.8394	0.8624	-
Pain in joint	0.7909***	0.9745	0.9724	-
Joint disorder, unspecified	0.4138***	0.9650	0.9748	-
Other osteonecrosis	1.5347***	1.4281***	1.8646***	0.9985*
Osteonecrosis, unspecified	1.2404**	1.4736***	1.9733***	0.9986***
Others	0.9579	1.0661	1.4303***	0.9987***
Observations	33709	33709	33709	33709
Stratification by hospitals	-	163	163	163

Note: *** p<0.01, ** p<0.05, *p<0.1
Robust standard errors

Figure 1: Kernel density plot of patient waiting time

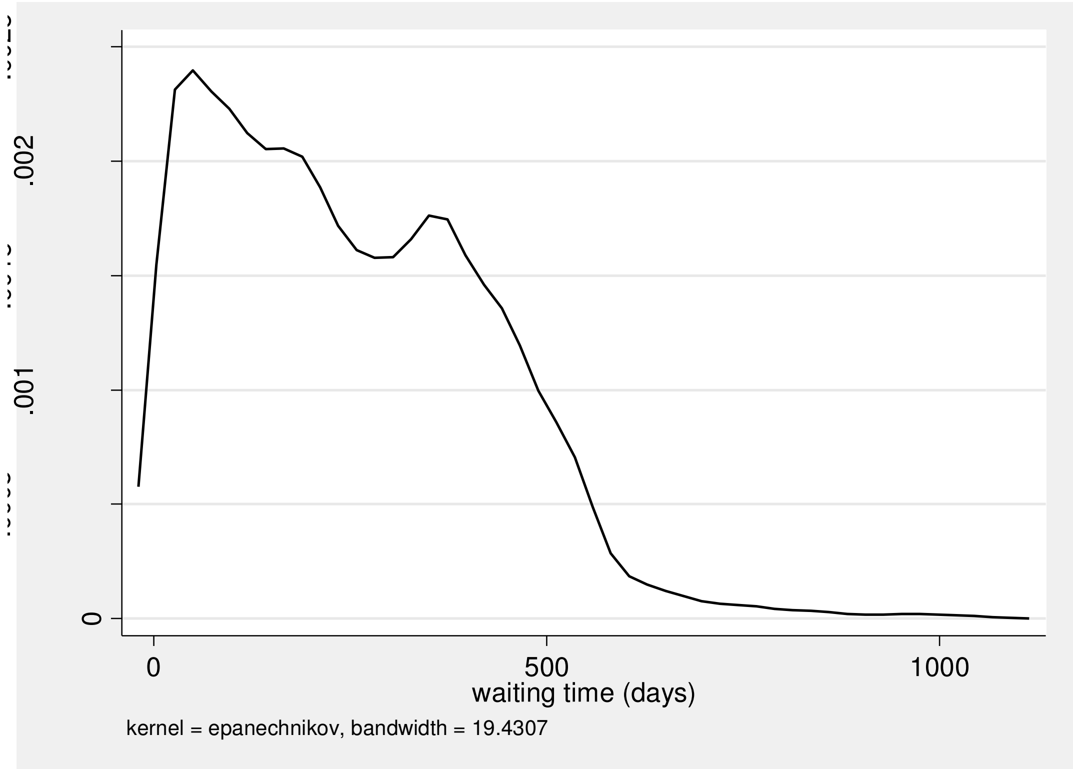
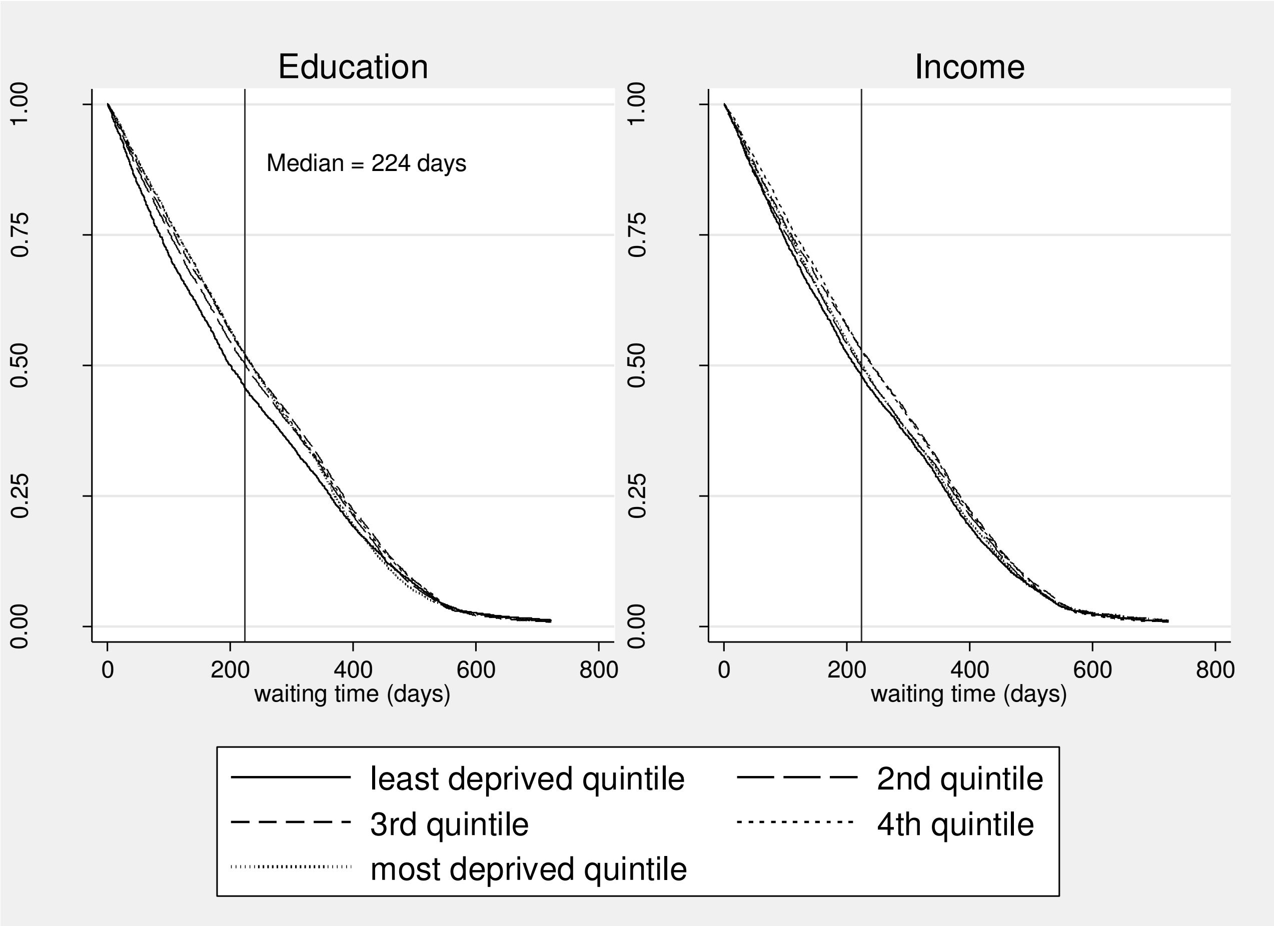
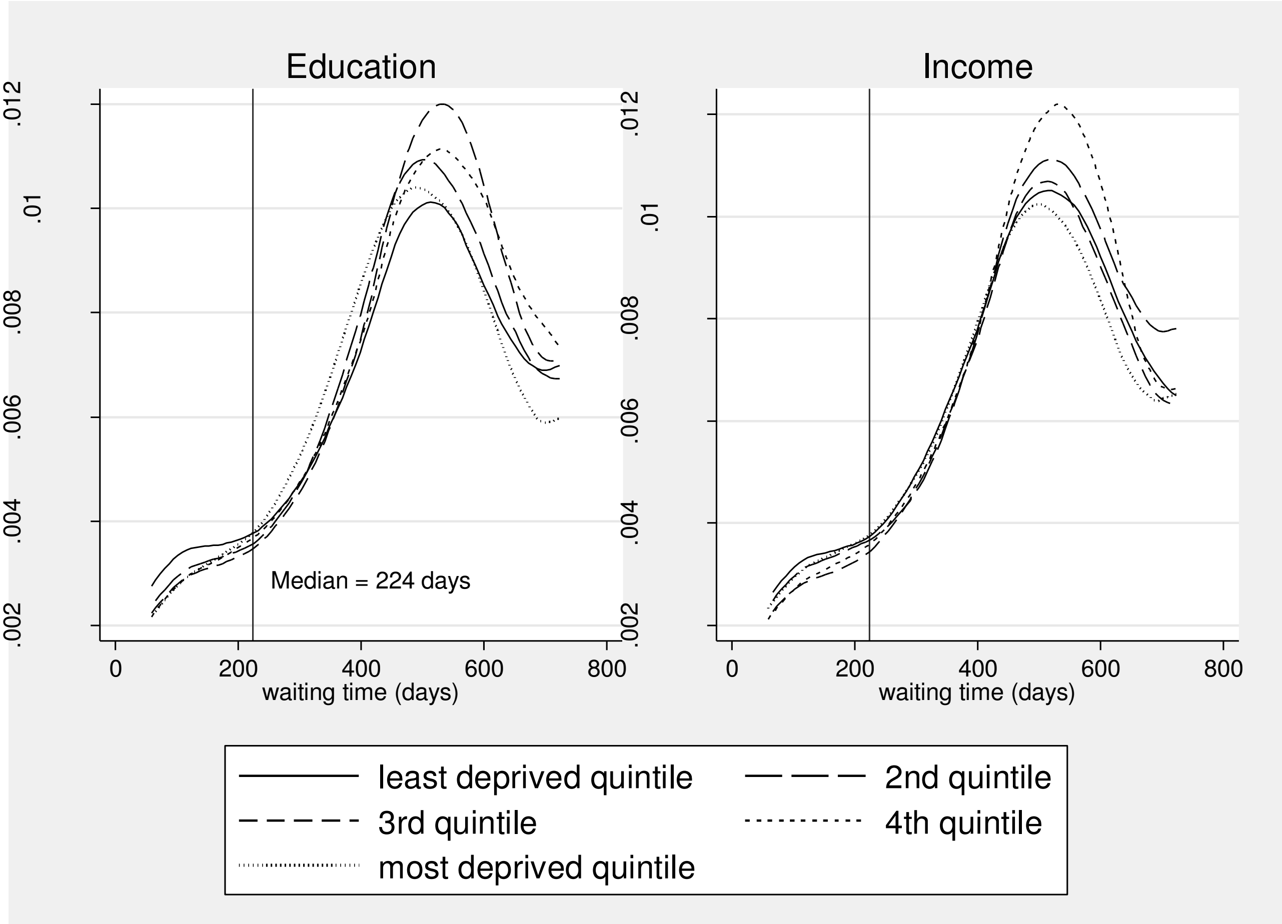


