Geographic differences in hospital waiting times

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Abstract
Access to elective surgery in Australian public hospitals is rationed using waiting lists. In this article, we undertake a DiNardo–Fortin–Lemieux reweighting approach to attribute variation in waiting time to clinical need or to discrimination. Using data from NSW public patients in 2004–2005, we find the discrimination effect dominates clinical need especially in the upper tail of the waiting time distribution. We find evidence of favourable treatment of patients who reside in remote areas and discrimination in favour of patients residing in particular Area Health Services. These findings have policy implications for the design of equitable quality targets for public hospitals.

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1. Introduction

Waiting times for elective surgery in Australia have been a policy concern for the past two decades and reducing public hospital waiting times is a central issue in the current health policy debate. In 2007, the government allocated $100 million to reduce elective surgery waiting times for patients who have been waiting beyond the clinically recommended time. There are also financial incentives of up to $300 million to States and Territories to create capacity to complete all elective surgery within the clinically recommended time by the end of 2011. Despite the substantial policy interest however, there is very little empirical analysis of elective surgery waiting times, in particular, the identification of factors determining a patient's waiting time *beyond clinical need*. Yet, effective policies to promote greater equity require information on the impact of non-clinical determinants of waiting times.

Patients waiting for elective hospital treatment in Australia are prioritised using a clinical urgency classification system. Other countries also use prioritisation systems that are clinically-based, although they vary in implementation. In Canada and New Zealand, explicit, systematic prioritisation rules are used. In Canada, for example, the Western Canada Waiting List Project develops prioritisation tools which include both clinical criteria and non-clinical social factors perceived to contribute to urgency, such as ability to live and work independently. Similarly, to assess patient urgency for surgery, New Zealand employs Clinical Priority Assessment Criteria tools, which include both clinical criteria and non-clinical patient characteristics. In other countries, such as the UK, Spain, Sweden and Australia, prioritisation is guided by clinical need but the scoring of patients is less formal and there is no explicit scoring tool for physicians to use (see Siciliani and Hurst (2005) for more discussion).

In Australia urgency categories, indicating the maximum recommended waiting times for each patient, are assigned by the treating specialist. The aim is to give priority to patients needing more urgent medical attention. For example, an urgency category of 30 days is assigned to patients with ‘a condition that has the potential to deteriorate quickly to the point that it may become an emergency’ (Department of Health and Ageing, 2008). A 90 day urgency is used for ‘a condition causing some pain, dysfunction or disability, but which is not likely to deteriorate quickly or become an emergency’ and a 365 day urgency 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 classes provide guidelines to doctors for prioritising patients but in contrast to the UK, New Zealand and some Canadian states, they are not explicit waiting time targets. The percentage of overdue patients (those waiting longer than the recommended urgency) are reported at the state level in annual reports by the Department of Health and Ageing (Department of Health and Ageing, 2006) but, prior to 2010, there were no financial incentives for meeting urgency targets (Department of Health and Ageing, 2010).

Observed waiting times show large geographical variation. In New South Wales (NSW), average waiting times in different areas can vary by up to 70 days, and for 10% of patients with the longest waiting times this extends to 239 days.[1] Even within a smaller area of comparison, such as Sydney, where uncongested travel time between locations is less than an hour, patients living in the northern suburbs can be admitted 51 days earlier on average than other Sydney patients. Can these substantial variations in waiting time be explained by patient’s demographic and disease profiles in different areas? Or do they suggest that the waiting list’s prioritisation depends on non-clinical factors?

[1] Authors’ calculation based on all public hospitals data in 2004-2005. The same data set is used for the empirical results.

In universal public health care systems, like Australia's, the possibility that some patients are less favourably treated in the delivery of health care is not often investigated.[2] In contrast, discrimination in health care is frequently found in the US where the health system is more market-based. For example, non-white Americans are more likely to experience delayed attendance in the emergency room than whites (Lopez et al., 2010; Park et al., 2009). To the extent that universality and equity underlie the Australian public health system, patients having similar clinical need should experience similar waiting times. A corollary, waiting time gaps across patient groups that cannot be attributed to clinical factors may have the interpretation of discrimination.

In this paper, we test for discrimination in the waiting list on the basis of patients' place of residence. When choosing a hospital, patients have recourse to the health system in its entirety; patients can be admitted to any public hospital they wish. Under the equity principle, residential location, which is a non-clinical factor, should not explain patients' waiting times. In the context of a regression model, this implies that, after controlling for patients' demographic and disease profile which measure clinical need, we should *not* find significant waiting time differentials across areas. Waiting time differences across areas which are unexplained by clinical needs may be due to supply side factors. However, under the equity principle, any supply-side dimension to waiting times for clinically comparable patients in different location forms part of discrimination. If patients in some areas have better access to public health resources that allow them to have shorter waiting times than clinically comparable patients living elsewhere, this is a form of discrimination.

Identifying the specific discriminatory mechanisms is beyond the scope of this paper. Our aim is more modest: to identify a policy instrument that could reduce the scope for discrimination with the aim of improving waiting time performance and promoting greater equity in the delivery of health care. The reporting structure may be one such

[2] An exception is Siciliani and Verzulli (2009) which finds a significant negative association between waiting time and education after controlling for health conditions in their elderly samples in Denmark, the Netherland and Sweden, and between waiting time and income in their elderly sample in Greece.

instrument. Waiting time statistics are reported by state, specialty and procedure; there is no reporting of the distribution across patients within state (AIHW, 2006).

In this paper we use the decomposition technique of DiNardo, Fortin and Lemieux (1996). Decomposition techniques have been widely used by labour economists to examine variation in labour market outcomes between groups of workers (for example. male and female wage differentials) that cannot be explained by differences in workers' human capital level (Oaxaca, 1973; Blinder, 1973; Oaxaca and Ransom, 1994).[3] Such unexplained differences are regarded as evidence of discrimination in labour market. In application to this study, we regard geographic waiting time variation that cannot be explained by clinical needs as discrimination in the waiting lists.

