Discrimination in a universal health system: Explaining socioeconomic waiting time gaps

Meliyanni Johar[a], Glenn Jones[a], Michael Keane[b], Elizabeth Savage*[a] and Olena Stavrunova[a]

[a]Economics Discipline Group, University of Technology, Sydney
[b]Department of Economics, University of Oxford

Funding

This work was supported by the Australian Research Council [DP0986785].

Acknowledgements

We thank Philip Haywood for clinical advice on mapping ICD codes in the hospital data to conditions relevant to hospitalisation. We also thank Pravin Trivedi, Jurgen Meineke, Lisa Cameron, Pedro Barros, Peter Sivey and participants at the 2nd Australasian Workshop on Health Economics and Econometrics, for useful comments. The NSW Inpatient and Waiting Time data is provided by the NSW Department of Health. The use of the data has program ethics approval from the University of Technology, Sydney.

*Corresponding author: Elizabeth Savage, University of Technology Sydney, Economics Discipline Groups, PO Box 123, Broadway NSW 2007 Australia. Email: Elizabeth.Savage@uts.edu.au T: +61295143202. F: +61295147722.

Abstract

One of the core goals of a universal health care system is to eliminate discrimination on the basis of socioeconomic status. We test for discrimination using patient waiting times for non-emergency treatment in public hospitals. Waiting time should reflect patients' clinical need with priority given to more urgent cases. Using data from Australia, we find evidence of prioritisation of the most socioeconomically advantaged patients at all quantiles of the waiting time distribution. These patients also benefit from variation in supply endowments. These results challenge the universal health system's core principle of equitable treatment.

Keywords: Public hospital, waiting time, discrimination, decomposition analysis

JEL codes: I11, J7, H51, C14, C21

1 Introduction

Equity is one of the primary objectives of the universal health care systems of most European countries, Canada, New Zealand and Australia. For example, one of the three guiding principles of the UK National Health System since its foundation has been that access to health care be based on clinical need, not ability to pay (Greengross et al., 1999). Similarly, the Australian Medicare system has always been grounded on 'access on the basis of health needs, not ability to pay' (Commonwealth of Australia, 2009). In contrast, in market-based health care systems such as that of the United States, equity goals are not explicitly formulated, and as a result, equity of access in the delivery of health services is under public scrutiny. Low-income Americans, who are likely to be uninsured, not only use fewer health services, but also receive less care when treated. Lopez et al. (2010) find that low income patients presenting with chest pain in the emergency department are less likely to be treated immediately and receive more basic cardiac testing than richer patients. Huynh et al. (2006) report that compared to richer patients, low income patients have lower access to medical care when sick (as measured by higher proportions of low income patients waiting six days or more for a doctor appointment) and are more likely to go without care because of cost. They also document a higher proportion of incorrect lab results or delay in receiving these results among uninsured individuals compared to insured individuals. Similarly, Doyle (2005) finds that hospitals provide less care (as measured by shorter length of stay and lower hospital costs) to uninsured patients injured in automobile accidents compared to insured patients, and that uninsured patients also have higher in-hospital mortality.

In universal health care systems, there has been less focus on the relationship between access to health care and socioeconomic status, perhaps because their core equity principle is simply assumed to hold. In this paper, we empirically test this presumption using waiting times for elective, or non-emergency, procedures as the measure of access. In public hospitals which are either free or heavily subsidised, waiting times are used to ration elective procedures. Prioritisation rules require that patients with the most life-threatening or urgent conditions, should be admitted first, regardless of their socioeconomic status. Countries differ in the way they implement clinical-based prioritisation rules. Canada and New Zealand have developed explicit, systematic prioritisation rules in the form of scoring tools which include both clinical criteria and non-clinical social factors perceived to contribute to urgency, such as inability to live and work independently. In contrast, in the UK, Spain, Sweden and Australia, prioritisation is guided solely by clinical need but without an explicit scoring procedure (see Siciliani and Hurst, 2005). Regardless of the method of implementation, there is a common theme in universal systems that no patient should be discriminated against on the basis of his/her socioeconomic status. In this paper, we test for discrimination in waiting times for elective procedures using data from public hospitals in Australia.

To access hospital care for an elective procedure in Australian public hospitals, a patient must obtain a referral from a GP for a specialist consultation. While the patient has free choice of specialist, typically the GP's advice will be relied upon to select the specialist. It is the specialist who books the patient onto a hospital waiting list and assigns an urgency category which determines priority on the waiting list. There are three urgency categories: (i) '30 day' is assigned to patients with 'a condition that has the potential to deteriorate quickly to the point that it may become an emergency'; (ii) '90 day' is used for 'a condition causing some pain, dysfunction or disability, but which is not likely to deteriorate quickly or become an emergency'; and (iii) '365 day' is used for 'a condition causing minimal or no pain, dysfunction or disability, which is unlikely to deteriorate quickly and which does not have the potential to become an emergency'. These urgency categories may be regarded as the maximum waiting time beyond which treatment can be considered overdue and possibly to carry health risks to patients.[1]

All Australian residents are eligible for public patient treatment at public hospitals by hospital specialists but they may elect to be treated as a private (paying) patient in which case they can choose their own specialist. Public patients are treated without charge and are financed from block grants under health agreements between the Commonwealth and State governments. Private patients are largely funded by insurance and this provides extra revenue to the public hospital as well as fees to the treating specialist.[2] Under hospital financing agreements, both public and private patients in public hospitals should be subject to exactly the same rationing rules.[3] However, Johar and Savage (2010) find dramatic waiting time differences between private and public patients waiting for the same procedure. They also find, even within the same urgency category, much shorter waiting times for

[1]The number of patients waiting beyond the clinically recommended time is part of hospital quality public reporting process however during the period of our data (2004-05) no financial sanction existed for performance.

[2]Specialist fees and pharmaceutical costs for private patients are subsidised under the Australian Medicare system.

[3]The principles governing funding of public hospitals are defined in the Australian Health Care Agreements between the Commonwealth and each state. Principle 7 requires that all public hospital services to private patients should be provided on the same basis as for public patients. Access to public hospital care should be on the basis of clinical need, not payment status. The Australian Health Care Agreement for 2003-08 can be found at http://www.health.gov.au/internet/main/publishing.nsf/content/B02C99D554742175CA256F18004FC7A6/$File/New%20South%20%20Wales.pdf

private patients in comparison to clinically comparable public patients. Because of the clear financial incentives for hospitals and specialists to expedite private patient admissions in public hospitals, we focus our analysis on public patients, who comprise 87% of all admissions to public hospitals. Private patients incur hospital and medical charges in exchange for choice of doctor and possibly a better standard of hospital accommodation which add to hospitals' fixed budgets. Excluding them avoids potential confounding effects due, for example, to preferences for different characteristics available with private care.

In principle a public hospital patient cannot choose the specialist who will perform the procedure. However, if the referring specialist has the right to admit private patients at the hospital to which the patient is referred, it is possible that the specialist may have influence on scheduling and may even perform the procedure on the public patient. There is no direct financial incentive for providers, both hospitals and specialists, to discriminate in favour of high income public patients, however providers may benefit from prioritising high income public patients by indirect means.

Discussions with hospital clinicians and administrators suggest that discrimination in favour of richer patients may extend even beyond the hospital, to the referring trail from GP to specialist and from specialist to hospital. In Australia, there is only anecdotal evidence on this, however, GP's influence in the referral trail has been found by Derrett (2005) using data from New Zealand. She finds that GPs help their patients obtain faster hospital admission by exaggerating their conditions when making specialist referrals.

Private health insurance provides an important link between patient income and observed referral patterns. Since high income patients are more likely to have private health insurance, they are more likely to use their insurance and elect to be admitted as private patients. Because of the financial incentives to increase throughput from private patients for both specialists and hospitals, preference may be given to patients from GP practices with many privately insured clients (i.e., GP practices in high income areas). To strengthen this relationship, this favourable treatment may extend to all patients from these GPs, including those electing for public treatment. Similarly, hospitals have an incentive to give preference to the referring recommendations of specialists who refer a greater volume of private patients to the hospital.

These indirect incentives are facilitated by the considerable variability in waiting list management procedures across hospitals. In principle, waiting time registers are managed by the hospital administrator who has the discretion to schedule patients on the lists. However, in some cases, the treating specialist, who may be contracted to the hospital, manages his/her own waiting list, and in other cases, groups of specialists may jointly manage scheduling. In addition, the absence of an explicit prioritisation scoring tool gives discretion to specialists in assigning urgency class to patients, especially where there is low mortality risk from delayed treatment.[4] In either case, there is major involvement by specialists and it is difficult to monitor the equity dimension of waiting times.

Discretion in waiting list management processes may also accommodate certain characteristics and behaviours of high income patients to reduce their waiting times. For example, high income patients may have a stronger GP-patient bond, and this may result in GPs taking greater account of non-clinical factors and assigning their high income patients to specialists who are more effective at scheduling treatment. Richer patients may tend to be more "active" patients, regularly checking with the waiting list administrator for last minute gaps or cancellations. They may be better able to negotiate their way through the waiting list system.

Although we cannot separately identify the impact of each of these pathways, all are inconsistent with the equity principle underlying Australia's universal health system. Each could contribute to shorter waiting times for patients with higher socioeconomic status unrelated to clinical factors. We find that the cumulative effect of these mechanisms creates a substantial and systematic advantage for high income patients and, as such, we interpret it as discrimination.

Our empirical approach consists of two stages. In the first stage, we establish the link between waiting time and socioeconomic status by means of regression. Past studies using this approach have found evidence of an independent socioeconomic effect on waiting times in European public hospital systems (Siciliani and Verzulli, 2009; Dimakou et al., 2009; Askilden et al., 2010; Siciliani et al., 2010). In an advance on this approach, we extend the regression framework by conducting a decomposition analysis of the socioeconomic waiting time gap. Decomposition analysis has been widely used by labour economists in studying the gender gap in wages and racial differences in wealth (Oaxaca, 1973; Blinder 1973; Blau and Khan, 1992; Doiron and Riddell, 1994; Hildebrand and Cobb-Clark, 2006) and is now being adopted in health economics applications (Wenzlow, Mullahy and Wolfe, 2004; Pylypchuk and Selden, 2008). In the second stage of our analysis, we decompose waiting time variation into that which can be explained by differences in clinical need and allocation of public health resources by patients' socioeconomic status (endowment effects), and that which is

[4]Gaming behaviour by doctors has been recognised in the literature (MacCormick et al., 2004; Propper et al., 2010).

due to differences in the return to these characteristics in terms of reduced waiting times (treatment effects). We employ the approach proposed by Firpo, Fortin and Lemieux (2007, 2009) which allows the endowment and treatment effects to vary across the waiting time distribution. Having a flexible approach is important because the endowment and treatment effects may be stronger at different parts of the distribution. For example, preferential treatment to patients on the basis of their socioeconomic status may be more likely to occur if there is lower mortality risk, so we might expect stronger preferential treatment on the basis of socioeconomic status in the upper tail of the waiting time distribution.

