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ABSTRACT

Waiting times for elective surgery, like hip replacement, are often referred to as an equitable rationing mechanism in publicly-funded healthcare systems because access to care is not based on 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 hospitals and over large part of the waiting time distribution. The inequality experienced by the lowest income group increases after controlling for hospital heterogeneity.

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 replacement (Siciliani and Hurst, 2004; 2005). They generate dissatisfaction for patients and the general public. Waiting times postpone and therefore reduce patients' benefits. They may deteriorate patients' health status, prolong suffering and generate uncertainty.

In the absence of other rationing mechanisms, waiting times help to bring into equilibrium the demand for and the supply of healthcare by deterring patients with small benefit from demanding treatment (Lindsay and Feigenbaum, 1984, Martin and Smith, 1999, Cullis et al., 2000). Other rationing mechanisms also exist. For example, co-payments might be an alternative to contain moral hazard (Zweifel et al., 2009, Chapter 6). However, co-payments are often perceived as inequitable as poor patients may be deterred from seeking care. In contrast, waiting times are perceived as equitable, as the patients' costs or disutility generated by waiting do not depend on their ability to pay (while the loss of utility generated by co-payments does).

This study investigates whether richer and more educated patients in need of hip replacement experience shorter waiting times than poorer and less educated ones. We use administrative data from Hospital Episodes Statistics (HES), which includes patients treated by the publicly-funded National Health Service (NHS) in England. We find evidence that patients with higher socioeconomic status wait less. Therefore, waiting times might be less equitable than previously thought.

Patients' socioeconomic status is proxied by income and education deprivation in their area of residence. OLS results suggest that patients in the first quintile with least deprivation in *education* wait 9% less than patients in the second quintile and 14% less than patients in the third-to-fifth quintile. Moreover, patients in the fourth and fifth most *income*-deprived quintile wait about 7% longer than patients in the least deprived quintile.

Results from Cox regression suggest that more deprived patients in the *education* domain experience 13-20% lower probability of being treated than least deprived ones, although this difference is decreasing with time waited. Patients in the most deprived quintile of the *income* domain have 9% lower probability of being treated than least deprived ones. The analysis also provides evidence that most inequalities occur within hospitals rather than across hospitals. Failure to control for hospital heterogeneity results in underestimation of the difference between the top and the bottom income-deprived group. Finally, Kaplan-Meier survival curves and estimated hazard functions show that inequalities between better educated patients and other patients occur over large part of the waiting-time distribution.

1.1 Related literature

Using data from SHARE in nine European countries Siciliani and Verzulli (2009) 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. For non-emergency surgery, high education reduces waiting times by 66% in Denmark, 48% in Sweden and 32% in the Netherlands. They also find the presence of modest income effects. Their analysis makes use of survey data, which has the advantage that income and educational attainment are measured at individual level. However, sample size is generally small especially for individual procedures, and waiting times are measured in weeks or months and are therefore approximated. Moreover, waiting time information is self reported.

In this paper we make use of an administrative database covering the whole of the publicly-funded English NHS. The large sample size allows us to test for the socioeconomic gradient accurately. As well as age and gender, the data includes the number and type of diagnoses which helps controlling for patient severity of illness. On the other hand, socioeconomic status is proxied through information on the income and education deprivation score of their area of residence, using 32,000 Lower Super Output Areas (LSOAs) with average population of 1,500 (Noble et al., 2004).

Cooper et al. (2009) investigate whether there was any change in waiting time inequality in some procedures (hip and knee replacement, cataract surgery) during the Labour government between 1997- 2007 in the English NHS. They find that waiting times rose initially and then fell steadily. In 1997 waiting times and deprivation tended to be positively related. By 2007 the relation was less pronounced. They conclude that recent reforms like patient choice, provider competition and higher capacity did not come at the cost of equity.

Similarly to Cooper at al. (2009) we make use of data from HES. Our analysis differs in several respects. First, they measure socioeconomic status using the Carstairs index of deprivation, which offers an appropriate measure of material deprivation but does not capture deprivation in the education domain (Carstairs, 2000). Instead we measure socioeconomic status using two distinct indices 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 shows that education deprivation and income deprivation have distinct effects on waiting time.

Second, we use accurate controls for patients' severity using the type and the number of diagnoses (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 such controls might generate biased results.