We explore discrimination effects at various points of the waiting time distribution. Focusing solely on measures of central tendency, such as the mean or median, a practice which is commonly adopted in decomposition studies, may be inadequate and even misleading. It is quite possible that discrimination effects change direction along the waiting time distribution. For instance, the scope for discrimination may be greater for less urgent patients who are concentrated in the upper tail of the waiting time distribution. This is because health risks associated with delaying treatment for these patients are lower.

Using data on all elective patients in NSW public hospitals in 2004-05, we first analyse whether there is discrimination on the basis of remoteness. Following the Australian Bureau of Statistics (ABS), remoteness is defined in relation to an area's accessibility to goods and services and opportunities for social interaction, based on physical road-distance to the nearest town or service centre. To measure remoteness, we use the ABS's Accessibility/Remoteness Index of Australia (ARIA) of the patient's postcode and the recommended grouping to define: very remote, remote, outer regional,

[3] In the health economics literature, decomposition analysis has not been widely used but is gaining in popularity (Wenzlow, Mullahy and Wolfe, 2004; Pylypchuk and Selden, 2008).

inner regional and major city (ABS, 2005).[4] It has been suggested that challenges in the delivery of health care services to rural areas result in longer waiting times for rural patients (National Rural Health Alliance, 2010) and that this causes many rural patients to travel to city hospitals to receive treatment (AIHW, 2006; Rankin et al. 2002). Secondly, we investigate whether the delivery of public hospital care by regional health authorities affects the waiting time distribution. We take advantage of the presence of Area Health Services (AHSs) in NSW which are responsible for managing and delivering public hospital treatment in their area.

In contrast to popular belief, we find that discrimination works in favour of remote and outer regional patients: they have shorter waiting times than clinically comparable patients living in the city and inner regional areas. Waiting times also vary greatly across AHSs. Using a reference AHS as the base, we find large discrimination effects, which sometimes dominate the total waiting time differentials. Even among AHSs within Sydney, the discrimination effect is sizable. The greatest discrimination effect is consistently found in the upper tail of the waiting time distribution where patients have low risk of developing into an emergency, giving providers more scope for discriminating patients on the basis of non-clinical factors. At the mean or median, the discrimination effect is considerably smaller and can have the opposite sign to that in the upper tail of the distribution. These results highlight the importance of analysis beyond common measures of central tendency.

2. Data

In July 1997, the NSW Department of Health commenced collecting administrative data on waiting times for elective inpatient procedures in accordance with urgency classifications. These data can be linked to detailed inpatient data, which contain

[4] An area can have an ARIA score of 0 to 15. Major city has a score of 0 to 0.2, inner regional a score greater than 0.2 to 2.4, outer regional a score greater than 2.4 to 5.92, remote area has a score greater than 5.92 to 10.53 and very remote has a score greater than 10.53.

information on urgency class[5], patient's diagnoses, planned procedure, age and gender. In addition, patient postcodes are recorded and can be used to identify remoteness and the AHS within which the patient resides. Within NSW, AHSs allocate funding from the NSW government to public hospitals within their area; this annual budget is set according to the needs of the local population.

Our analyses use data on patients on the waiting list for planned procedures who completed a hospital stay in NSW public hospitals during the period 2004-2005. We focus on Medicare-eligible, public patients (excluding Veteran's Affairs, Defence Forces and Worker's Compensation patients). This ensures that all observations are non-charge patients who are not subject to the advantageous treatment received by private patients in public hospitals. For example, Johar and Savage (2010) find that in the 90 day urgency category, public patients wait about twice as long as private patients and in the 365 day urgency category the average waiting time can be three times shorter for private patients.[6]

We focus on hospitals that treat acute illnesses. This restriction excludes smaller health facilities, such as small non-acute hospitals, hospices, multi-purpose units and rehabilitation units. We also exclude patients with zero waiting days (5%) as they are likely to represent quasi emergency admissions especially in areas with no emergency departments. Finally, inter-state patients are excluded since the postcode mapping uses postcodes located within NSW. The final sample size consists of 194,198 patients.

In our data there are four ARIA groups: remote, outer regional, inner regional and major city. No patient in the data lives in a very remote area. For AHS boundaries, we use the 17 AHSs that existed in NSW in 2004-05. Within an AHS, there may be multiple ARIA groups; an exception is Far West AHS, which is almost exclusively remote. We use Central Sydney AHS as the reference AHS.

[5] In NSW in 2004-05, in addition to urgency classes of 30, 90 and 365 days, there was also an urgency category with target waiting times of 7 days.
[6] Waiting time variation across socioeconomic status is explored in Johar et al. (2010).

The means of waiting times and selected explanatory variables by ARIA and AHS are presented in Tables 1 and 2. Across ARIA groups, remote patients have the lowest mean waiting times whilst inner region patients have the longest mean waiting time. However this varies along the waiting time distribution. The wait at the 25th percentile (P25), the median (P50) and the wait at the 75th percentile (P75) are longest in remote areas and shortest in the city. The mean waiting times in different areas are largely driven by waiting times in the top 10% of the distribution. This highlights the importance of analysis beyond the mean. The distributions of age, gender and number of conditions are comparable across ARIA groups. However city patients are more likely to be assigned higher urgency than more remote patients.

Across AHSs, there are wide variations of waiting times, even at the lower tail of the waiting time distribution. Northern Sydney has the shortest average wait, which is half that of patients in Central Coast, Illawarra and Mid North Coast, and two thirds of that of patients in Far West, Greater Murray, and Mid Western AHSs. In Northern Sydney, 10% of patients wait less than 3 days compared with 7 days in Mid North Coast. This is a substantial difference given that patients in the bottom of the waiting time distribution are likely to have the most life-threatening or urgent conditions. Northern Sydney also has the shortest waits at the top of the distribution; 10% of patients wait more than 138 days compared with 397 days in the Central Coast and 377 days in Illawarra.