We find evidence of prioritisation of the most socioeconomically advantaged patients at all quantiles of the waiting time distribution. At the 90th percentile of the waiting time distribution, the least socioeconomically advantaged patients wait over 4 months longer for an elective procedure compared to the most advantaged patient group. None of this gap can be attributed to differences in clinical needs. About a third of it can be attributed to favourable treatment of the most socioeconomically advantaged patients and the remaining gap is due to supply-side endowments that work in their favour. Our results suggest that the burden of long waits falls disproportionately on the least socioeconomically advantaged patients and that the current waiting list operation in Australia falls short of the policy goal of equity.

2 Data

Our data are derived from administrative records of completed waiting list episodes during the period 2004-2005 in public hospitals in the state of New South Wales (NSW), the most populous state of Australia. This data set contains information on urgency category, patient's age, gender, detailed chronic conditions (diagnoses), procedures and postcode of residence. We focus on NSW residents and public hospitals that treat acute illnesses. This excludes smaller health facilities, such as small non-acute hospitals, hospices, multi-purpose units and rehabilitation units. Further, we consider only patients who have spent at least a day on the waiting list because patients with zero waiting days are likely to represent quasi emergency admissions especially in areas with no emergency departments.[5] We do not have reliable information on private health insurance status, however previous studies suggest that those without private health insurance are much more likely to use the public system than those privately insured (Savage and Wright, 2003).

[5]Patients with zero waiting days make up 5% of admissions.

We make two more restrictions to get a clearer interpretation of the socioeconomic gap in waiting time. First, as mentioned, we include only non-charge or public patients[6] who make up the vast majority of admissions to public hospitals (87%). Second, we focus on patients who live in the state capital, Sydney, who have similar geographic access to public hospitals. The final sample size consists of 90,162 patients.

As with most, if not all, registry data, information on personal income is not available. We therefore use information on patients' residential postcode to combine the individual patient clinical data with census data on socioeconomic status. The Australian Bureau of Statistics (ABS) constructs a number of summary measures of economic advantage and disadvantage, known as SEIFA (Socio-Economic Indexes for Areas) indices, for geographic areas (ABS, 2001). We use the Index of Relative Advantage and Disadvantage. This index is constructed using a list of socioeconomic measures such as income, education, employment status and housing characteristics. The score underlying the index is given by the first principal component in a principal component analysis; it is the single variable that best summarises the common relationship among the above set of socioeconomic indicators. Areas are then ordered according to their scores, and the Index of Relative Advantage and Disadvantage is the decile of the score for that area (i.e. 1, 2, ... 10). An area with a high index has a relatively high incidence of advantage and a relatively low incidence of disadvantage. We re-group the deciles into quintiles, SEIFA 1 to 5, and interpret the bottom 20%, SEIFA 1, as the least socioeconomically advantaged group and the top 20%, SEIFA 5, as the most advantaged group. To give an idea of the income disparities across the SEIFA groups, the median individual income of the most advantaged group is about 1.4, 1.7, 2.0 and 2.2 times greater than that of SEIFA 4, 3, 2 and 1, respectively.[7]

It is possible that the socioeconomic gap in waiting time is not due to discrimination per se, but because better-off individuals tend to live in areas with a greater supply of hospital services. Therefore, we also control for a rich set of hospital supply measures. We supplement patient-level data with information on hospital characteristics obtained from the NSW Health Services Comparison Data Book(s). The books contain detailed in-hospital information including activity level, expenditures and staffing. We use the 1997-1998 and 2007-2008 data, which are the closest available books to our sample period. For each variable of interest, we take the average values from the two periods. We tested the sensitivity of

[6]These are Medicare-eligible, public patients excluding Veteran's Affairs, Defence Forces and Worker's Compensation patients.

[7]Results using only the median household income to define economically advantaged or disadvantaged groups are qualitatively the same. They are available from authors upon request.

our results to using a weight of 0.3 for 1997-1998 and a weight of 0.7 for 2007-2008, but the weighting rule does not substantially alter the results. This indicates that hospital characteristics tend to change slowly.

We consider the following supply variables: (i) to capture the potential bed competition with admissions from emergency departments we use admission from emergency as a proportion of total admissions; (ii) to measure activity we use same day admissions as proportion of total admissions and the bed occupancy rate; (iii) to measure the share of private (paying) patients we use private beds as a proportion of occupied beds; (iv) to capture complexity we use average length of stay of acute episodes; and (v) to measure human resources we use inpatient clinical equivalent full-time staff per available bed and the shares of total hospital expenses of medical salaries and visiting medical officer (VMO) payments and nursing salaries. The supply variables are entered as deviations from the overall sample mean. This is done to aid the interpretation of results.

The means of waiting times and some explanatory variables by SEIFA are presented in Table 1.[8] Across SEIFA groups, the most socioeconomically advantaged patients (SEIFA 5) are older and assigned more urgent categories. Their mean waiting time is markedly shorter than that of other patients (74 days compared with 112 days for the least socioeconomically advantaged patients (SEIFA 1)). Because the distribution of waiting time is positively skewed, for estimation we use the log of waiting time.

A potential source of bias in the data is that we do not observe patients who choose to be treated at private hospitals. To the extent that the choice of a private hospital is more likely to be exercised by socioeconomically advantaged patients with long expected waits, this may lead to underestimation of their average waiting times. If they are non-urgent and tend to elect for private hospital admission, we would expect to observe a substantially lower share of most socioeconomically advantaged in the 365 day urgency class than for lower socioeconomic groups. We do not have data on private hospital admissions, however, we do observe a considerable share of the most socioeconomically advantaged patients in the least urgent class (see Table 1). This suggests that any bias due to selection of socioeconomically advantaged patients with long expected waits into private hospitals is likely to be minimal.

With regard to supply characteristics, SEIFA 5 patients are treated in hospitals with higher levels of all supply variables apart from medical staffing cost shares. Noticeably, they use hospitals with a high share of private bed days whilst the opposite is true for the SEIFA

[8]For conciseness, we suppressed the summary statistics related to diagnoses. They are represented by 28 dummy variables. The number of conditions are based on conditions which are associated with hospitalisation (e.g., short-sightedness is excluded).

1 patients.

Table 1: Variable means by SEIFA quintile

3 Estimation

3.1 Oaxaca and Blinder decomposition

To quantify the role of various factors in driving the observed socioeconomic waiting time gap, we undertake a decomposition analysis that has been extensively used in the labour economics literature. Seminal papers of Oaxaca (1973) and Blinder (1973) (here onwards OB) decompose gender gap in wages into the contribution of human capital, job types and industry, other demographics, and interpret the contribution of unexplained factors as a discrimination effect.

The OB decomposition takes advantage of a linear regression model to decompose the expected outcomes of any two distinct groups, A and B. Let W be waiting time and X be a row vector of K individual covariates. The conditional mean of W for group j ($j = A, B$) is $E(W|X, J = j) = E(X|J = j)\boldsymbol{\beta}_j$ where $E(X|J = j)$ is the mean of X among group j, and is a $[Kx1]$ vector of regression coefficients, which can be estimated by OLS. The OB approach would decompose the overall difference in mean waiting times into two components: 'endowment', which measures how waiting time setting factors are unequally distributed across groups, and 'treatment', which relates to differences in coefficients applied to different groups. By adding and subtracting a counterfactual conditional mean, for instance $E(X|J = A)\boldsymbol{\beta}_B$, which reflects a situation in which group B individuals have the covariates of group A, it is possible to identify the two components:

$$\begin{aligned} \Delta^{\mu} &= \mu_A - \mu_B \\ &= E(X|J = A)\boldsymbol{\beta}_A - E(X|J = B)\boldsymbol{\beta}_B + E(X|J = A)\boldsymbol{\beta}_B - E(X|J = A)\boldsymbol{\beta}_B \\ &= (E(X|J = A) - E(X|J = B))\boldsymbol{\beta}_B + E(X|J = A)(\boldsymbol{\beta}_A - \boldsymbol{\beta}_B) \qquad (1) \\ &\equiv \Delta^{\mu}_E + \Delta^{\mu}_T, \end{aligned}$$

where Δ^{μ}, Δ^{μ}_E and Δ^{μ}_T denote the overall difference in means, the difference in means due to endowment and the difference in means due to differences in $\boldsymbol{\beta}$ or 'treatment', respectively. The latter is the unexplained part of the socioeconomic waiting time gap.

Moreover, the additivity assumption allows identification of the contribution of each covariate to the endowment and treatment component. Rewriting equation (1) and replacing it with its sample counterparts, we have

$$\widehat{\Delta}^{\mu} = \overline{W}_A - \overline{W}_B = \sum_k (\overline{X}_{Ak} - \overline{X}_{Bk})\widehat{\beta}_{Bk} + \sum_k \overline{X}_{Ak}(\widehat{\beta}_{Ak} - \widehat{\beta}_{Bk}) + (\widehat{\alpha}_A - \widehat{\alpha}_B) = \widehat{\Delta}^{\mu}_E + \widehat{\Delta}^{\mu}_T, \quad (2)$$

where $\overline{W}_A$ and $\overline{W}_B$ are sample mean waiting times for group A and B, respectively, $\widehat{\beta}_{jk}$ is the OLS slope estimate for variable X_k $(k = 1, ..., K)$ for group j, $\overline{X}_{jk}$ is its corresponding sample mean, and $\widehat{\alpha}_j$ is the intercept. Throughout this study, we define group B as the most socioeconomically advantaged group, SEIFA 5.

We partition X_k into two sets. The first set reflects clinical need and consists of patient's age, gender, procedure, chronic diagnoses, number of chronic diagnoses and urgency assignment. The second set consists of the supply characteristics mentioned above. With two sets of waiting time determinants, the socioeconomic waiting time variations can be attributed to 4 sources: (i) an endowment effect associated with patients' clinical needs; (ii) an endowment effect associated with supply characteristics; (iii) a treatment effect associated with patients' characteristics; and (iv) a treatment effect associated with supply characteristics.

We argue that (ii)$-$(iv) have interpretations as discrimination. Discrimination associated with patients' health endowments can be explained by the behaviour of the providers responsible for scheduling procedures. For example, being assigned an urgency classification of 365 days results in a longer waiting time for SEIFA 1 patients compared with SEIFA 5 patients. Meanwhile, discrimination related to supply in a universal health care system can take two forms: unequal access to public hospital resources and differential impacts of hospital resources by socioeconomic status. The former reflects a very broad dimension of discrimination extending beyond the behaviour of doctors or hospitals. It partly reflects the allocation procedure that assigns patients to specialists and hospitals but also access to transport and information about alternative hospitals.

We attribute differences in intercepts $(\widehat{\alpha}_A - \widehat{\alpha}_B)$ in equation (2) to patient treatment effects. The intercept has an interpretation of the expected waiting time of the omitted patient group in an average hospital. The differences in intercepts can reflect (a) unmeasured clinical need; (b) the ability of patient to negotiate the system; (c) unmeasured hospital characteristics (eg quality of hospital management); or (d) pure discrimination effects. We have detailed data on patient diagnoses and procedures that it is unlikely that differences in the intercept reflect unmeasured clinical need. Once we rule out (a), we are left with (b),

(c) and (d) all of which can have interpretations as discrimination.