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

Fourth, we investigate inequalities in patients' wait using duration analysis in addition to OLS. Although the latter provides easily interpretable results, the former is more appropriate for comparing the duration of states, like the time waited. Duration analysis allows investigating differences in waiting times over the whole distribution of time waited enlarging the scope of inequality analyses. Moreover, it allows for modelling non-normal dependent variables relaxing some parametric assumptions of the linear models.

Scholder et al. (2003) find that the probability of reporting 'problematic' waiting times does not differ across individuals with different socioeconomic status in the Dutch healthcare system. Alter et al. (1999) find that in Canada an increase in neighbourhood income from the lowest to the highest quintile were associated with a 45 percent decrease in waiting times for coronary angiography. Dimakou et al. (2009) employ duration analysis to identify the effect of government targets in the English NHS. They show that the hazard rate increases as time approaches the target. They do not control for socioeconomic status, which is our main focus. Carlsen and Kaarboe (2010a) find that in Norway women with low priority have lower income and less education than women with high priority. Among men below 50 years, patients with low priority have less education than patients with high priority. Carlsen and Kaarboe (2010b) investigate variations in waiting times across different socioeconomic groups in Norway.

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 (visits to specialist or family doctor), controlling for need (self-reported health), within a publicly-funded health system. The evidence broadly suggests pro-rich inequity for physician visits. If visits are split between specialist visits and family-doctor consultations, the evidence suggests pro-rich inequity for the former and of pro-poor inequity for the latter (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

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:

$$\ln(w_{ij}) = \alpha_j + \boldsymbol{\beta}_1'\mathbf{y}_{\mathbf{ij}} + \boldsymbol{\beta}_2'\mathbf{e}_{\mathbf{ij}} + \boldsymbol{\beta}_3'\mathbf{s}_{\mathbf{ij}} + u_{ij} \qquad (1)$$

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 for each of the four bottom quintiles of income and education distribution respectively; $\mathbf{s}_{\mathbf{ij}}$ is a vector of dummies that captures the severity of patients' health condition; α_j is a hospital-specific fixed effect and u_{it} is the idiosyncratic error. Inequalities arise if $\boldsymbol{\beta}_1 \neq 0$ or $\boldsymbol{\beta}_2 \neq 0$. If $\boldsymbol{\beta}_1 > 0\,(\boldsymbol{\beta}_2 > 0)$ then wealthier (more educated) patients wait less. We use a log transformation of the dependent variable to reduce the skewness of the waiting-time distribution.

Equation (1) includes controls for the severity of patients' health condition $\mathbf{s}_{\mathbf{ij}}$. Typically, doctors prioritise patients based on their health condition and capacity to benefit (Gravelle and Siciliani, 2008a). Patients in poor health might be at greater risk of a negative outcome from surgery if kept waiting or might experience greater disability and pain while waiting. Moreover, severe health conditions might be correlated (negatively) both with waiting and socioeconomic status. Failure to control for severity might generate biased results.

Hospital fixed effects are introduced to investigate whether socioeconomic inequalities are explained by differences in waiting times across hospitals. For instance, wealthier and better educated patients might be more likely to be treated in hospitals with low waiting times, since they travel longer distance (Propper et al., 2007). Under such a hypothesis the social gradient should decrease after controlling for hospital effect. Instead, if inequalities occur within hospitals the social gradient should remain unchanged. Moreover, hospital characteristics might be correlated with the socioeconomic characteristics of the patients' area of residence. For example, hospitals with high supply may be located in urban areas where low-income patients are concentrated. Omitting hospital effect might underestimate inequalities.

Duration analysis is used to investigate differences between socioeconomic groups over the whole distribution of time waited. A key concept is the hazard rate, $h(t)$, which measures the instantaneous probability of leaving the list (i.e. of being treated) at time *t* conditional on having waited until time *t*. First, we employ the Cox regression model to estimate the effect of socioeconomic status on the probability of leaving the list. This model is semi-parametric since it does not require assumptions over the distribution of the time waited. The Cox model identifies the effect of each covariate on waiting time in terms of hazard *ratios*, i.e. the ratio between the hazard *rates* of different groups of patients. The Cox model calculates the conditional hazard rate, $h(t;\ x)$, as:

$$h(t;\ x) = h_0(t)\exp\left(\textstyle\sum_k \beta_k x_k\right) \qquad (2)$$

where $x_k = \mathbf{y}', \mathbf{e}', \mathbf{s}'$ and $h_0(t)$ is the baseline hazard rate, i.e. the probability of leaving the list when all covariates are zero. The Cox model assumes the hazard ratio between two different groups, for example those treated in hospital *j* and hospital *j'* ,