[Insert Tables 1 and 2]

3. Methodology

Our analysis has two stages. First, using linear regression, we show that group membership (ARIA and AHS), which should in principle be irrelevant, has an independent effect on waiting time. Second, we conduct a decomposition analysis which summarises the portion of the waiting time gap that can and cannot be explained by differences in clinical need at various points of the waiting time distribution.

We use the decomposition technique proposed by DiNardo, Fortin and Lemieux (1996), hereafter DFL. The DFL reweighting approach is based on a matching technique which does not assume any functional form (e.g. linearity) on how various factors affect waiting times. It constructs a counterfactual distribution of waiting time, which is the distribution of waiting time of patients in one group had they had the distribution of characteristics of patients in another group. Standard matching assumptions apply: the presence of common support (i.e., there is substantial overlap in the waiting time distributions for the two groups) and ignorability. The common support requirement is more readily satisfied with a large sample size. We discuss ignorability below.

We first describe the DFL reweighting approach assuming common support and ignorability. Consider a comparison of waiting times of any two groups, group A and B. Let F_W^g represents the cumulative distribution function (cdf) of waiting times observed in group *g* (*g* =A,B). F_W^g can be written as:

(1) $$F_W^g(w) = \int F_{W|X}^g(w \mid X = x)dF^g(x)$$

where $F_{W|X}^g$ represents the conditional cdf of waiting times observed in group *g* given *X*, F^g is the cdf of *X* for group *g*, and X are covariates. Under the principle of equity of access to care, we specify *X* to include measures of clinical need (urgency assignment, dummy variables for nearly 200 procedures, number of diagnoses, age and gender). In this paper, we adopt aggregate decomposition which treats all covariates as a single set of determinants.[7] When *g*=B, the counterfactual cdf $F_W^C(w)$ can be constructed as:

(2) $$F_W^C(w) = \int F_{W|X}^B(w \mid X = x)dF^A(x)$$

[7] The DFL reweighting approach would need to be amended to undertake decomposition analysis by subsets of covariates as it is path dependent (Fortin et al., 2010). Like any decomposition technique, the DFL technique is sensitive to the choice of the reference group in the sense that reversing the roles of groups A and B may produce different decomposition results. To check the sensitivity of our results, we performed the decomposition exercises reversing the roles of groups A and B. The absolute values of the magnitudes of the explained and unexplained differences in the characteristics of the distribution of waiting times did not change substantially, while the sign of the differences reversed, as expected.

That is, the counterfactual marginal distribution of waiting time is obtained by integrating the conditional distribution of waiting time given *X* in group B over the marginal distribution of *X* in group A. It reflects the distribution of waiting time that would prevail if patients in group B have clinical needs like patients in group A.

In practice, the DFL approach obtains the counterfactual distribution $F_W^C(w)$ by reweighting the observations in group B to achieve the same distribution of exogenous characteristics as group A. Observations in group B with comparable X to those in group A receive larger weights. To motivate this reweighting procedure, equation (2) can be written as

(3) $$F_W^C(w) = \int F_{W|X}^B(w \mid X = x)dF^A(x) = \int F_{W|X}^B(w \mid X = x)\psi(X)dF^B(x)$$

where

(4) $$\psi(X) = \frac{dF^A(X)}{dF^B(X)}$$

is a reweighting function. Hence, the DFL algorithm can be seen as a form of "importance sampling" (see Keane, 1994 for an application in a different context, that of high dimensional integration). Using Bayes' rule, we obtain

(5) $$\psi(X) = \frac{\Pr(g = A \mid X)/\Pr(g = A)}{\Pr(g = B \mid X)/\Pr(g = B)} = \frac{\Pr(g = A \mid X)}{\Pr(g = B \mid X)}\frac{\Pr(g = B)}{\Pr(g = A)}.$$

To estimate the conditional probabilities, we estimate $\Pr(g = A \mid X)$ with a logit model as a function of observed covariates. The unconditional probabilities are given by the sample proportions of group A and B.

Given the weights, we can compute statistics of interest. Let the mean waiting time for patients in group, A and B, be $\overline{W}_A$ and $\overline{W}_B$, respectively. We can then decompose the difference in mean waiting times as:

(6) $$\overline{W}_A - \overline{W}_B = \left(\overline{W}_A - \overline{\hat{W}}_C\right) + \left(\overline{\hat{W}}_C - \overline{W}_B\right),$$

where $\overline{\hat{W}}_C = 1/N_B \sum_{i \in B} \hat{\psi}_i \cdot W_i$, is the sample mean of the counterfactual waiting times. The first term reflects the unexplained gap in waiting times. This term has an interpretation of discrimination, since it captures the waiting time gap remaining after adjusting for the distribution of factors used to determine waiting time across groups. It is hard to think of a valid reason why group per se should matter except as an outcome of discrimination. Discrimination in favour of group B patients is consistent with positive first term; $\overline{W_A} > \overline{\hat{W}_C}$. The second term, $\overline{\hat{W}_C} - \overline{W_B}$, is the explained portion of the variation in waiting times. If there are no group differences in the distribution of the waiting time setting factors, the second term is zero.

To enrich our analysis beyond the decomposition of mean waiting time, we also compute percentiles of the waiting time distribution (P10, P25, P50, P75 and P90). Just like the mean, we can compute the *k*th percentile waiting time from the counterfactual distribution and compare it with its counterpart from the actual waiting time distribution in the manner of equation (6) in order to quantify the discrimination effect.[8] This reveals where discrimination occurs across the waiting time distribution, and which group is advantaged. It is quite possible that scope of discrimination is less at the lower end of the waiting time distribution because urgent cases are associated with high mortality risks from delayed treatment. We use the bootstrap method to obtain the standard errors of these statistics with 200 replications.