While the OB approach is popular and has intuitive appeal, it suffers from several well-recognised drawbacks. OB focus on the mean but it is quite possible, for example, that waiting time gaps are larger in the upper tail of the waiting time distribution because patients' conditions are less urgent with lower mortality risk of delayed treatment. Another potential bias comes from the fact that OLS coefficients $\boldsymbol{\beta}$ depend on the distribution of covariates. This means that when they are estimated for different groups, the difference between them can be an empirical manifestation of the different covariate distributions between groups, rather than reflecting the true differences in treatment effects.

DiNardo, Fortin and Lemieux (1996) and Firpo, Fortin and Lemieux (2007; 2009) (here onwards FFL) propose a more flexible method of decomposition analysis that generalises the OB approach by allowing OB-type decomposition of any characteristic of a distribution (e.g. variance, quantiles, etc.). The FFL method consists of two stages. In the first stage a counterfactual distribution of waiting time is constructed using a matching technique. The counterfactual distribution is the distribution which would have prevailed under the waiting time generating process for SEIFA 5 patients (group B) but with the characteristics of less socioeconomically advantaged patients (group A). This stage, as proposed in DiNardo et al, removes waiting time differentials due to differences in the distribution of covariates between the two groups by reweighting observations in group B. In particular, for each comparison group A, we estimate a weighting function to construct a counterfactual distribution of waiting time for SEIFA 5 patients when they are assigned characteristics of group A. The weights are estimated using a logit model predicting group A membership as a function of all patient and supply characteristics.[9] There are four counterfactual distributions for SEIFA 1 to 4 with the SEIFA 5 waiting time distribution. In each comparison pair, the counterfactual group is called group C.

In the second stage of FFL decomposition these counterfactual distributions are used to compute treatment and endowment effects for selected characteristics of the waiting time distribution (i.e. quantiles in our study) and to decompose these effects into contributions of various characteristics (i.e. patient and supply characteristics) using re-centred influence function (RIF) regressions. Next section will discuss the second stage of FFL decomposition in detail.

[9] Details of the weighting function can be found in DiNardo, Fortin and Lemieux (1996). Based on the logit estimates, we can find weights on observations that equalise the patient and supply characteristics across groups (so SEIFA group is the only difference).

3.2 FFL decomposition

Unlike the mean, which can be decomposed using OLS (as in OB), we cannot decompose quantiles using the standard quantile regressions. The coefficients in OLS indicate the effect of covariates X on the conditional mean $E(W|X)$ in the model $E(W|X) = X\boldsymbol{\beta}$. This yields an unconditional mean interpretation where $\boldsymbol{\beta}$ can be interpreted as the effect of increasing the mean value of X on the (unconditional) mean value of W.

By contrast, only the conditional quantile interpretation is valid in the case of quantile regressions. A quantile regression model for the τ^{th} conditional quantile postulates that $q_\tau(X) = X\boldsymbol{\beta}_\tau$. By analogy with the case of the mean, $\boldsymbol{\beta}_\tau$ can be interpreted as the effect of X on the τ^{th} conditional quantile of W given X. However, the law of iterated expectations does not apply in the case of quantiles so, $q_\tau \neq E_X[q_\tau(X)] = E(X)\boldsymbol{\beta}_\tau$, where q_τ is the unconditional quantile. It follows that $\boldsymbol{\beta}_\tau$ cannot be interpreted as the effect of increasing the mean value of X on the unconditional quantile . This greatly limits the usefulness of quantile regressions in decomposition problems.

FFL suggest estimating the recentered influence function (RIF) for quantiles of waiting times and then conducting the OB-style decomposition exercise using the RIF regression coefficients. Consider the influence function $IF(w; v)$ which measures how much influence an observation w has on the distributional statistic of interest v, such as a quantile. The RIF is defined as $RIF(w; v) = v(F_W) + IF(w; v)$, where F_W is the waiting time distribution. By definition, the expectation of the IF with respect to the distribution of w is equal to zero. Hence, the expectation of the RIF is equal to the statistic of interest.

It can be shown that for observation w the RIF for quantile q_τ has the form:

$$RIF(w; q_\tau) = q_\tau + \frac{\tau - \iota\{w \leq q_\tau\}}{f_W(q_\tau)}, \tag{3}$$

where the second term is the IF, q_τ is the τ^{th} percentile of waiting time, $\iota\{.\}$ is an indicator function for waiting time up to and inclusive of the τ^{th} percentile and $f_W(q_\tau)$ is the density of W evaluated at q_τ. The RIF function can be computed for each observation w (after replacing $f_W(q_\tau)$ with its kernel density estimate), and the conditional (on X) expectation of the RIF can be estimated by OLS regression in which the RIF acts as a dependent variable. The estimated coefficients $\boldsymbol{\gamma}$ from the RIF regression can be interpreted as the effect of increasing the mean value of X on the unconditional quantile q_τ (using FFL's terminology, measures the 'unconditional quantile partial effect').

To save notation, let v_A,v_B and v_C be the quantile of interest for groups A, B and a counterfactual group C, respectively. Recall that the expectation of the RIF is equal to the statistic of interest. Hence in the presence of covariates we can apply the law of iterated expectations to write

$$v_j = E(RIF(w_j; v_j)|J = j) = E_X\{E(RIF(w_j; v_j)|X, J = j)\} \text{ for } j = A, B$$

and

$$v_C = E(RIF(w_B; v_C)|J = A) = E_X\{E(RIF(w_B; v_C)|X, J = A)\},$$

where the notation w_j means that observation w belongs to group j.

To allow direct comparison with the OB approach, suppose that the conditional (on X) expectation of the RIF can be well approximated by a linear function of covariates as in OB, i.e. $E(RIF(w_j; v_j)|X, J = j) \approx (X|J = j)\boldsymbol{\gamma}_j^v$, where $\boldsymbol{\gamma}_j^v$ are the RIF regression coefficients. Then the unconditional quantile v_j is the expectation of $(X|J = j)\boldsymbol{\gamma}_j^v$ with respect to $X|J = j$ and thus can be represented as a product of $E(X|J = j)$ and $\boldsymbol{\gamma}_j^v$:

$$v_j \approx E(X|J = j)\boldsymbol{\gamma}_j^v \text{ and } v_C \approx E(X|J = A)\boldsymbol{\gamma}_C^v. \tag{4}$$

With this approximation, it follows that the endowment and treatment components can be written as:

$$\begin{aligned} \Delta_E^v &= v_C - v_B = E(X|J = A)\boldsymbol{\gamma}_C^v - E(X|J = B)\boldsymbol{\gamma}_B^v \\ \Delta_T^v &= v_A - v_C = E(X|J = A)\boldsymbol{\gamma}_A^v - E(X|J = A)\boldsymbol{\gamma}_C^v \end{aligned} \tag{5}$$

We can write a version of equation (2) for quantile of interest v as:

$$\begin{aligned} \widehat{\Delta}_E^v &= \sum_k \overline{X}_{Ak}^C \widehat{\gamma}_{Ck}^v - \sum_k \overline{X}_{Bk}\widehat{\gamma}_{Bk}^v = \sum_k (\overline{X}_{Ak}^C - \overline{X}_{Bk})\widehat{\gamma}_{Bk}^v + \widehat{R}_1^v \\ \widehat{\Delta}_T^v &= \sum_k \overline{X}_{Ak}(\widehat{\gamma}_{Ak}^v - \widehat{\gamma}_{Ck}^v) + \widehat{R}_2^v, \end{aligned} \tag{6}$$

where $\overline{X}_{Ak}^C$ is the sample mean of variable X_k in the SEIFA 5 sample, weighted using the characteristics of group A, $\widehat{R}_1^v = \sum_k \overline{X}_{Ak}(\widehat{\gamma}_{Ck}^v - \widehat{\gamma}_{Bk}^v)$ and $\widehat{R}_2^v = \sum_k \widehat{\gamma}_{Ck}^v(\overline{X}_{Ak} - \overline{X}_{Ak}^C)$. Compared to equation (1), apart from $\widehat{R}_1^v$, $\widehat{\Delta}_E^v$ is similar to the OB endowment component, while $\widehat{\Delta}_T^v$ resembles the OB treatment component but with $\widehat{\gamma}_{Ck}^v$ instead of $\widehat{\gamma}_{Bk}^v$. So for the treatment effect, we are using group C as the reference group, instead of group B. This minimises potential bias in the treatment effect due to the distinct distribution of covariates between groups. $\widehat{R}_1^v$ can be interpreted as an error associated with the fact that a potentially incorrect specification may be used for the RIF regression (Firpo et al., 2007). Meanwhile, $\widehat{R}_2^v$ measures the appropriateness of the weighting function. If the weighting function is valid, $\widehat{R}_2^v$ should be small.

It is noteworthy that because FFL is based on linear regressions like OB, the FFL approach is path independent, that is, the order in which the different elements of the detailed decomposition are computed does not affect the results of the decomposition. This contrasts with the DiNardo et al.'s reweighting approach, which is path dependent. In estimation, we take the natural logarithm of waiting times, which are highly positively skewed. The RIF is computed following Fortin's (2009) sample code and given the RIF regression results, the decomposition exercise is implemented using *oaxaca* command in STATA (Jann, 2008).

4 Results

4.1 Regression results

Before we proceed to the decomposition results, we confirm that socioeconomic status has independent effects on waiting time by running a linear regression. Table 2 reports the results of two regression models that differ in the sets of covariates included. Model 1 includes only clinical needs and SEIFA groups while Model 2 also includes supply factors. In both models, the coefficients on SEIFA categories are jointly significant at the 1% level (F-statistics of 140 and 92 for Model 1 to 2, respectively). Socioeconomic groups have significant and independent effects on waiting time. When controlling only for clinical need (Model 1), relative to SEIFA 5 patients, SEIFA 1-3 patients wait on average 30% longer (about 28 days at the overall mean waiting time of 94 days) and SEIFA 4 patients wait 19% longer (18 days).

When both patient and supply characteristics are added in Model 2, the socioeconomic waiting time gaps are narrowed compared to those found in Model 1. However, the estimates still imply that the lower socioeconomic groups wait 16-24% longer than SEIFA 5 patients, depending on the SEIFA group. If health resources reduce waiting times, this upward bias suggests a positive relationship between supply and socioeconomic status. Supply consists of several measures and they have differing effects on waiting times. Waiting times increase with emergency admissions, bed occupancy rates and share of hospital expenditure to pay for medical staff and visiting medical officers (VMO). However, waiting times decrease with the proportion of private patients, the average length of stay, the staffing level per bed and the nursing share in total hospital expenditure.