Figure 2. Kaplan-Meier survival curves



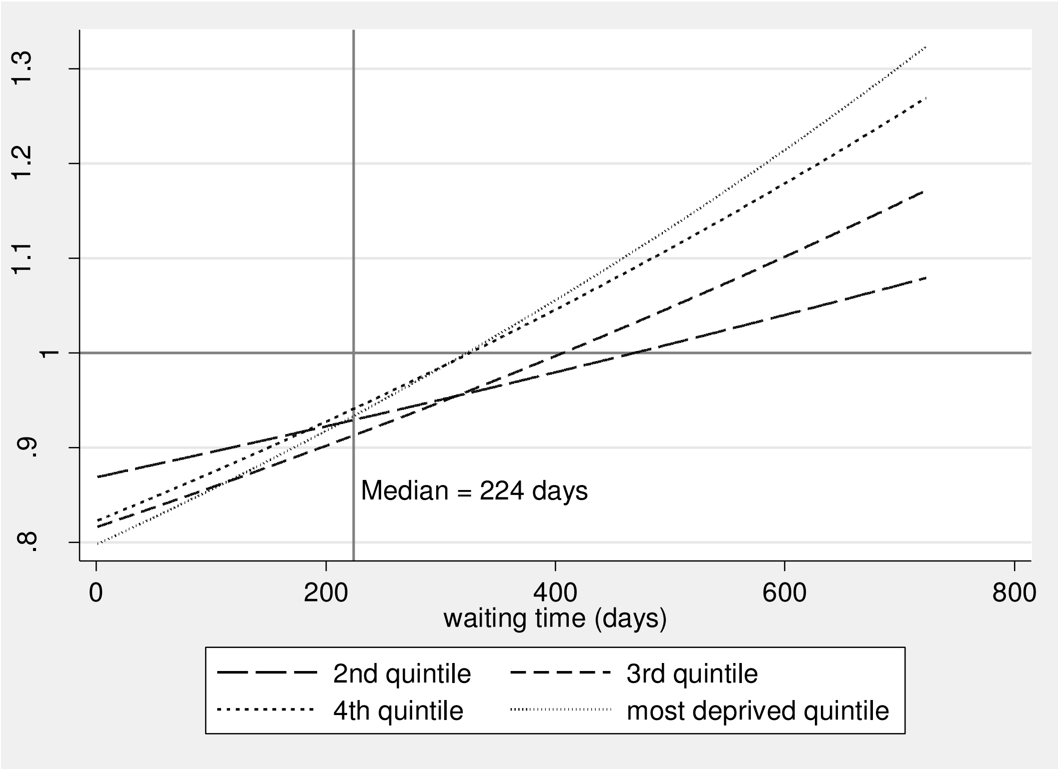
Note: graph truncated at 99% of the sample (i.e. waiting time <= 724 days). Reference line: median waiting time (224 days)

Figure 3. Estimated hazard curves



Note: graph truncated at 99% of the sample (i.e. waiting time <= 724 days). Reference line: median waiting time (224 days).

Figure 4. Time-dependent hazard ratios by quintiles of deprivation in education; estimates from Model 2c; baseline: patients from the least education-deprived quintile.



Note: graph truncated at 99% of the sample (i.e. waiting time <= 724 days). Reference line: median waiting time (224 days).

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