We now revisit the ignorability assumption. Ignorability allows correlation between the unobservables and clinical needs as long as their conditional distributions given *X* are the same across groups. This may be violated if clinical needs and unobserved factors influencing waiting time, such as negotiation skills and search activity, are determined by group. If they are correlated, we are unable to separate the contribution of clinical needs to waiting time from that of negotiation skill. Patients in a certain group may be good negotiators and be able to get their doctors to assign them to a more urgent class, which lowers their waiting times. For example, the share of patients with urgency class 7 days is lower in remote and regional areas than it is in the city (Table 1). As urgency has a negative effect on waiting time, we would be overestimating the explained component of the waiting time gap and underestimating the size of discrimination. Arguably, finding a

[8] The counterfactual percentiles are computed using STATA command *summarize w [weight=wvar], detail*, where *w* is waiting time, *wvar* is the weight $\psi(X)$ from equation (4).

lower bound for discrimination is less serious than overestimating it. Selection biases are another potential source of ignorability violation. In the labour market literature, self-selection into the labour market is a common concern in analysing wages. In the case of waiting time, the argument that there is a significant selection bias in joining a waiting list by group is less compelling. Selection into a group based on unobservables is also less likely unless there is a strong reason why individuals with good negotiation skills live in certain areas.

4. Results

4.1. Regression results

In the first stage of our analysis, we use linear regression (Ordinary Least Square) to test the role of ARIA and AHS in explaining patient waiting times. The dependent variable is individual patient waiting time. The regressors are measures of clinical needs (as described above) plus dummies for geographic groups. Table 3 reports the regression results.

[Insert Table 3]

Controlling for differences in clinical need, we find significant variations by ARIA (omitted group major city) and AHS (omitted group Central Sydney). On average, remote patients wait 22 days less than clinically comparable patients in the city, while outer region patients wait 12 days less and inner region patients wait 3 days less. With regard to AHS, all but 2 AHSs have significantly different waiting time to Central Sydney patients. The AHS effect can be as large as 47 days on average in the comparison with Illawarra.

With regard to clinical needs, as expected, urgency class is the strongest predictor of waiting times. Young children have the shortest waiting times, followed the elderly, and middle-aged patients have the longest wait. Waiting times are longer for those with more conditions which may reflect complexity. Gender differentials are small.

4.2. DFL reweighting results

4.2.1. ARIA

Table 4 presents the DFL results by ARIA groups.[9] For instance, in the column reporting the DFL estimates at the 'Mean', the comparison between remote and city patients shows that, compared to city patients, remote patients wait 4.57 days less on average. The 'explained' component indicates that the clinical need of patients in remote areas makes them wait 16 days longer than city patients on average. In this example, the explained component is greater than the total difference implying that the unexplained component (-20.99), interpreted as discrimination, goes in the opposite direction. That is, while remote patients have clinical needs that are associated with long wait, the current waiting list operation gives favourable treatment to them, admitting them faster than clinically comparable city patients. The "unexplained" row suggests that for other reasons beside clinical needs, patients in remote areas wait on average 21 days less than city patients. This is comparable to the regression coefficient for remote in Table 3. We find similar results for other comparison pairs except in the comparison pair of patients in inner regions and cities where discrimination is relatively small, resulting in longer waiting time overall for inner region patients. In the last two columns, we report the traditional Oaxaca-Blinder (OB) decomposition results for comparison. These suggest consistent finding with the DFL approach at the mean.

[Insert Table 4]

Analysis by percentile reveals important information that is not obvious from the regression alone; it shows large discrimination in the upper tail of the waiting time distribution. At the top of the waiting time distribution (P90), remote patients are admitted 3 months earlier than their clinically comparable counterparts in the city. In comparison with clinically comparable inner region patients, remote patients also wait 3 months less

[9] The logit weighting equation results are not reported and available from authors. Children and females in the waiting list population are more likely to live in the cities, as do patients who are assigned with low urgency classes (90 days and 365 days) and patients with more conditions.

and in comparison with clinically comparable outer region patients, remote patients wait 1 month less. In contrast, at lower points of the waiting time distribution, waiting time gaps are largely explained by an unequal distribution of health profiles in different areas.

While maintaining our assertion that waiting time variation due to supply factors forms part of discrimination, we experiment by including a measure of the supply of public hospital beds in the patient's postcode of residence. This measure follows Stavrunova and Yerokhin (2011) and takes into account available beds, distance to other hospitals and population. This measure is highest in remote areas largely due to lower population density. Including this measure as a covariate in the weighting function does not change the substantive results. We still find a large discrimination effect in favour of remote and outer region patients.[10]

If our prior expectation is that city patients are an advantaged group relative to those in more remote regions, this finding of discrimination against them is quite unexpected. For example, from the waiting time percentiles in Table 1, city patients always have shorter waiting times than patients in other areas, except at the very top of the waiting time distribution. A potential explanation for this result could lie in a greater willingness of patients in more remote areas to travel for treatment. It is patients who are more active and concerned about quality of their treatment that seek care far away from where they leave. They can also be more assertive in requesting faster treatment. To explore this possibility, we identify the ARIA of the treating hospital.

Table 5 reveals that only 45% of remote patients go to hospitals in remote areas. 35% of remote patients go to hospitals in outer regions, 10% go to hospitals in inner regions and the remaining 10% go to hospitals in the city. The fact that city hospitals are not the most popular destination by remote patients who travel for care is interesting. It may suggest that travel costs increase greatly with distance and/or there are large

[10] Results are available from authors.

differences in health resources between hospitals in remote areas and those in outer regions.[11] About 60% of patients in regional areas go to hospitals in the same ARIA. Most outer region patients who travel outside their ARIA attend hospitals in inner regional areas, while most inner region patients who travel go to the city. In the city, almost all patients are treated in city hospitals.

[Insert Table 5]

Table 6 reports the DFL results by mobility. We define ‘movers’ as patients who are treated in a hospital located outside their ARIA group and ‘stayers’ as patients who are treated in a hospital within their ARIA group. We use city patients who are stayers as the reference group.