Table 2: Regression results of log waiting time

4.2 Distribution of log waiting times

Figure 1 plots kernel density estimates of log waiting times by socioeconomic status. It is clear that a greater mass of SEIFA 5 waiting times is concentrated in the lower half of the distribution compared with other patients. This implies that the share of patients experiencing extensive delays is lower for SEIFA 5 patients than for any other patient group. The upper tail is the thickest for the two lowest SEIFA groups. The noticeable hump at zero is explained by the presence of patients who are on the waiting list for just a day before they are admitted. SEIFA 5 has a higher share of these one-day patients than other SEIFA groups.

Figure 2 shows the density of counterfactual waiting time for SEIFA 5 patients for each comparison pair (the first stage of the FFL approach). Recall that the counterfactual waiting time reflects the waiting time that would occur had SEIFA 5 patients had the covariates of less socioeconomically advantaged patients. We can see that at the lower tail of the waiting time distribution (short waits), the counterfactual distribution drifts somewhat from the actual waiting time distribution of SEIFA 5 towards that of the less advantaged patients suggesting that covariates have a lot to do with socioeconomic waiting time gaps for short waits. At the upper tail of the waiting time distribution (long waits), the counterfactual distribution approaches the waiting time distribution of less advantaged patients but the relatively large remaining gap suggests that factors other than the distribution of covariates are important in driving the socioeconomic waiting time gaps for long waits.

Figure 1: Density of log waiting times

Figure 2: Density of actual and counterfactual log waiting time by SEIFA pair

4.3 FFL Results

From equation (3), for each patient, we compute the $RIF(w_j; q_{j,\tau})$ using an estimate of q_τ from each group in the pairwise sample. $f(q_\tau)$ is estimated by an Epanechnikov kernel with a bandwidth of 0.12.[10] We decompose the waiting time gap for 9 waiting time quantiles, from the 10^{th} to the 90^{th}) quantile. However, for reporting purposes, we report the results for only 3 quantiles, Q10, Q50 (the median) and Q90. We will first discuss the decomposition results for overall patient and supply characteristics. Later, we present the results of a detailed decomposition of supply characteristics.

4.3.1 Decomposition of overall patient and supply characteristics

Table 3 reports the total endowment and treatment effects for patient and supply characteristics, as well as the total differences in log waiting times and residuals. The first two rows assure us that the observed log waiting time gap and the estimated RIF gap (equation (5)) are very close. In general, waiting time gaps are large and do not decrease in high waiting time quantiles. At the bottom of the waiting time distribution, a 65% (exp(0.5055)-1) waiting time difference translates to 2 days, but at the top of the distribution, a 65% waiting time difference means that the most socioeconomically advantaged patients are admitted over 4 months earlier than the least advantaged patients. This is a substantial delay which can be costly to patients (e.g. declining work ability and prolonged inconvenience). The last two rows in Table 3 report the size of the residuals in equation (6). In general, they are relatively small, lending support to the use of the FFL approach. $\widehat{R}_1^v$, which can be seen as an adjustment factor to the endowment effect in the case where the linear specification is inaccurate, tends to be negative at short waits and positive at long waits.[11] Since we observe that the most socioeconomically advantaged patients access better health resources (Table 1), the positive adjustment factor may reflect a flatter relationship between waiting times and supply as supply gets larger. Meanwhile, $\widehat{R}_2^v$ reveals no noticeable pattern and is mostly insignificant.

Table 3: Decomposition of overall patient and supply characteristics

A striking feature of Table 3 is that in the comparisons between SEIFA 5 and each of the less advantaged groups the patient endowment effect is an important factor only at low waiting times and that its importance declines markedly as waiting time increases to become

[10]We experimented with different bandwidths and Gaussian weights and our results are robust to these alternative specifications.

[11]In the labour literature where the decomposition exercise often focuses on the evolution of wage gaps, residuals are often found to be small. This is because groups are defined by time and group membership is well predicted by covariates such as age and the unemployment rate.

approximately zero at Q90. For short waits, a substantial part of the socioeconomic waiting time gap can be explained by less advantaged patients' health characteristics. At Q10 patient endowments explain 35% (0.1784/0.5055) and 33% (0.2108/0.6378) of the waiting time gap with SEIFA 1 and 2 patients, respectively, and about a half of the waiting time gap with SEIFA 3 and 4 patients. However, at Q90, surprisingly the endowments of the better-off patients tend to make them wait longer, but the effects are trivially small except for the comparison with SEIFA 3.

The endowment effect associated with supply characteristics is positive in all quantiles of the waiting time distribution. This indicates that differential public health resource availability by socioeconomic status contributes to the waiting time differential. The supply endowment effect gets larger at the top of the waiting time distribution. For SEIFA 1 to 3, it explains the bulk of the socioeconomic waiting time gap. For SEIFA 4, the supply endowment effect is significant, but is not the dominant source of the waiting time gap. This exception suggests that public health resource availability is relatively similar for the 40% of the most socioeconomically advantaged patients.

The patient treatment effect behaves very differently from the patient endowment effect: it is positive and dominates at the top of the waiting time distribution. The positive patient treatment effect indicates discrimination in favour of the most socioeconomically advantaged patients. At Q90, the size of the discrimination ranges from 33% to 54% (for the natural log of the waiting times), which translates to 30 to 60 days.[12] Of the four aggregate effects, the supply treatment effect is relatively small and not generally significant.

Figure 3 depicts the size of the four aggregate effects across 9 waiting time quantiles. The patient and supply endowment effects are equal at Q60 (Q70 for SEIFA 2 patients) as the latter assumes a greater role in explaining gap in long waits. The patient treatment effect is relatively flat, except for SEIFA 4, where it steepens post-median. The patient treatment effect dominates the patient endowment effect post-median for SEIFA 1, but more quickly for other comparison groups. Lastly, as discussed, the supply treatment effect is flat around zero (except at the middle of distribution for SEIFA 1).

[12]The shares are the ratios of the patient treatment effects to the overall differences in Q90 of the natural log of waiting times between SEIFA groups 1-4 and SEIFA group 5. To obtain the results in days, note that from (6) the relationship between the quantiles of waiting times in levels, $q_j \equiv e^{(v_j)}$ for $j = A, B$, is given by $q_A \approx q_B \cdot e^{pe} \cdot e^{se} \cdot e^{pt} \cdot e^{st}$, where pe, se, pt and st denote patient and supply endowment and patient and supply treatment effects for logs, respectively. The contribution of each factor to the difference between q_A and q_B is not path independent in the sense that this contribution depends on the order in which the factor-specific rate of change is applied to the quantile q_B of the baseline group. To estimate the size of it's contribution in days, we apply the patient treatment effect first. For example, for the SEIFA group 1 the contribution of the patient treatment in days is computed as $197 \cdot (e^{0.17} - 1) = 37$ days.

In general, the patient treatment effect and the supply endowment effect (both of which we interpret as discrimination) account for the bulk in of the waiting time gap in long waits especially at Q90. While their relative sizes vary across the distribution their combined effect explains most of the difference in waiting time. For short to median waits, the patient endowment effect is also an important factor

Figure 3: Aggregate endowment and treatment effects

4.3.2 Detailed decomposition of supply factors

In this section, we conduct detailed decomposition of supply factors to get more information about public health resource use and public hospital operation. From a policy perspective, supply factors are potential policy instruments and targets. Figure 4 plots the RIF regression coefficients of supply variables in the SEIFA 5 sample at each waiting time quantile, $\widehat{\gamma}^{v}_{Bk}$.[13] These coefficients are used to compute the supply endowment effect (see equation (6)).

Figure 4: RIF regression coefficients for SEIFA 5 patients

Four of the eight supply variables have changing signs along the waiting time distribution. This highlights the importance of analysis beyond the means. The rate of admissions from an emergency department (ED) has a negative impact on waiting times. This result is surprising since we expect an increase in emergency admission rate to delay the admission of non-emergency procedures to manage bed occupancy. Unlike demand for elective surgeries, arguably hospitals have less control over emergency admissions. Reconciling this result with other SEIFA groups, we find that this negative effect is unique to SEIFA 5 patients. The waiting times of patients in SEIFAs 1 to 4 increase with admission rates of ED patients.

A higher proportion of same day admissions and clinical full-time staff are associated with shorter waiting times except at the bottom of the waiting time distribution (Q10). On the other hand, bed occupancy rates, which measure hospital activity, tend to increase waiting time, as do medical staff and visiting medical officers (VMOs). These two results may capture long waiting lists in large teaching hospitals (e.g. Principal Referral hospitals).

The share of private activity increases the waiting time at low quantiles but reduces waiting time at high quantiles. This suggests that the most socioeconomically advantaged patients who are waiting for least urgent procedures like cataract and knee replacements

[13]For conciseness, the full RIF regression coefficients are not reported but are available from the authors upon request.

(i.e. those at the top quantiles) benefit from being treated at hospitals with high share of private activities. Put another way, this result hints at a positive association between the socioeconomic status of public patients and the share of private patients in the hospitals they attend. The most socioeconomically advantaged public patients are more likely than others to be admitted as private patients. Public hospitals in Australia operate under fixed budgets, and increasing the share of privately financed hospital activities is one of the few ways they can generate additional revenues. There is some evidence that public hospitals have been increasing efforts to boost their private revenues (Private Health Insurance Administration Council, 2006).

The upper panel of Table 4 reports endowment effects for each supply variable. ED and complexity contribute positively to waiting time gaps at any point of the distribution. Given that these two variables shorten waiting times, their inequality-enhancing effect implies that the most socioeconomically advantaged patients access hospitals with higher ED rates and complexity. In contrast, bed occupancy rates have a global negative effect, but relatively small in size. Given that bed occupancy rates increase waiting time, its inequality-reducing effect implies that the most socioeconomically advantaged patients tend to be treated in hospitals with high bed occupancy rates. All in all, these results suggest that the most socioeconomically advantaged patients access large hospitals which have busy ED and treat complex cases.

Table 4: Detailed decomposition of supply characteristics

Other supply variables have changing signs along the waiting time quantiles. The proportion of same day admissions and fulltime staff ratios widen the waiting time gap at Q10 but narrow it elsewhere. Spending on medical and nursing staff reduce waiting time gaps at Q90. A policy implication of the negative effect of these variables is that a reduction in the waiting time gap can be promoted by more equal access to hospital medical professionals.

The endowment effect due to private activity is negative at the lower half of the waiting time distribution and positive at high waiting time quantiles. It dominates the supply endowment effect at Q90, mitigating the inequality-reducing effects of some of the other supply variables. The most socioeconomically advantaged patients tend to use hospitals with high private activity. Those who are waiting for less urgent procedures (long waits) benefit from this higher share of private activities in the form of shorter waiting times. The impact of the proportion of private patients is comparable in size to the overall patient treatment effect. It explains 35%, 28%, 52% and 27% of waiting time gap (in logs) with

SEIFA 1, 2, 3, and 4, respectively, which translates to earlier admissions of SEIFA 5 patients by 22 to 48 days. ED and Complexity add to the waiting time gap at this point.