$$\exp\left[\textstyle\sum_k \hat{\beta}_k \left(x_j - x_{j'}\right)_k\right] \qquad (3)$$

is constant with time waited (Cameron and Trivedi, 2005, Chapter 17.8, see Dimakou et al., 2009, Appleby et al., 2005). If this assumption is violated, then the *stratified* Cox model and the *extended* Cox model may be more appropriate. The former introduces group-specific baseline hazards, $h_{0j}(t)$. Therefore, the conditional hazard rate becomes:

$$h(t;\ x) = h_{0j}(t)\exp(\sum_k \beta_k x_k) \quad (4)$$

The main advantage of the stratified Cox model is that it relaxes the common baseline hazard assumption. The main disadvantage is that hazard ratios between the stratified groups cannot be identified.

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

$$h\big(t;\ x(t)\big) = h_0(\mathrm{t})\exp\big[\sum_k \beta_k\, x_k + \sum_k \delta_k\, x_k g_k(t)\big] \quad (5)$$

where δ_k are the coefficients of the time interactions. Now the hazard ratio between two groups of patients, *j* and *j'*, is a function of the time waited:

$$\exp\left[\sum_k \beta_k \left(x_j - x_{j'}\right)_k + \sum_k \delta_k \left(x_j - x_{j'}\right)_k g_k(t)\right] \quad (6)$$

In the extended Cox model the functional form of $g_k(t)$ should be based on the data generating process (Therneau and Grambsch, 2000, Chapter 6.5). Common specifications include: (i) $g_k(t) = t$, (ii) $g_k(t) = ln(t)$, (iii) $g_k(t)$ is a step function. Ignoring time dependency can result in biased standard errors and coefficients for time-dependent covariates. Specifically, the power of the test for these covariates decreases because suboptimal weights are used in combining the information. Moreover, the coefficients of covariates with hazard ratios converging[4] over the time waited are underestimated (Schemper, 1992).

Second, 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 being on the list after *t* periods. $S(t)$ is estimated using the non-

[4] Here "converging" means that the hazard rates for two groups of patients tend toward the same rate with the time waited.

parametric maximum-likelihood estimator (Kalbfleisch and Prentice, 2002, Chapter 15):

$$\hat{S}(t) = \prod_{z|t_z \leq t} \left(\frac{n_z - d_z}{n_z}\right) \qquad (7)$$

where t_z is the time at which patients exit the list (with z = 1,...,T), n_z is the number of patients still on the list before time t_z, and d_z is the number of patients who leave the list at time t_z.

The hazard function, $\hat{h}(t)$, is estimated from the baseline hazard, $\hat{h}_0(t_z)$, obtained from the Cox 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):

$$\hat{h}(t) = b^{-1} \sum_{z=1}^{D} K\left(\frac{t - t_z}{b}\right) \Delta\hat{h}_0(t_z) \qquad (8)$$

where *b* is the bandwidth of the kernel and the summation is over the *D* number of days waited at which the patient exits the list.

3 Data

We use individual hospital records for patients admitted for elective hip replacement in English NHS Hospitals in financial year 2001/2. We include all elective admissions involving primary total prosthetic replacement of the hip joint,[5] identified

[5] Patients requiring revisions or conversions of previous hip operations, other types of hip replacement operation such as hybrid prosthetic replacements, resurfacings and prosthetic replacement of the neck of femur were 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 patients' population. We also exclude: i) 538 missing waiting time observations (i.e. 340 concentrated in two Hospitals reporting no records); ii) 70 observations with a waiting time larger than three years; iii) four hospitals with a volume lower than 50 operations (98 observations). The latter are hospitals that occasionally supply extra capacity (a regular orthopaedic speciality manages an average of 206 primary hip operations). Our final sample includes 33,709 admissions divided in 163 Hospital Trusts.

under HRG H01, H02 and OPCS-4 codes W37.1, W38.1 and W39.1 reported in the first episode of care.[6]

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 hospital for treatment. If patients do not attend or are unfit for surgery on admission this time is not subtracted from the total waiting time.

The patients' health status is measured using dummies for her primary diagnosis and total number of diagnoses in the first episode of care. Primary diagnosis identifies the main reason for patient admission and is recorded using International Classification of Disease codes. We identify 15 most frequent primary diagnoses (Table 1), such as osteoarthrosis, coxarthrosis and gonarthrosis. The number of diagnoses per patient runs from 1 to 7 in 2001/2. It provides a useful instrument for case-mix adjustment (Wray et al., 1997, Hamilton and Bramley-Harker, 1999).