The difference between movers and city stayers, *Total*, is between 6 and 15 days on average and favours the non-city movers. This gap is largely due to favourable treatment (*Unexplained*) for non-city movers. On average, movers from inner regions wait 4 days less than clinically comparable stayers, while movers from outer and remote regions wait considerably less than their clinically comparable counterparts, 13 and 32 days less, respectively. The favourable treatment to non-city patients extends to the non-city stayers as well. Stayers in remote areas wait 9 days less than their clinically comparable city counterparts. Likewise stayers in outer regional areas wait 12 days less and stayers in inner regions wait 2 days less. Thus the apparent difference in waiting times in favour of remote patients compared to city patients in the pooled model (Table 4) is driven by remote patients who move. However, in *Total*, non-city stayers wait between 1 and 16 days more on average for their treatment due to their health conditions.

Examining favourable treatment over the waiting time distribution, we find that relative to city stayers, remote movers receive favourable treatment at all points of the distribution. By contrast, remote stayers wait more than clinically comparable city

[11] In NSW, currently remote patients who require specialised care that is not available within 200 kilometre (threshold applied during 2004/2005) from their home may be eligible for patient travel assurance schemes, which partly subsidise travel and accommodation costs.

patients. This result holds at all percentiles of the waiting time distribution except at the very top, where remote stayers receive favourable treatment relative to clinically comparable city patients, although to a lesser extent (103 days less for remote movers relative to city patients; 78 days less for remote stayers relative to city patients). This suggests remote stayers with similar clinical needs to their mobile counterparts are disadvantaged by the resource allocation or the management of the waiting list.

For outer region patients, stayers are in better health than movers and the *Unexplained* component is about the same. In contrast, inner region stayers are considerably healthier than movers yet there is only a small advantage from moving (17 days less even at P90.

These results suggest that preferential treatment of more remote patients is not solely due to willingness to travel. The discrimination effect tends to be greater for patients who move than those who stay. This is inconsistent with the conjecture that waiting time in remote areas is shorter due to excess capacity in remote areas. Under this hypothesis, more remote patients who move should have smaller gains than those who stay.

[Insert Table 6]

4.2.2. AHS

Table 7 presents the decomposition results by AHS.[12] To make comparisons tractable, we take Central Sydney as the reference group. For instance, compared to Central Sydney patients, Central Coast patients wait on average 53 days longer, of which 21 days is attributed to clinical needs. In comparison with Illawarra patients, the difference

[12] The logit weighting equation results are available from authors. Patients who are assigned with more urgent classes (7 days and 30 days) are more likely to live in Central Sydney. Other waiting list demographics vary across pairs. Compared with North Sydney, patients with more conditions are more likely to live in Central Sydney. Compared with other Sydney AHSs, patients with fewer conditions and middle-age patients are more likely to live in Central Sydney. Compared with other AHSs outside Sydney, in general, middle-age patients are more likely to live in Central Sydney. Patients with more conditions are more likely to live in Central Sydney in 3 comparison pairs, less likely to live in Central Sydney in 6 comparison pairs and have equal probability to live in either area in 3 comparison pairs.

in average waiting times is also 53 days, but only 4 days is due to differences in clinical needs. The remaining 49 days (93%) is due to discrimination.

[Insert Table 7]

Summarising the results for other comparison pairs, we find that Central Sydney patients are advantaged over clinically comparable patients in about half of the AHSs. In some comparison pairs with Central Sydney patients, clinical needs and discrimination go in opposite directions. In comparison with Northern Sydney patients, at the mean, the discrimination effect dominates; based on clinical needs, Northern Sydney patients should face 6 days longer wait than Central Sydney patients, however they get admitted 22 days faster.

In some comparison pairs we find significant discrimination effect among patients with urgent conditions. At P10, patients in Far West, Mid North Coast, Northern Rivers, South Western Sydney and Western Sydney wait longer than clinically comparable patients in Central Sydney. At this point, even a day delay may be serious. For other AHSs at P10, the waiting time gaps are mostly explained by clinical needs.

Waiting time gaps can be very large at the upper tail of the waiting time distribution. Comparing Central Sydney patients with Central Coast patients for instance, the total waiting time gap is 15 days at the median, 90 days at P75 and 173 days at P90. In the comparison pair with Illawarra, the total difference in waiting times at P90 is 153 days. The bulk of these waiting time gaps are not explained by clinical needs; discrimination is responsible for delaying the treatment of Central Coast patients by 101 days and for Illawarra patients by 135 days.

Clinical needs and discrimination have consistent signs throughout the waiting time distribution, but they may counteract one another. Health profiles and discrimination contribute to longer waiting times of patients in Central Coast, Greater Murray, Illawarra, Mid North Coast, Northern Rivers, South Eastern Sydney, South Western Sydney and

Wentworth. On the other hand, the distribution of health profiles in Hunter, Macquarie, New England, Northern Sydney and Southern tend to increase their waiting times, but patients in these areas are admitted earlier than their comparable counterparts in Central Sydney.

A large discriminatory component is found even among Sydney-based AHSs (i.e. in comparison pairs Northern Sydney, South Eastern Sydney and South Western Sydney with Central Sydney). Less urgent patients in Northern Sydney are admitted 23 days faster at P75 and 86 days faster at P90 than their counterparts living in Central Sydney. In contrast, less urgent patients in South Eastern Sydney and South Western Sydney wait 21-90 days longer.

An *apparent* equity improvement may be achieved by grouping AHS. As a concrete example, in 2005 the 17 AHSs in NSW were amalgamated into 8 with a pairing rule that tended to group AHSs with short and long waiting times subject to proximity. Northern Sydney, which had the shortest average waiting time of all AHSs in 2004-05, was paired with the Central Coast which had the second longest average waiting time (see Table 2). Central Sydney was paired with South West Sydney, which had the third longest wait. As a result of the amalgamation, waiting time advantages in areas like Northern Sydney and Central Sydney would be concealed.

A caveat to our results is that we may not adequately deal with the potential endogeneity of patients' residential location. However, the most probable direction of bias suggests that the "true" magnitude of discrimination in waiting time is likely to be larger than our estimates suggest.