The lower panel of Table 4 reports the supply treatment effects. Many of these lack statistical significance. The treatment effects associated with ED, Bed, Doctors and Staff are generally smaller than their respective endowment effects. The aggregate supply treatment effect is driven mainly by the proportion of private beds and complexity. Complexity tends to reduce waiting time inequality. This may suggest that when hospitals are more advanced (as measured by complexity), they benefit less advantaged patients more. In contrast, private activity has a sizeable positive effect at the median for SEIFA 1. This explains the hump in the aggregate supply treatment effect we saw earlier in Figure 3. A positive treatment effect associated with private activity suggests that hospitals give the most socioeconomically advantaged patients priority when faced with increased private activity. At the middle of the distribution, such preferential treatment is likely to affect mid-urgent patients whose target waiting times are between 30 to 90 days.

In summary, the socioeconomic waiting time gap is driven by both patient and supply factors. The most socioeconomically advantaged patients are prioritised in the waiting list despite having similar clinical needs to other patients. This source of discrimination is observed in almost all points of the waiting time distribution, meaning even urgent patients are affected. Socioeconomically advantaged patients benefit from higher private activity in the hospitals they attend. In contrast less advantaged patients may be delayed to accommodate admissions of ED patients and private patients in hospitals with low private revenues.

4.3.3 Robustness of the patient treatment effect

We conduct several robustness checks. First, to entertain the possibility more socioeconomically advantaged patients are more informed about waiting times and travel to hospitals with the shortest waiting times, we include distance to hospital as part of patient characteristics. We use the haversine formula for computing great-circle distances between the centre point of the postcode where the patient lives and the location of the treating hospital. The mean distance ranges from 9.5 to 14.6 kilometers across SEIFA groups. Row 1 of Table 5 reproduces the results for patient treatment effects from Table 3 and the results including distance as a patient characteristic are reported in row 2. It can be seen that the patient treatment effects remain positive and significant, and are even larger in the comparisons with the lowest two SEIFA groups.

Second, if privately insured patients, who expect a long wait in public hospitals, substitute to private treatment, we may overestimate the socioeconomic waiting time gap at the upper tail of the distribution. We do not have reliable insurance information at the patient level. As a proxy, we include the proportion of households with private insurance at the postcode level as a patient characteristic. The mean insurance rate is increasing with socioeconomic status, from 42% for SEIFA 1 to 69% for SEIFA 5. Row 3 of Table 5 shows that patient treatment effects at long waits are largely unchanged.

Third, another test of substitution to private hospitals is to repeat the analysis excluding procedures that are predominantly undertaken in private hospitals. Of procedures on eye and adnexa and ear, nose and throat (ENT), 67% are performed in private hospitals (AIHW, 2006). In the sample we find that ophthalmology and ENT specialties have the longest average public hospital waiting times (213 and 202 days, respectively). These long expected waits may motivate more socioeconomically advantaged patients to choose private hospitals where waiting times are negligible. As a sensitivity test we exclude patients in the two specialties from the sample. This reduces the sample to 69,425 (77%). Row 4 of Table 5 reports patient treatment effects from the restricted sample. At long waits, we find patient treatment effects are larger, except in the comparison with SEIFA 3.

Fourth, our analysis implicitly assumes within-SEIFA variation is negligible. To reduce within-group income variation which may contaminate comparisons across groups, we focus on postcodes within a SEIFA group have "similar" income. We take the median household income from Census data for each postcode and calculate the mean and standard deviation for each SEIFA group. In each SEIFA group we select only postcodes which are within one standard deviation away from the mean.[14] Row 5 of Table 5 row shows the re-estimated patient treatment effects remain significant and are largely unchanged.

Fifth, the literature from the US finds evidence of differences in health care utilisation based on race/ethnicity and language barriers, which may also be linked to socio-economic status (e.g., Yoo et al., 2009; Leighton and Flores, 2005; Fiscella et al, 2005). The US health care market is privately driven, so access is contingent on ability-to-pay. In contrast, Australia has a public health system (Medicare) which guarantees access to free public hospital treatment for all residents. Our analysis includes only Medicare eligible patients. We do not have information about ethnicity however we know country of birth and that

[14]For SEIFA 1 and SEIFA 5, we place one-sided restrictions, excluding postcodes with medians above one standard deviation of the mean for SEIFA 1 and below one standard deviation of the mean for SEIFA 5. For the other SEIFA groups we place two-sided restrictions. This reduces the sample to 80,398 (89% of original sample); the new samples for SEIFA 1 to 5 are 6,864 (88%), 8,960 (89%), 15,315 (87%), 23,998 (86%) and 25,261 (95%), respectively.

98% of the sample is non-indigenous (Aboriginal or Torres Straits Island) patients. To test the sensitivity to indigenous status and being foreign born, we conduct a robustness check excluding indigenous patients, those born overseas and those whose main language is not English. The sample size is reduced to 58,572 (65% of the original sample). Row 6 Table 5 reports the patient treatment effects, which are consistent with the main results.

Sixth, we restrict the sample to Sydney patients. The restriction was primarily to ensure patient access to large public hospitals. Furthermore, some areas outside Sydney border other states and patients who seek treatment interstate are missing from our data. Because Australian public hospitals are managed by state governments, there can be state variations in policies and waiting times, so including border regions may induce sample selection bias by omitting patients who face shorter waits in different states. We test the sensitivity of the results by adding non-border regions with major cities to the Sydney sample. Row 7 of Table 5 reports the patient treatment effects for this sample. The result of positive patient treatment effects across the waiting time distribution is robust to the new sample. However, the impact of socioeconomic status is larger in the upper tail of the distribution (long waits). This is consistent with the inclusion of regions outside Sydney which have higher concentrations of retirees with chronic conditions requiring non-urgent treatment.

Table 5: Robustness of patient treatment effect

5 Conclusion

Waiting time is the rationing device used to equate supply and demand of non-emergency procedures in public hospital systems where treatment is free at the point of care. Equitable access to care requires that the length of time to treatment should solely reflect patients' clinical needs. Extended delays in receiving treatment have been found to prolong suffering, decrease earning capacity and cause deterioration of quality of life (Oudoff et al. 2007; Hodge et al. 2007).

Using the case of public (non-paying) patients in Australian public hospitals, we find that waiting times are strongly influenced by patients' socioeconomic status. While we are unable to identify the exact mechanism(s) driving lower waiting times for the most advantaged patients, which could be multiple and interrelated, it is clear that it is not determined by clinical need. In accordance with the equity principle of universal health systems, we interpreted the gap not attributable to clinical factors as discrimination. We find that the largest contributor to discrimination is favourable treatment given to the most advantaged patients and inequality in access to health resources that works in their favour.

Going beyond mean-based results, distributional analysis reveals that discrimination occurs at all quantiles of the waiting time distribution. For the most urgent patients, while differences in clinical needs explain some of the waiting time gap, discrimination effects dominate. At the top of the distribution, where urgency is the lowest and there is greater scope for discretion, almost all of the waiting time gap can be attributed to discrimination; in terms of waiting period, the most socioeconomically advantaged patients are admitted over 4 months sooner than their less advantaged counterparts.

One implication of our finding that supply endowments favour more advantaged patients is that there is a potential gain in Australia from changes to treatment patterns among hospitals. While staffing patterns do not explain waiting time gaps, differences in hospital preferences for private patients act to substantially widen the waiting time gap for less urgent public patients. This suggests that there may be scope for a centrally managed system for assigning private patients to public hospitals.

In the literature there have been suggestions to make waiting time prioritisation accord more with clinical need. Noseworthy et al. (2002), Gravelle and Siciliani (2008) and Curtis et al. (2010) have suggested that a more systematic and consistent system of urgency assignment may promote greater equity. Our findings indicate that the assignment of urgency by specialists does not guarantee equitable waiting time outcomes. One way to promote greater equity could be to require adherence to detailed guidelines for urgency assignment by procedure and patient co-morbidities. In countries with universal health care systems, prioritisation mechanisms used by health practitioners and hospitals should be transparent to the general public, in accordance with equity and fairness principles. Another way to minimise the scope for discrimination may be to make it visible by requiring that hospitals report waiting times for procedures by indicators of patient socioeconomic status, as indicated by postcode of residence and payment status. This would be useful, not only for Australia, but also for countries without explicit waiting list prioritisation rules.

Table 1: Variable means by SEIFA quintile

Variable		SEIFA 1	SEIFA 2	SEIFA 3	SEIFA 4	SEIFA 5
Waiting time (days)	Mean	111.90	110.90	104.40	96.84	73.68
Waiting time (log)†	Mean	3.738	3.771	3.694	3.483	3.201
	std.dev	1.553	1.497	1.510	1.591	1.571
	P10	1.609	1.792	1.609	1.386	1.098
	P50	3.784	3.807	3.761	3.526	3.296
	P90	5.801	5.805	5.704	5.670	5.283
Age	0-4	0.042	0.045	0.041	0.040	0.038
	0-4	0.048	0.043	0.046	0.039	0.029
	5-9	0.028	0.023	0.028	0.020	0.017
	10-14	0.027	0.026	0.027	0.020	0.019
	20-24	0.031	0.034	0.033	0.027	0.031
	25-29	0.039	0.041	0.039	0.036	0.044
	30-34	0.055	0.049	0.054	0.049	0.055
	35-39	0.063	0.064	0.056	0.054	0.054
	40-44	0.067	0.066	0.070	0.064	0.065
	45-49	0.075	0.075	0.078	0.064	0.063
	50-54	0.073	0.078	0.069	0.064	0.062
	55-59	0.083	0.072	0.082	0.072	0.069
	60-64	0.081	0.070	0.075	0.076	0.069
	65-69	0.089	0.088	0.081	0.088	0.079
	70-74	0.080	0.079	0.080	0.092	0.091
	75-79	0.064	0.075	0.080	0.099	0.097
	80-84	0.034	0.047	0.041	0.060	0.066
	85	0.018	0.026	0.021	0.036	0.051
Gender	male	0.470	0.466	0.455	0.483	0.483
Urgency	≤30 days	0.439	0.451	0.458	0.502	0.513
	90 days	0.269	0.294	0.278	0.284	0.282
	365 days	0.292	0.255	0.264	0.214	0.205
Number of diagnoses	0	0.051	0.045	0.050	0.045	0.051
	1	0.279	0.287	0.293	0.273	0.321
	2	0.287	0.291	0.292	0.294	0.281
	3	0.215	0.208	0.207	0.211	0.193
	4	0.116	0.118	0.112	0.124	0.108
	≥5	0.051	0.051	0.047	0.052	0.045
% ED admissions	Mean	-1.270	1.084	-1.940	-0.550	1.825
	std.dev	8.999	9.809	9.963	10.431	11.298
% Same day	Mean	-1.425	-1.454	-0.653	0.772	0.589
admissions	std.dev	9.698	9.638	10.001	8.680	9.398
Bed occupancy	Mean	-0.198	-0.006	-0.178	0.101	0.073
rate	std.dev	5.567	5.517	5.997	5.004	4.274
% private bed days	Mean	-4.263	-2.796	-3.237	0.713	3.704
	std.dev	5.375	5.158	5.410	5.543	4.414
Average length	Mean	-0.502	-0.091	-0.292	0.153	0.214
of stay	std.dev	1.191	0.992	1.111	1.145	0.942
Clinical FT staff	Mean	-0.057	0.005	-0.067	0.015	0.044
per bed	std.dev	0.415	0.369	0.436	0.400	0.429
Med salary &	Mean	-0.372	1.326	0.072	-0.087	-0.350
VMO expenses	std.dev	3.044	2.828	2.915	2.734	2.068
% Nursing salary	Mean	1.206	0.567	1.080	-0.223	-1.050
	std.dev	3.061	2.802	3.436	3.352	3.314
N		7800	10088	17654	27983	26637

†Dependent variable.
Note: Patients with 0 chronic diagnoses are those who only have diagnoses that are not considered chronic (e.g., short sightedness or hay fever). The 30 day urgency class pools the 7-day and 30-day urgency categories used in NSW.