The socioeconomic characteristics of the patients are proxied using the socioeconomic deprivation score of their area of residence. These are measured using the income domain and the skill sub-domain of the English Indices of Multiple Deprivation 2004 (Noble et al., 2004) 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 provides the proportion of the LSOA population 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 IMD measures the proportions of working age adults (aged 25-54) in the area with no or low qualifications[7]. No qualification describes

[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.

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.[8] The index is based on the adult qualification data collected in the Census 2001. The raw 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).

The income deprivation score was divided into five quintiles using cut-off points based on the distribution of such variable in the general population. These quintiles contain 20% of the population by definition. Instead, the proportion of patients belonging to each quintile can be above or below 20% (see Table 1), since the deprivation mix among hip-replacement patients may differ from that of the general population. A dummy variable for each of the quintiles is created. The same procedure was applied to obtain the quintiles of the education deprivation index.

Table 1 presents descriptive statistics. Our sample covers 33,709 patients who received treatment in 2001 in 163 hospitals. The median and mean waiting time for hip replacement is respectively 224 and 259 days (Figure 1 plots the entire distribution). 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. Differences across areas are substantial. Some patients live

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[7] 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.

[8] 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.

[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, the standardized and the 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 one quintile to the next in the distribution of the deprivation in education equivalent to 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.

in areas where no residents are on benefits while others live in areas where 96% are on benefits (standard deviation is around 10%). Patients have on average 2.2 diagnoses with a minimum of 1, a maximum of 7, and a standard deviation of 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%).

Figure 1: Kernel density plot of patient waiting time

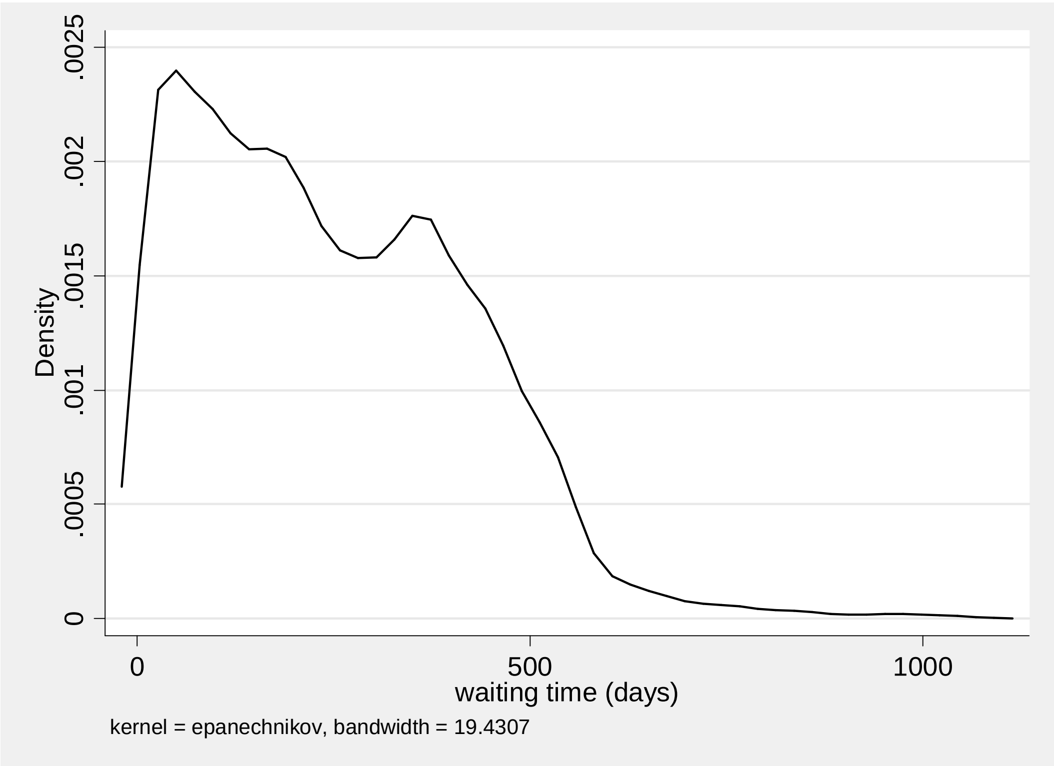


Table 1. Descriptive statistics

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 describes waiting times across different income groups. Least deprived patients, i.e. the richest in the first quintile, wait on average 239 days. Patients in the second quintile wait 246 days, while those in the third and fourth quintile wait 257 days. Most deprived patients, i.e. the poorest in the fifth quintile, wait 248 days. The relationship between income and waiting is non-monotonic: patients in the fifth quintile (the poorest) wait as much as those in the second quintile (the second richest).