5. Conclusion

Waiting time is the rationing device used to equate supply and demand in the public hospital system where treatment is free at the point of care. Equitable access to care requires that the length of time to treatment should reflect patients' clinical needs. Our results show that this is far from the reality in NSW, challenging both the current waiting list system and the equity goal of a universal public health system. The equity of universal health systems is often assumed, but rarely tested. We find that patient waiting times exhibit large geographic variation and most of the variation, particularly at the top of the distribution, cannot be attributed to clinical needs.

We interpret unexplained variation in waiting times as discrimination. The extent of discrimination can be very large: over 2 weeks for patients assigned a 30 day urgency category and over 3 months for less urgent cases. Distributional analysis reveals that discrimination in concentrated in the upper tail of the waiting time distribution (P50 and above) where the extent of discrimination can be very large (up to 135 days for the AHS comparisons and 97 days for comparisons by ARIA). Heterogeneous discrimination effects along the waiting time distribution highlight the importance of our empirical strategy that goes beyond standard mean-based analysis.

We find evidence of favourable treatment for all non-city patients relative to those in the city and this advantage in waiting times is especially pronounced for remote patients who travel to less remote areas for treatment. We find those who move from inner regional areas (mostly to the city) are in greater clinical need than those who stay but the waiting time advantage of moving is small. These results suggest there is scope for improved resource allocation and management of the waiting list across regions and AHSs.

There are many potential sources of discrimination. It may be due to differences in the quality of patient-doctor relationships or in patients' searching skills in different locations. Discrimination could also be due to inequitable access to public health care resources by different patients. All such channels are inconsistent with the equity assumption of clinically-based prioritisation and universal public health care system. The discrimination effect we find is robust to a measure of supply capacity. Future research will explore discriminatory mechanisms further.

Given that waiting times are strongly influenced by urgency, the incidence of discrimination at the top of the distribution, which reflects lowest urgency, might be explained by more provider discretion when delaying treatments carry lower risks. This discretion gives providers more scope to give preferential treatment to favoured patients, although the evidence on this is mixed (MacCormick et al., 2004; Propper et al., 2010). In our study all patients are non-paying public patients, so the incentives for doctors to discriminate between patients must be non-monetary or indirect. 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 bring an outcome that promotes greater equity. Our findings suggest that the design of equitable waiting time targets for public hospitals cannot rely solely on the assignment of urgency by providers.

In addition, waiting time reporting, which is currently highly aggregated, should be more detailed to expose, and perhaps discourage, favourable treatment to some patient groups. It should also report information on the lower and upper tails of the waiting distribution in addition to central tendencies. Issues surrounding reporting structures will have greater prominence as Australia embarks on greater transparency in health care through performance reporting.

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Table 1: Waiting time distribution and summary statistics of selected covariates by ARIA

Variable	Remote	Outer	Inner	City
Mean waiting time	90.944	93.624	101.605	95.510
(std.dev)	(121.46)	(141.596)	(157.831)	(155.387)
P10 waiting time	5	5	5	4
P25 waiting time	16	14	13	12
P50 waiting time	44	40	38	35
P75 waiting time	117	106	112	101
P90 waiting time	235	271	307	281
Demographics				
0 to 4	3.36%	2.70%	3.75%	3.87%
5 to 9	4.11%	3.67%	3.96%	3.59%
10 to 14	2.61%	2.06%	2.34%	2.04%
15 to 19	2.61%	2.42%	2.62%	2.19%
20 to 24	3.76%	2.96%	3.21%	3.07%
25 to 29	4.08%	3.19%	3.66%	4.04%
30 to 34	4.86%	4.23%	5.06%	5.15%
35 to 39	5.72%	4.86%	5.24%	5.50%
40 to 44	6.26%	6.04%	6.02%	6.40%
45 to 49	6.40%	6.33%	6.11%	6.81%
50 to 54	7.12%	6.75%	6.23%	6.52%
55 to 59	7.30%	8.08%	7.48%	7.23%
60 to 64	8.37%	8.62%	7.71%	7.41%
65 to 69	8.80%	10.54%	9.39%	8.61%
70 to 74	9.55%	10.50%	9.76%	9.05%
75 to 79	8.91%	9.38%	9.46%	9.31%
80 to 84	3.25%	4.94%	4.85%	5.63%
85+	2.93%	2.73%	3.16%	3.59%
male	44.03%	47.82%	45.72%	46.98%
Urgency				
urgency < 7 days	8.66%	10.88%	11.02%	13.74%
urgency < 30 days	28.00%	30.63%	30.01%	34.92%
urgency < 90 days	35.94%	32.98%	33.45%	28.54%
urgency < 1 year	27.40%	25.51%	25.53%	22.80%
Number of acute conditions				
0 condition	4.90%	6.65%	5.34%	4.56%
1 condition	23.61%	35.58%	31.08%	28.59%
2 conditions	31.15%	30.55%	30.07%	28.79%
3 conditions	23.61%	16.68%	19.62%	20.81%
4 conditions	12.20%	7.67%	9.94%	12.03%
5 or more conditions	4.54%	2.86%	3.95%	5.22%
Number of observations	2,795	27,505	69,828	94,070

Note: For conciseness, we suppressed the summary statistics related to procedures because there are close to 200 procedures. The number of conditions are based on more than 10,000 codes for chronic conditions (principal and 5 other diagnoses), from which we select only those which are associated with hospitalisation (e.g., short-sightedness is excluded) and put into broader group. We obtained clinical advice for this mapping.