Table 2: Regression results (dependent variable: log waiting time)

		Model 1		Model 2	
		Coeff	t-stat	Coeff	t-stat
SEIFA	1 Least advantaged 20%	0.332	22.09	0.191	11.49
	2 20% - 40%	0.352	26.01	0.237	15.88
	3 40% - 60%	0.307	26.95	0.195	15.08
	4 60% - 80%	0.192	19.14	0.160	15.31
Urgency	30 days or less	-1.165	-122.88	-1.165	-123.26
	365 days (base: 90 days)	0.331	28.19	0.323	27.50
Age	0-4	-0.196	-6.64	-0.191	-5.73
	5-9	-0.006	-0.21	-0.023	-0.73
	10-14	-0.064	-1.95	-0.083	-2.35
	15-19	-0.227	-7.03	-0.237	-7.18
	20-24	-0.184	-6.39	-0.185	-6.43
	25-29	-0.156	-6.07	-0.156	-6.11
	30-34	-0.133	-5.59	-0.131	-5.53
	35-39	-0.072	-3.14	-0.070	-3.06
	40-44	-0.008	-0.39	-0.008	-0.36
	50-54	0.023	1.11	0.022	1.07
	55-59	0.004	0.20	0.005	0.23
	60-64	0.002	0.08	0.000	0.00
	65-69	0.031	1.50	0.029	1.42
	70-74	0.049	2.43	0.048	2.37
	75-79	0.037	1.82	0.029	1.42
	80-84	0.063	2.78	0.048	2.14
	85	-0.018	-0.69	-0.030	-1.15
Number of diagnoses	0	-0.327	-5.53	-0.333	-5.65
	2	0.019	0.34	0.022	0.40
	3	0.012	0.11	0.014	0.13
	4	0.008	0.05	0.007	0.04
	$\geq$5	-0.001	0.00	-0.003	-0.01
Gender	Male	-0.014	-1.62	-0.015	-1.73
Supply	% Admissions from emergency department			0.004	7.36
	% Same day admissions			-0.004	-5.80
	Bed occupancy rate			0.021	17.75
	% private bed days			-0.013	-11.48
	Average length of stay			-0.090	-14.69
	Clinical FT staff per bed			-0.096	-4.78
	% doctors & VMO payments			0.013	8.26
	% nurse salary			-0.004	-1.64
Constant		3.348	56.98	3.434	58.39
R-sq		0.464		0.473	

Note: also included in the model are 28 dummy variables for primary and up to five secondary diagnoses (not mutually exclusive) and 196 dummy variables for procedures (the omitted group is other surgical).

Table 3: Decomposition of overall patient and supply characteristics

	SEIFA 1			SEIFA 2			SEIFA 3			SEIFA 4		
	10	50	90	10	50	90	10	50	90	10	50	90
$v_A - v_B$	0.5110	0.4884	0.5174	0.6930	0.5108	0.5220	0.5108	0.4654	0.4206	0.2877	0.2306	0.3867
$\widehat{v}_A - \widehat{v}_B$	0.5055**	0.4853**	0.5146**	0.6378**	0.5052**	0.5207**	0.5489**	0.4597**	0.4200**	0.2776**	0.2321**	0.3861**
Patient Endowment	0.1784**	0.1693**	-0.0307	0.2108**	0.1859**	-0.0034	0.2599**	0.2018**	-0.1208*	0.1472**	0.1031**	-0.0087
Supply Endowment	0.1347**	0.1249**	0.3766**	0.0125	0.0879**	0.2983**	0.1939**	0.1113**	0.3426**	0.0580*	0.0628**	0.1721**
Patient Treatment	0.2469**	0.06660	0.1739*	0.2717**	0.2277**	0.2670**	0.2890**	0.1603**	0.1399**	0.1807**	0.1109**	0.2127**
Supply Treatment	-0.1019	0.1173*	-0.0026	-0.0268	-0.0385	-0.0666	-0.0532	0.0065	0.0021	-0.0074	0.0000	0.0357**
$\widehat{R}_1$	-0.0027	0.02180	0.1131	-0.0206	0.0218	0.0555	-0.1785**	-0.0305	0.1541**	-0.0872**	-0.0473*	0.0034
$\widehat{R}_2$	0.0501	-0.01470	-0.1157	0.1902*	0.0204	-0.0301	0.0377	0.0102	-0.0979	-0.0137	0.0026	-0.0291

Note: statistical significance is based on bootstrapped standard errors with 100 replications. * and ** indicate statistical significance at 5% and 1% respectively. Based on two-sample mean difference test, raw gaps are all statistically significant at any conventional level.

Table 4: Detailed decomposition of supply characteristics

	SEIFA 1			SEIFA 2			SEIFA 3			SEIFA 4		
	10	50	90	10	50	90	10	50	90	10	50	90
ENDOWMENT												
ED	0.0444**	0.0306**	0.0480**	0.0213**	0.0147**	0.0230**	0.0670**	0.0461**	0.0724**	0.0515**	0.0355**	0.0557**
Same day	-0.0017	0.0046	0.0165*	-0.0017	0.0045	0.0162*	-0.0017	0.0046	0.0164*	0.0002	-0.0004	-0.0015
Bed	-0.0090	-0.0165	-0.0258	-0.0045	-0.0082	-0.0129	-0.0469**	-0.0860**	-0.1346**	-0.0067*	-0.0124**	-0.0194**
Private	-0.1285**	-0.0369	0.1893**	-0.1005**	-0.0288	0.1480**	-0.1483**	-0.0425	0.2184**	-0.0722**	-0.0207	0.1063**
Complexity	0.1825**	0.0941**	0.1798**	0.1029**	0.0531**	0.1014**	0.233**	0.1202**	0.2296**	0.0515**	0.0266**	0.0508**
Staff	-0.0069	0.0102	0.0362	-0.0005	0.0007	0.0026	-0.0154	0.0229*	0.0811**	-0.0057	0.0085*	0.0301**
Doctors & VMO	0.0039	-0.0029	-0.0064	-0.0353**	0.0263**	0.0575**	0.0269**	-0.0201**	-0.0439**	0.0045*	-0.0034*	-0.0073*
Nurse	0.0500	0.0417*	-0.0609	0.0307	0.0256	-0.0374	0.0792	0.0661	-0.0965	0.0349	0.0291*	-0.0425
TREATMENT												
ED	0.0109	0.0024	0.0073	0.0101	-0.0095	-0.0064	-0.0134	-0.0062	-0.0010	0.0008	-0.0004	0.0032
Same day	0.0244	0.0243**	0.0008	0.0147	-0.0043	-0.0139	0.0075	-0.0002	0.0055	-0.0126*	-0.0034	0.0099*
Bed	-0.0012	-0.0006	0.0112*	-0.0001	0.0000	0.0003	-0.0026	-0.0019	0.0086*	-0.0004	-0.0013	-0.0002
Private	-0.0795	0.1772**	0.1245	-0.0095	-0.0630*	-0.0911*	-0.0107	-0.0024	0.0561	-0.0031	0.0053	0.0317**
Complexity	-0.1017	-0.0200	-0.1392**	-0.0012	0.0138*	-0.0230**	-0.0436	0.0157	-0.0835**	0.0068	0.0040	0.0082
Staff	0.0089	-0.0095	-0.0393	0.0007	-0.0008	0.0006	0.0329	0.0239	-0.0266	-0.0018	-0.0017	0.0001
Doctors & VMO	-0.0008	-0.0099	-0.0045	-0.0309	0.0091	0.0172	-0.0028	-0.0004	0.0004	0.0015	0.0001	0.0003
Nurse	0.0371	-0.0465	0.0366	-0.0106	0.0162	0.0497*	-0.0205	-0.0221	0.0426	0.0015	-0.0026	-0.0175*

Note: statistical significance is based on bootstrapped standard errors with 100 replications. * and ** indicate statistical significance at 5% and 1% respectively.

Table 5: Robustness of patient treatment effect

		SEIFA 1			SEIFA 2			SEIFA 3			SEIFA 4		
Row		10	50	90	10	50	90	10	50	90	10	50	90
1	Original sample	0.2469**	0.0666	0.1739*	0.2717**	0.2277**	0.2670**	0.2890**	0.1603**	0.1399**	0.1807**	0.1109**	0.2127**
2	Controlling for distance	0.2474**	0.0893*	0.2519**	0.3054**	0.2667**	0.3710**	0.2694**	0.1495**	0.0895	0.0943**	0.1229**	0.1979**
3	Controlling for PHI	0.3349*	0.1416**	0.1499*	0.2121*	0.2405**	0.2299**	0.2098**	0.1595**	0.1491**	0.1783**	0.1134**	0.1984**
4	Restricted procedures	0.2464*	0.0682	0.1749*	0.3174**	0.1983**	0.3267**	0.2912**	0.1249**	0.0994**	0.1020**	0.0920**	0.2261**
5	Homogenous income	0.3070**	0.1038*	0.1416*	0.2796**	0.2047**	0.2799**	0.3378**	0.1508**	0.2009**	0.1417**	0.1442**	0.2263**
6	Non-indigenous, Australian born, English main language	0.2594**	0.0930*	0.1400	0.2844**	0.2199**	0.2711**	0.3245**	0.1746**	0.1515**	0.1116**	0.1467**	0.2062**
7	Sydney and regions with major cities	0.3051**	0.1660**	0.3151**	0.1528**	0.1491**	0.3032**	0.1937**	0.1768**	0.3418**	0.1139**	0.0858**	0.2305**

Note: statistical significance is based on bootstrapped standard errors with 100 replications. * and ** indicate statistical significance at 5% and 1% respectively.