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 2 also describes waiting times across education groups. A similar picture emerges. Patients in the least deprived areas wait least (233 days). Patients in the second quintile wait 247 days. Those in the third and fourth quintile wait about 255 days. 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 income and education. Although income and education are positively correlated, the number of patients with low education and medium income, or high education and medium income is substantial.

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

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 for age and gender only; Model 1b also includes controls for type and number of diagnoses; Model 1c adds fixed effects for 163 hospitals. The dependent variable is the log of waiting time. Therefore regression coefficients can be interpreted as proportional changes in average time waited. All models are estimated using cluster-robust standard errors by hospital provider. Since each hospital records the waiting time and clinical characteristics of its own patients, reported data are likely to be correlated within hospitals resulting in autocorrelated error terms. Failing to control for such autocorrelation can result in invalid standard error estimates.

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)

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 (the least deprived) 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 variation in the socioeconomic gradient by education or income after introducing additional controls for the severity of patient's health, i.e. primary diagnosis and number of co-diagnoses. Therefore, we find no evidence that heterogeneity in patients' health explains the social gradient in waiting times.

In contrast, introducing hospital fixed effects does impact on our results (Model 1c). Patients in the bottom quintile of the income domain now wait 7.5% longer than those in the highest quintile (p-value < 0.05). This supports the hypothesis that patients from areas most deprived in income are more likely to be treated in hospitals with short waiting times. This might be explained by the fact that hospitals with lower waiting times are generally located in urban areas where income-deprived people are concentrated (Noble et al., 2004). Moreover, the education gradient remains substantially unchanged suggesting that socioeconomic inequalities in waiting times operate within hospitals. Model 1c therefore does not support the hypothesis that inequalities in waiting times are explained by wealthier and better educated patients self-selecting into hospitals with shorter waiting times. Under such a hypothesis, we would expect a substantial fall in the overall education gradient after controlling for hospital fixed effects, which instead we do not observe.

Patients admitted with a primary diagnosis of "rheumatoid arthritis" or "osteonecrosis" experience substantially shorter waiting, i.e. 27% and 45-53% less than patients with "arthrosis" which is our baseline group. These two conditions are sensibly more severe and disabling than other diagnoses, and are thus a legitimate source of inequality in waiting. In particular, rheumatoid arthritis might seriously impair the authonomy of individuals in their daily life and is most effectively treated if tackled early in the course of the illness (Sathi et al., 2003). Therefore, it is not suprising that patients reporting such diagnosis are given priority in the waiting list. A similar argument applies to the waiting times of patients aged 75 and over, who wait about 17-30% less and are more likely to experience greater disabilities than patients aged 45-54 (the baseline). Male patients wait 3.5% longer. The number of secondary diagnoses has no effect on waiting once controlled for hospital fixed effects and primary diagnosis.

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

Results from Cox models are reported in Table 5. Such models relax some of the parametric assumptions of the OLS regression. Estimates from the Cox regression model described in Equation (2) are reported under Model 2a in the first column. In the second column, Model 2b controls for hospital effects stratifying the sample by hospitals as described in Equation (4). This allows the baseline hazard to vary by hospital and over time waited. Finally, Model 2c reports the estimates of the extended Cox regression model introducing covariates which vary with the time waited as described in Equation (5). Moreover it includes hospital stratification (as in Model 2b).

Tests based on Schoenfeld residuals (Schoenfeld, 1982) and estimated non-parametric hazard functions are used to examine potential time dependency on all covariates described in Table 1 and hospitals' fixed effects.[10] The results suggest that the proportional hazard rate assumption is not satisfied across hospitals, education, age and some of the diagnostic covariates, i.e. the hazard ratios for these covariates are not constant over time waited. For example, different hospitals might experience long queues that periodically need to be tackled by increasing hospital activity over different parts of the year. In order to control hospital heterogeneity, the Cox model is stratified by hospital (Model 2b) as described in Equation (4). Model stratification is coherent with the objectives of our inequality analysis as we are not interested in identifying hospital effects but only to control for them. In contrast, 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.