Table 2: Waiting time distribution and summary statistics of selected covariates by AHS

Variable	Central Coast	Central Sydney	Far West	Greater Murray	Hunter	Illawarra	Macquarie	Mid North Coast	Mid Western	New England	Northern Rivers	Northern Sydney	South East Sydney	South West Sydney	Southern	Wentworth	Western Sydney
Waiting time	131.7	78.7	91.3	94.5	78.5	131.9	87.9	118.6	85.2	72.1	107.1	62.4	109.1	113.6	82.9	106.3	90.7
(std.dev)	195.4	139.9	108.0	144.9	124.5	173.7	134.9	158.2	145.1	97.8	176.7	110.5	187.8	168.4	101.7	179.3	143.2
P10 waiting time	4	3	6	4	5	4	5	7	5	4	4	3	3	6	6	3	5
P25 waiting time	14	8	18	14	13	14	14	20	10	13	12	8	10	17	20	12	13
P50 waiting time	42	27	47	38	34	52	38	56	28	35	38	25	34	47	44	41	37
P75 waiting time	167	77	138	110	86	197	87	156	80	91	105	62	112	126	106	112	99
P90 waiting time	397	224	223	279	207	377	245	346	257	190	348	158	340	343	216	285	244
Demographics																	
0 to 4	2.64%	3.33%	2.86%	3.99%	3.60%	3.27%	3.43%	2.49%	3.11%	3.24%	4.61%	3.54%	4.50%	4.43%	2.21%	4.80%	4.03%
5 to 9	2.96%	3.05%	4.32%	3.96%	4.12%	2.62%	4.80%	2.62%	3.73%	3.02%	6.38%	2.82%	3.53%	4.78%	3.07%	4.65%	4.30%
10 to 14	1.74%	1.47%	2.53%	2.30%	2.47%	1.75%	2.75%	1.76%	1.71%	1.94%	3.17%	1.64%	1.64%	2.66%	1.52%	3.47%	2.80%
15 to 19	1.86%	1.70%	2.69%	2.10%	2.82%	2.27%	2.57%	2.32%	2.38%	2.18%	3.35%	1.89%	1.82%	2.70%	2.72%	3.86%	2.59%
20 to 24	2.56%	2.55%	3.37%	2.88%	3.56%	2.79%	2.95%	2.25%	3.94%	3.75%	3.12%	3.13%	2.57%	3.23%	2.88%	4.22%	3.38%
25 to 29	2.83%	3.88%	3.42%	3.67%	4.66%	3.06%	3.87%	2.34%	3.85%	3.61%	2.56%	3.97%	4.12%	3.61%	3.24%	5.46%	4.42%
30 to 34	4.21%	5.22%	4.71%	4.77%	5.95%	4.37%	4.56%	3.37%	4.93%	4.82%	3.96%	4.96%	4.76%	4.99%	4.67%	6.30%	5.93%
35 to 39	4.33%	5.35%	5.84%	4.65%	5.88%	4.24%	5.12%	4.44%	5.38%	5.11%	4.70%	5.36%	4.69%	5.72%	5.52%	5.97%	6.57%
40 to 44	5.06%	7.00%	6.40%	6.13%	6.38%	5.15%	5.64%	5.85%	6.50%	6.22%	5.33%	6.28%	5.40%	6.58%	6.15%	5.96%	7.42%
45 to 49	4.90%	6.59%	6.23%	5.56%	6.77%	5.64%	5.86%	6.22%	6.46%	6.46%	6.15%	6.52%	5.82%	7.58%	6.82%	6.81%	7.32%
50 to 54	5.52%	6.66%	7.24%	6.23%	5.96%	5.28%	6.70%	6.57%	7.07%	6.35%	6.64%	6.11%	6.13%	7.31%	6.98%	7.10%	6.66%
55 to 59	6.48%	7.60%	7.86%	7.00%	7.03%	7.03%	7.69%	7.83%	7.89%	8.33%	7.82%	6.97%	6.93%	7.47%	8.38%	7.83%	7.90%
60 to 64	7.76%	7.91%	8.81%	7.30%	7.51%	8.49%	8.55%	9.39%	7.83%	8.42%	7.43%	6.68%	7.45%	7.27%	8.41%	6.82%	7.50%
65 to 69	10.46%	9.32%	8.36%	10.18%	8.55%	10.65%	10.01%	11.46%	9.91%	10.69%	9.06%	7.75%	8.71%	8.70%	10.11%	6.79%	7.68%
70 to 74	11.91%	9.92%	9.37%	10.93%	8.50%	12.45%	9.61%	12.47%	9.26%	9.93%	9.39%	8.96%	9.50%	8.11%	10.54%	6.66%	7.75%
75 to 79	12.50%	8.97%	9.32%	9.70%	8.51%	12.18%	8.97%	11.38%	8.59%	8.80%	8.76%	10.47%	10.65%	8.08%	9.33%	6.82%	7.42%
80 to 84	7.26%	5.65%	3.31%	5.24%	4.40%	5.87%	4.41%	5.03%	4.49%	4.66%	4.63%	7.47%	6.99%	4.50%	4.32%	4.06%	3.92%
85+	5.02%	3.83%	3.37%	3.41%	3.34%	2.93%	2.51%	2.20%	2.96%	2.46%	2.93%	5.49%	4.82%	2.28%	3.13%	2.40%	2.40%
male	46.12%	49.17%	43.49%	48.99%	43.27%	46.44%	45.57%	46.01%	44.14%	47.19%	51.14%	45.81%	52.33%	45.76%	46.98%	43.87%	45.65%
Urgency																	
urgency < 7 days	9.49%	17.49%	8.92%	13.73%	7.85%	17.01%	8.11%	9.22%	7.86%	10.32%	18.05%	16.72%	16.24%	10.53%	9.07%	14.11%	11.96%
urgency < 30 days	25.79%	38.34%	30.19%	29.24%	30.34%	37.26%	23.88%	34.16%	31.68%	28.80%	36.26%	31.88%	36.81%	34.24%	24.76%	32.39%	33.02%
urgency < 90 days	35.01%	26.05%	36.03%	32.95%	40.01%	25.72%	34.80%	26.57%	40.97%	32.86%	22.10%	30.38%	27.67%	28.71%	38.97%	27.74%	28.05%
urgency < 1 year	29.71%	18.12%	24.86%	24.08%	21.81%	20.02%	33.21%	30.04%	19.49%	28.03%	23.59%	21.03%	19.27%	26.52%	27.21%	25.76%	26.98%
# acute conditions																	
0 condition	3.87%	4.95%	5.27%	6.52%	4.55%	4.31%	4.31%	3.93%	5.73%	7.38%	8.52%	5.19%	4.49%	4.94%	6.47%	7.16%	4.68%
1 condition	31.69%	29.28%	19.92%	28.75%	27.57%	26.91%	27.53%	29.80%	31.35%	36.92%	44.67%	33.35%	27.38%	29.25%	39.05%	34.92%	28.32%
2 conditions	31.89%	29.05%	31.26%	30.35%	27.24%	29.47%	31.93%	31.33%	32.93%	30.61%	26.90%	28.82%	28.03%	29.88%	30.17%	27.78%	28.38%
3 conditions	19.75%	20.61%	24.58%	20.22%	20.35%	22.55%	21.99%	21.02%	18.52%	15.80%	12.11%	18.17%	21.19%	20.51%	15.31%	17.66%	21.32%
4 conditions	9.53%	11.51%	13.08%	10.08%	13.15%	12.51%	10.78%	10.03%	8.18%	6.83%	5.47%	10.16%	13.09%	10.97%	6.50%	9.06%	12.10%
5 or more conditions	3.27%	4.61%	5.89%	4.08%	7.14%	4.24%	3.47%	3.89%	3.28%	2.46%	2.33%	4.32%	5.82%	4.45%	2.50%	3.41%	5.20%
N	12,460	13,434	1,782	8,946	16,505	11,913	5,017	9,182	10,643	9,529	4,294	13,687	16,302	25,222	6,847	6,918	21,517