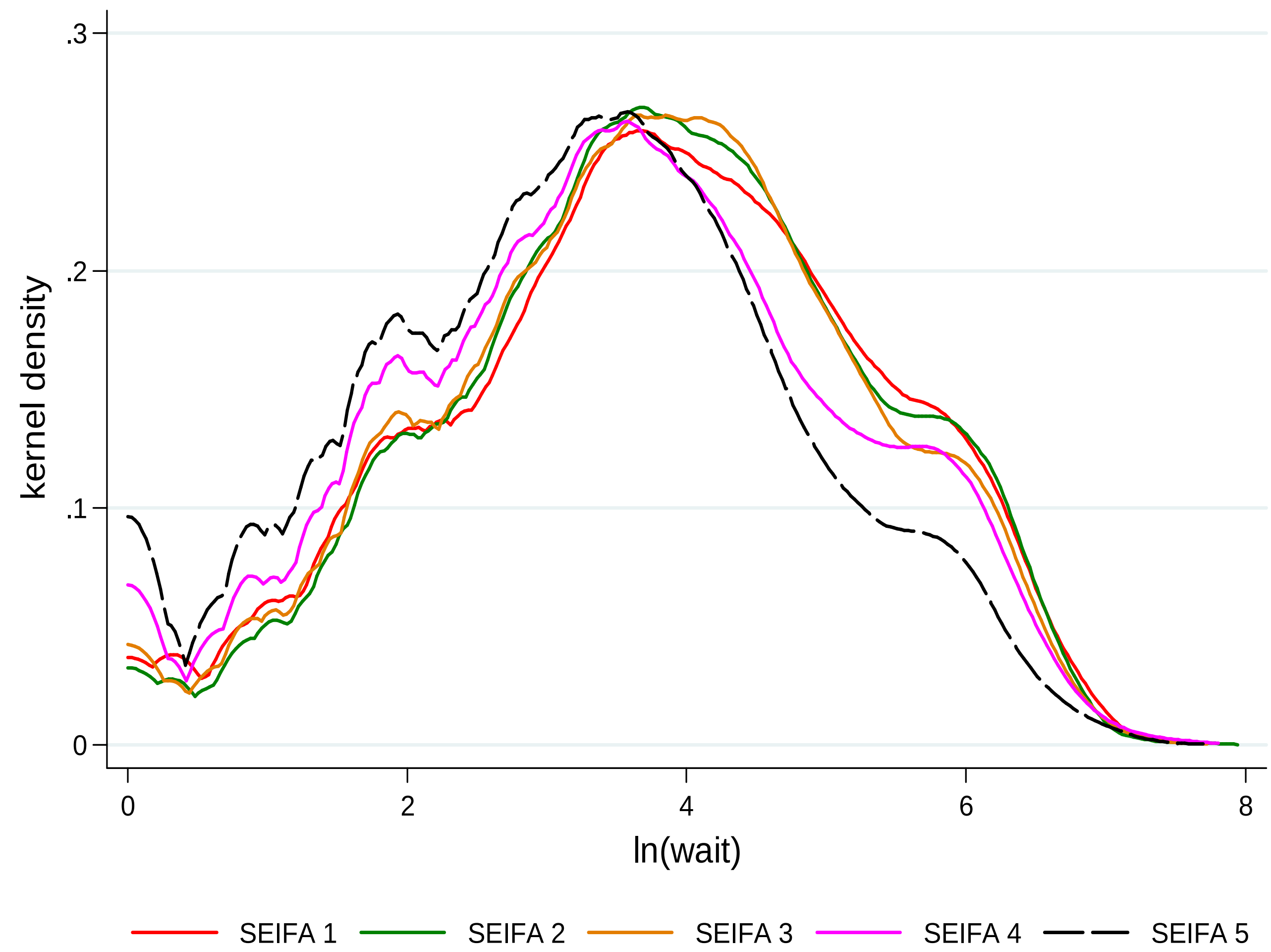

Figure 1: Density of log waiting times

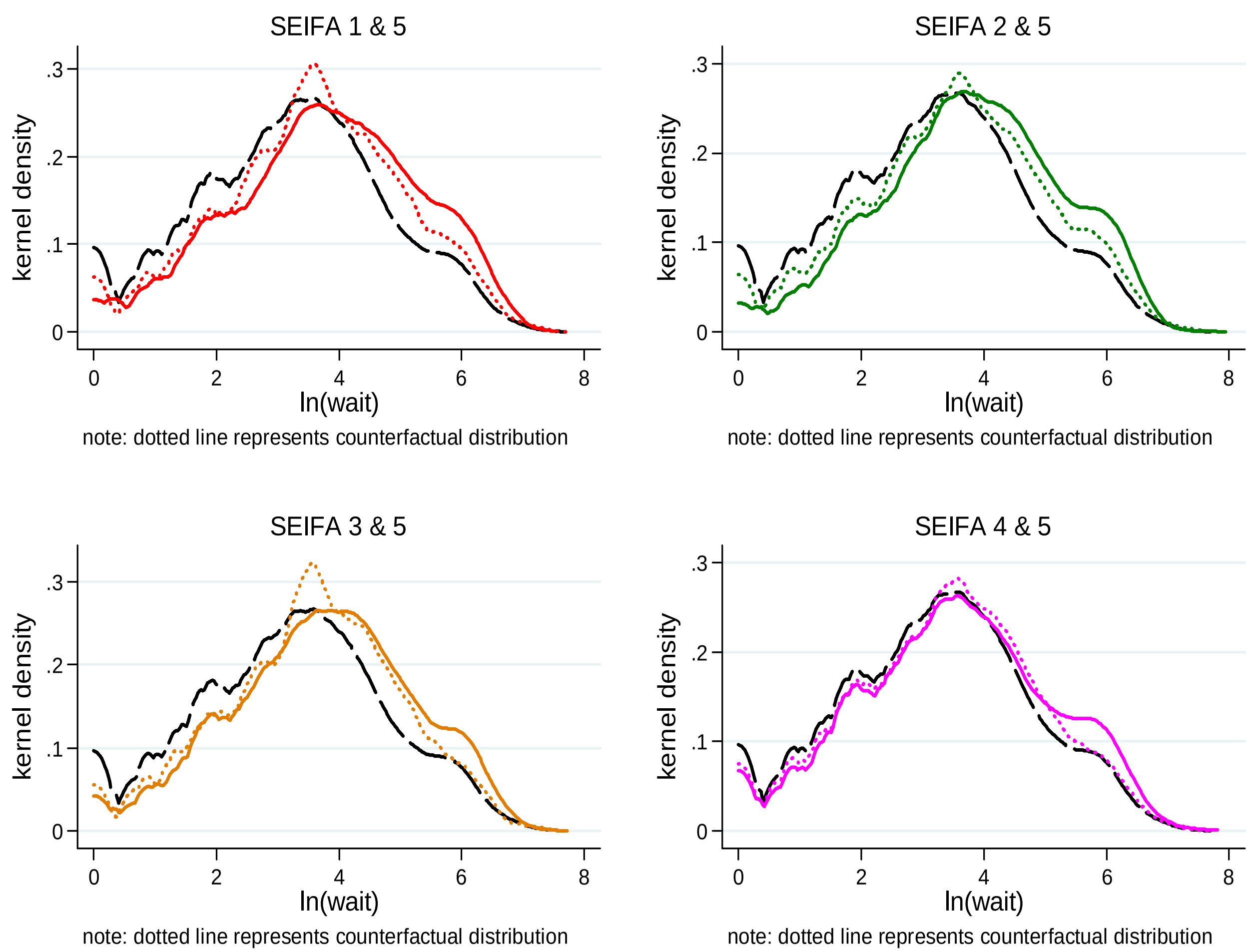

Figure 2: Density of actual and counterfactual log waiting time by SEIFA pair

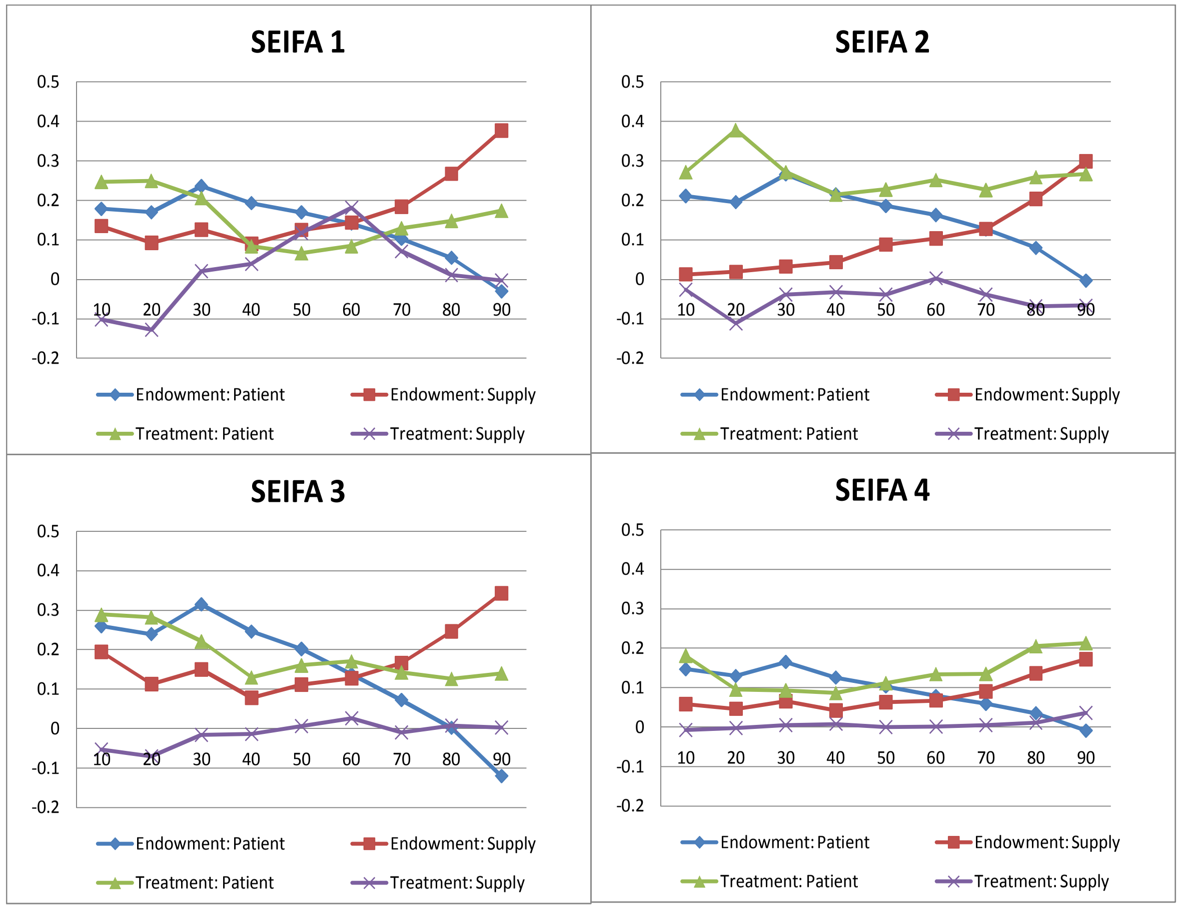

Figure 3: Aggregate endowment and treatment effects

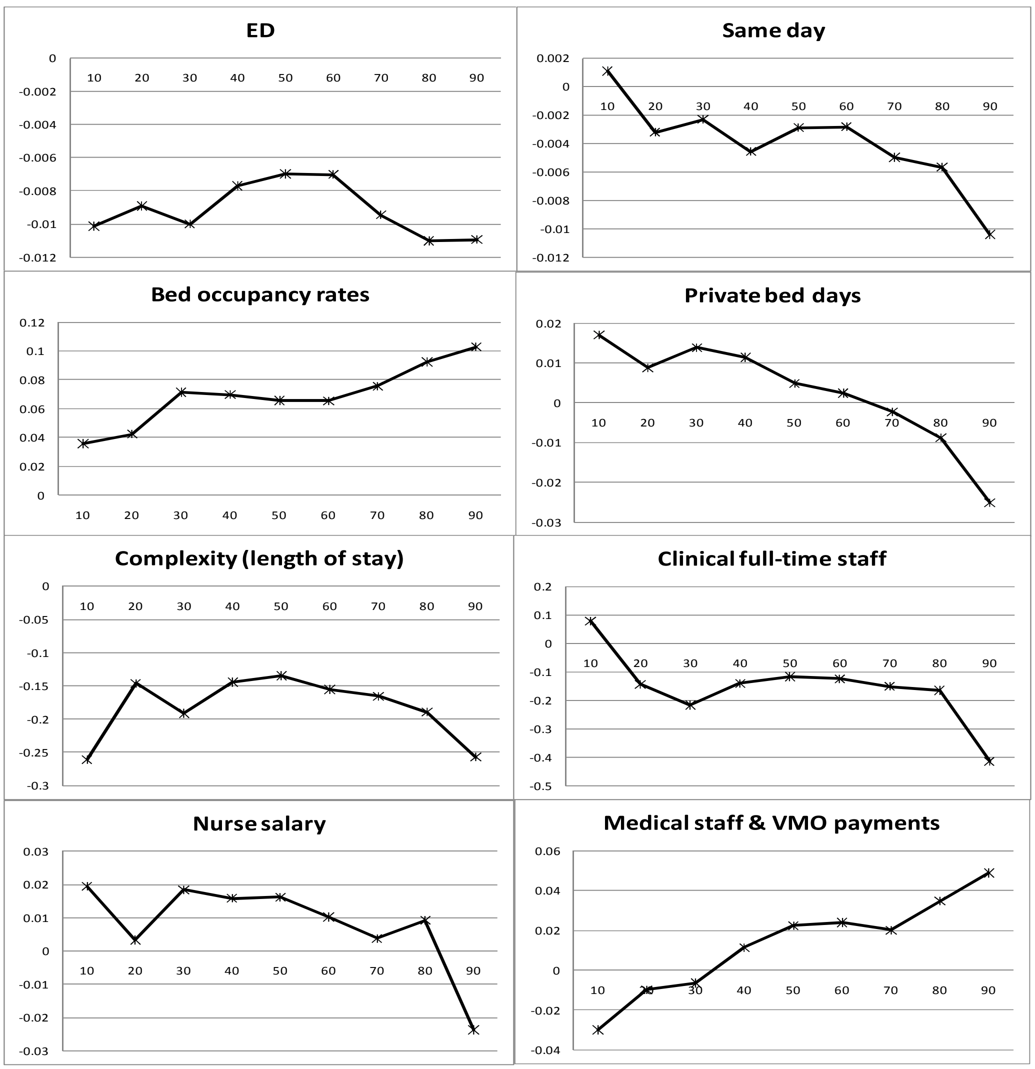

Figure 4: RIF regression coefficients for supply variables in SEIFA 5 samples

References

[1] Askildsen, J.E., Tor Helge, H. and Oddvar, K. (2010) Prioritization and patients' rights: Analysing the effect of a reform in the Norwegian hospital sector. Social Science and Medicine 70(2), 199-208.

[2] Australian Bureau of Statistics. (2001) Census of Population and Housing: Socio-Economic Indexes for Area's (SEIFA). Technical Paper 2001 Cat 2039.0.55.001. ABS, Canberra.

[3] Australian Institute of Health and Welfare. (2007) Australian Hospital Statistics 2005-06. AIHW, Canberra.

[4] Blinder, A.S. (1973) Wage discrimination: Reduced form and structural estimates. Journal of Human Resources 8, 436 - 455.

[5] Blau, F.D. and Lawrence, M.K. (1992) The gender earnings gap: Learning from International Comparisons. American Economic Review 82, 533-538.

[6] Cobb-Clark, D.A. and Hildebrand, V.A. (2006) The wealth of Mexican Americans. Journal of Human Resources 41(4), 841-868.

[7] Commonwealth of Australia. (2009) A healthier future for all Australians: National Health and Hospitals Reform Commission - Final report June 2009. Canberra.

[8] Curtis, A.J., Russell, C.O.H., Stoelwinder, J.U., et al. (2010) Waiting list and elective surgery: Ordering the queue. Medical Journal of Australia 192(4), 217-220.

[9] Derrett, S. (2005) Booking Systems for Elective Services in New Zealand, A report by the Centre for Health Planning and Management to the National Ethics Advisory Committee, New Zealand (http://www.neac.health.govt.nz/moh.nsf/pagescm/519/$file/booking-systems-elective-services-nz-feb05.pdf)

[10] Dimakou, S., Parkin, D., Devlin, N. and Appelby, J. (2009) Identifying the impact of government targets on waiting times in the NHS. Health Care Management Science 12(1), 1-10.

[11] DiNardo, J., Fortin, N.M. and Lemieux, T. (1996) Labor market institutions and the distribution of wages, 1973-1992: A semiparametric approach. Econometrica 64(5), 1001-1044

[12] Doiron, D.J. and Riddell, W.C. (1994) The impact of unionization on male-female earnings differences in Canada. Journal of Human Resources 29, 504-534.

[13] Doyle, J.J. (2005) Health insurance, treatment, and outcomes: Using auto accidents as health shocks. Review of Economics and Statistics 87(2), 256-270.

[14] Firpo, S., Fortin, N. and Lemieux, T. (2007) Decomposing wage distributions using recentered influence function regressions. Available: http://www.economie.uqam.ca/pages/docs/Lemieux_Thomas.pdf

[15] Firpo, S., Fortin, N. and Lemieux, T. (2009) Unconditional quantile regressions. Econometrica 77(3), 953 - 973.

[16] Firpo, S., Fortin, N. and Lemieux, T. (2010) Decomposition methods in Economics. NBER Working Paper 16045.

[17] Fiscella, K., Franks, P., Doescher M.P. and Saver B.G. (2002) Disparities in health care by race, ethnicity, and language among the insured: findings from a national sample. Medical Care 40(1), 52-59.

[18] Fortin, N. (2009) RIF-Regression STATA ado file from Firpo, Fortin and Lemieux (2009). Downloadable: http://faculty.arts.ubc.ca/nfortin/datahead.html.

[19] Gravelle, H. and Siciliani, L. (2008) Is waiting time prioritisation welfare improving? Health Economics 17, 167-184.

[20] Greengross, P., Grant, K. and Collini, E. (1999) The history and development of the UK National Health Service 1948 1999. Health System Resource Centre, United Kingdom.