Model 2a and Model 2b show that the hazard ratio of leaving the list between the least and most deprived patients (the baseline) is respectively 0.96 and 0.91. This means that the probability of leaving the waiting list for wealthier patients is only 4% greater than for poorer ones if no hospital controls are used (Model 2a) and 9% greater after controlling for hospital heterogeneity (Model 2b). Moreover, this hazard ratio is statistically significant in Model 2b (p-value < 0.01), while it is not in Model 2a. Therefore, we find that controlling for hospital heterogeneity results in enlarging

[10] Results from tests and non-parametric hazard functions are available upon request from the authors.

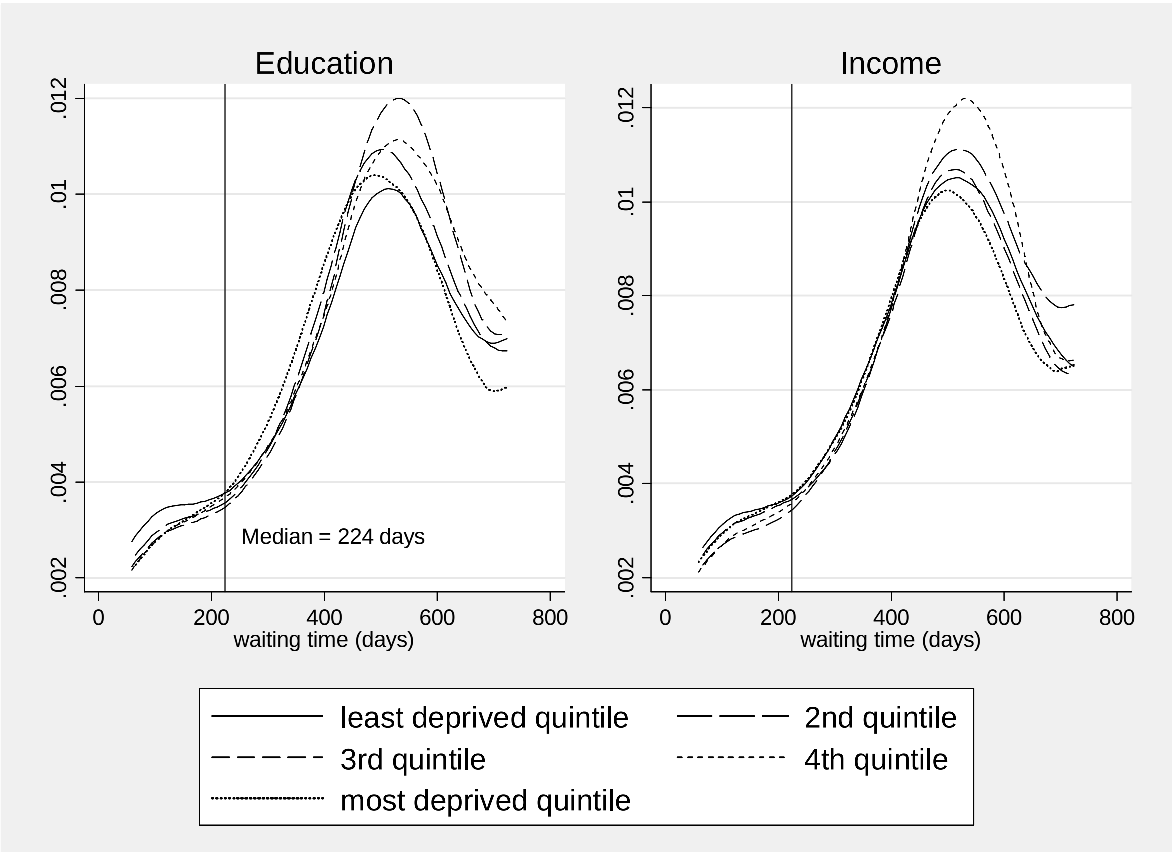
the hazard ratio between patients from the most and the least income-deprived quintiles, which is line with our OLS results.