[21] Huynh, P.T., Schoen C., Osborn, R. and Holmgren, A.L. (2006) The US health care divide: Disparities in primary care experiences by income. The Commonwealth Fund Publication no. 900, New York.

[22] Hodge, W., Horsley, T., Albiani, D., et al. (2007) The consequences of waiting for cataract surgery: A systematic review. Canadian Medical Association Journal 176(9), 1285-1290.

[23] Jann, B. (2008) The Blinder-Oaxaca decomposition for linear regression models. Stata Journal 8(4), 453-479.

[24] Johar, M., Jones, G., Keane, M., Savage E. and Stavrunova, O. Forthcoming, Waiting times for elective surgery and the decision to buy private health insurance, Health Economics, DOI: 10.1002/hec.1707

[25] Johar, M. and Savage, E. (2010) Do private patients have shorter waiting times for elective surgery? Evidence from New South Wales public hospitals. Economic Papers 29(2), 1-15.

[26] Leighton, K. L. and Flores G. (2005) Pay now or pay later: providing interpreter services in health care. Health Affairs 24(2), 435-444.

[27] Lopez, L., Wilper, A.P., Cervantes, M., et al. (2010) Racial and sex differences in emergency department triage assessment and test ordering for chest pain, 1997-2006. Academic Emergency Medicine 17(8), 801-808.

[28] Lindsay, C.M. and Feigenbaum, B. (1984) Rationing by waiting lists. American Economic Review 74(3), 404-417.

[29] MacCormick, A.D., Tan, C.P. and Parry, B.R. (2004) Priority assessment of patients for elective general surgery: Game on? ANZ Journal of Surgery 74(3), 143-145.

[30] Noseworthy T.W., McGurran, J.J., Hadorn, D.C., et al. (2002) Waiting for scheduled services in Canada: Development of priority-setting scoring systems. Journal of Evaluation in Clinical Practice 9(1), 23-31.

[31] Oaxaca, R. (1973) Male-Female wage differentials in urban labor markets. International Economic Review 14, 693 - 709.

[32] Oudhoff, J.P., Timmermans, D.R.M., Knol, D.L., et al. (2007) Waiting for elective general surgery: Impact on health related quality of life and psychosocial consequences. BMC Public Health 7, 164.

[33] Park, C.Y., Lee, M.A. and Epstein, A.J. (2009) Variation in emergency department wait times for children by race/ethnicity and payment source. Health Services Research 44(6), 2022-2039.

[34] Pylypchuk, Y. and Selden, T.M. (2008) A discrete choice decomposition analysis of racial and ethnic differences in children's health insurance coverage. Journal of Health Economics 27(4), 1109-1128.

[35] Private Health Insurance Administration Council. (2006) Operations of the Registered Health Benefits Organisations Annual Report 2005-06. PHIAC, Canberra.

[36] Propper, C., Sutton, M., Whitnall, C. and Windmeijer, F. (2010) Incentives and targets in hospital care: Evidence from a natural experiment. Journal of Public Economics 94, 318-335.

[37] Productivity Commission. (2008) Report on Government Services, Volume 2 Health, Community Services and Housing. AGPS, Canberra.

[38] Savage E. and Wright D. (2003) Moral hazard and adverse selection in Australian private hospitals: 1989-1990. Journal of Health Economics 22, 331-359.

[39] Siciliani, L. and Martin, S. (2007) An empirical analysis of the impact of choice on waiting times. Health Economics 16, 763-779.

[40] Siciliani, L. and Verzulli, R. (2009) Waiting times and socioeconomic status among elderly Europeans: Evidence from SHARE. Health Economics 18, 1295-1306.

[41] Siciliani, L. and Laudicella, M. (2010) Waiting time and socioeconomic status: Evidence from England. HEDG working papers 2010/05.

[42] Wenzlow, A.T., Mullahy, J. and Wolfe, B. (2004) Understanding racial disparities in health: The income-wealth paradox. La Follette School Working Paper 2004-008.

[43] Yoo HC., Gee GC. and Takeuchi D. (2009) Discrimination and health among Asian American immigrants: disentangling racial from language discrimination. Social Science and Medicine 68(4), 726-732.