Similar patterns are shown by the hazard ratios of the education quintiles. The hazard ratio of leaving the list between the least and most deprived patients is 0.98 (Model 2a) and 0.94 (Model 2b), which correspond to a higher probability of leaving the list by 2% and 6% in favour of the most educated patients. Most differences in waiting time across primary diagnosis vanish after controlling for hospital effect in Model 2b. This might be due to some hospitals being less accurate 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. Including time interactions in the model can be appropriate. However, it is necessary to specify a functional form for the time interactions, $g_k(t)$ (see Equation (5)). We adopt a linear specification, $g_k(t) = t$, assuming that hazard ratios decrease (or increase) at 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. Figure 2 shows that differences between the hazard rates of the education groups reduce at a constant rate over large parts of the distribution. Other functional forms are not supported by our data.

The results from Model 2c are similar to Model 1c. Socioeconomic inequalities in waiting times are larger by education rather than income. Patients from least deprived areas in the education domain experience a sensibly higher hazard of leaving the list. In Model 2c the differences in waiting times by education groups are allowed to vary with time waited. The hazard ratios shown under the first column of Model 2c refer to the hazard at the start of the patient's waiting (i.e. t=0). Figure 3 plots the hazard ratios of the education groups against the time waited using Equation (6). At the start of the waiting time, the probability of leaving the list for patients from the least education-deprived quintile (the baseline) is 20% higher than for patients from the most education-deprived quintile (0.80 hazard ratio). This gap reduces with 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 list for these two groups becomes equal only for patients still waiting after 322 days (about 34% of the patients). The hazard ratio for the fourth quintile of education shows a 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 at a lower rate with time waited (becoming equal at 406 days). The fourth quintile starts with at a difference of 13% in the probability of leaving the list (0.87 hazard ratio at t=0) and decreases at the lowest rate with time waited.

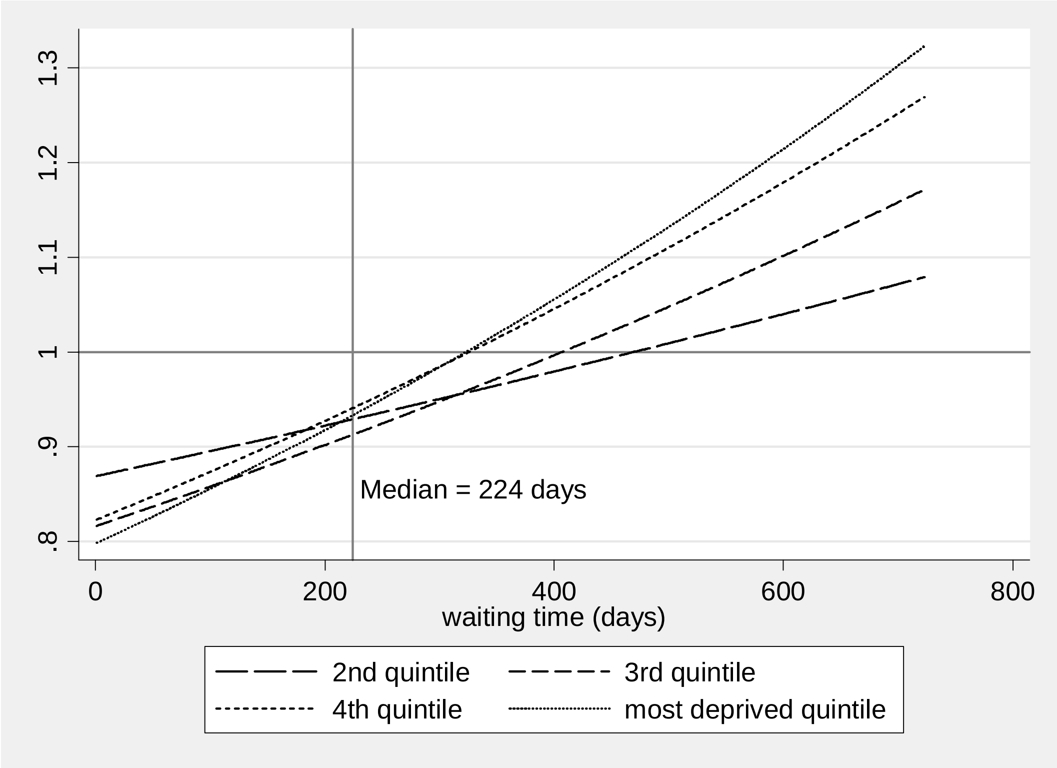
Figure 2. Estimated hazard curves



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

Reference line: median waiting time (224 days).

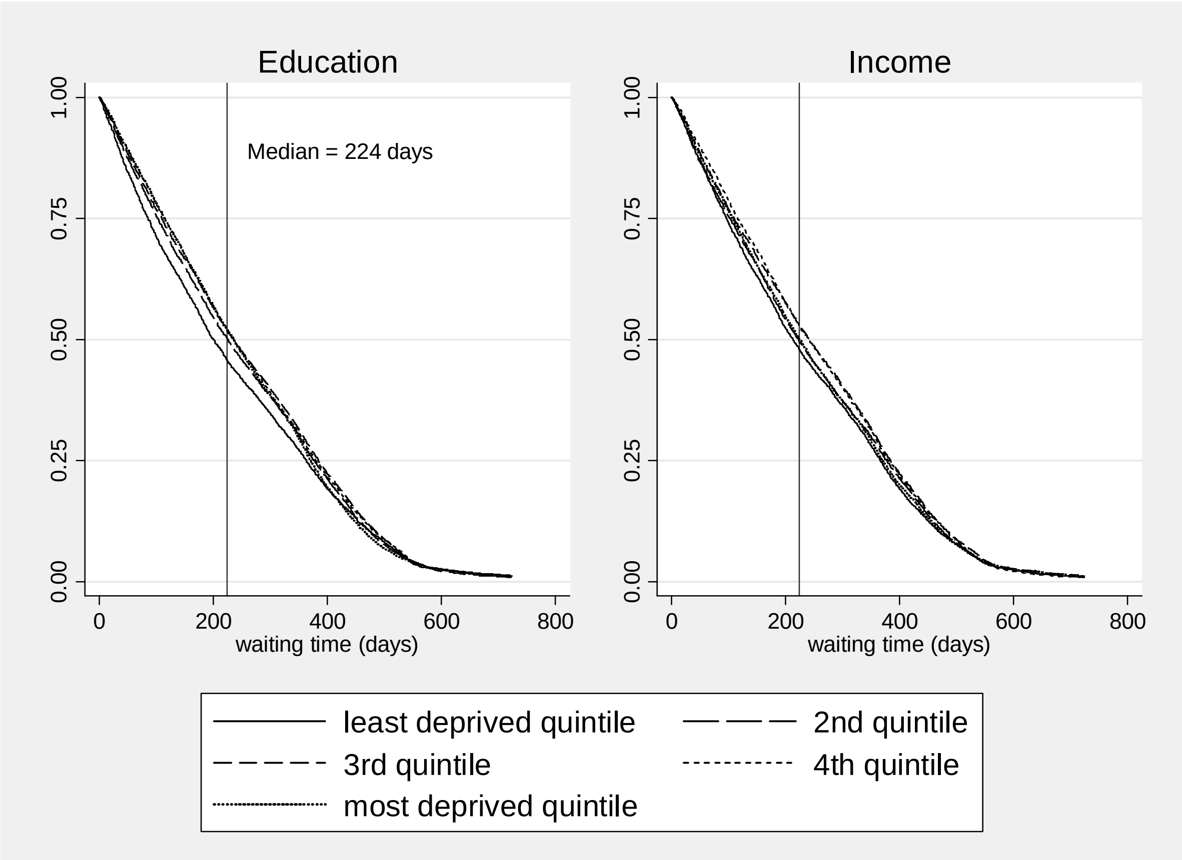
Figure 3. Time-dependent hazard ratios by quintiles of deprivation in education; estimates from Model 2c; baseline: patients from the least education-deprived quintile.



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

Reference line: median waiting time (224 days).

Figure 4. 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 4 shows Kaplan-Meier survival curves by quintiles of education and income using Equation (7). 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 pronounced only for patients waiting more than 400 days, who represent 20% of the patients. This can be interpreted in terms of fist-order stochastic dominance: for any given point in the first 80% of the waiting time distribution, the probability of leaving the list for least deprived patients is always higher.

5 Concluding remarks

This study investigates socioeconomic inequalities in waiting times for elective hip replacement using administrative data by English public hospitals in 2001. The analysis identifies the effect of two different indicators of the patient's socioeconomic status, income and education, on the time waited and shows that both have a distinct effect on the inequality in waiting times. Overall, it provides evidence of inequity favouring more educated individuals and, to a lesser extent, richer individuals. Inequalities occur within hospitals and over large part of the waiting-time distribution. Our study highlights the importance of controlling for hospital heterogeneity. Omitting hospital effects underestimates 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.

There are different explanations for our results. First, individuals with higher socioeconomic status may have better social networks. 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. Future work might be devoted to understand which of these factors explain the relationship between waiting times and socioeconomic status highlighted in this study.

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