Table 3: Regression results (dependent variable: individual waiting times)

	Coeff	t-stat
Urgency: 7 days	-143.14	-135.40***
Urgency: 30 days	-121.11	-114.95***
Urgency: 90 days	-73.29	-65.54***
Age: 0-4	-32.04	-18.36***
Age: 5-9	-14.70	-6.98***
Age: 10-14	-8.54	-3.49***
Age: 15-19	-14.86	-6.72***
Age: 20-24	-8.65	-4.32***
Age: 25-29	-6.60	-3.63***
Age: 30-34	-4.80	-2.77***
Age: 35-39	-1.75	-1.04
Age: 40-44	-0.83	-0.52
Age: 50-54	-1.33	-0.83
Age: 55-59	-2.53	-1.64
Age: 60-64	-2.87	-1.84*
Age: 65-69	-1.00	-0.66
Age: 70-74	0.15	0.10
Age: 75-79	-1.46	-0.97
Age: 80-84	-2.47	-1.41
Age: 85+	-9.08	-4.71***
0 conditions	-6.30	-5.01***
2 conditions	0.43	0.56
3 conditions	1.79	2.03**
4 conditions	1.72	1.59
>=5 conditions	4.84	3.07***
Male	-1.41	-2.17**
Central Coast	24.04	13.85***
Far West	-12.43	-5.23***
Greater Murray	-0.52	-0.32
Hunter	-10.27	-7.73***
Illawarra	47.17	28.75***
Macquarie	-22.58	-11.74***
Mid North Coast	15.30	8.56***
Mid Western	-6.70	-4.47***
New England	-27.62	-20.62***
Northern Rivers	18.47	7.09***
Northern Sydney	-23.40	-18.18***
SES	23.79	15.10***
SWS	19.32	14.56***
Southern	-21.21	-14.65***
Wentworth	20.93	10.24***
WS	0.83	0.63
Constant	264.91	114.86***
R-sq	0.3272	

	Coeff	t-stat
Urgency: 7 days	-140.51	-133.46***
Urgency: 30 days	-119.21	-112.37***
Urgency: 90 days	-74.06	-65.88***
Age: 0-4	-29.99	-17.17***
Age: 5-9	-12.85	-6.05***
Age: 10-14	-6.80	-2.76***
Age: 15-19	-13.50	-6.05***
Age: 20-24	-8.81	-4.36***
Age: 25-29	-6.84	-3.73***
Age: 30-34	-4.77	-2.72***
Age: 35-39	-1.94	-1.14
Age: 40-44	-1.17	-0.71
Age: 50-54	-1.16	-0.72
Age: 55-59	-2.53	-1.63
Age: 60-64	-2.32	-1.47
Age: 65-69	-0.28	-0.18
Age: 70-74	1.25	0.81
Age: 75-79	-0.41	-0.27
Age: 80-84	-2.08	-1.18
Age: 85+	-10.15	-5.24***
0 conditions	-6.64	-5.22***
2 conditions	0.85	1.10
3 conditions	2.56	2.88***
4 conditions	2.31	2.12**
>=5 conditions	4.15	2.62***
Male	-1.30	-1.97*
Remote	-22.71	-11.55***
Outer region	-11.76	-13.73***
Inner region	-2.55	-3.89***
Constant	273.61	126.61***
R-sq	0.3118	

Note: *, ** and *** indicate 10%, 5% and 1% significance level, respectively. Also included in the model are dummy variables for procedures. The base groups are urgency 365 days, age 40-50, 1 condition and female. For AHS the base group is Central Sydney and for ARIA the base group is City. The sample size is 194,198.

Table 4: Results of the DFL reweighting approach by ARIA

		Mean		P10		P25		P50		P75		P90		OB	
Remote	*Explained*	16.42***	[-359%]	2***	[200%]	4***	[100%]	12***	[133%]	28***	[175%]	47***	[-102%]	19.71***	[431%]
& City^ [a]	*Unexplained*	-20.99***	[459%]	-1*	[-100%]	0	[0%]	-3**	[-33%]	-12***	[-75%]	-93***	[202%]	-14.28***	[-331%]
	Total	-4.57	[100%]	1	[100%]	4	[100%]	9	[100%]	16	[100%]	-46	[100%]	-4.57	[100%]
Outer	*Explained*	10.19***	[-539%]	1 [b]	[100%]	2***	[100%]	8***	[160%]	19***	[380%]	32***	[-320%]	10.63***	[-562%]
& City^	*Unexplained*	-12.08***	[639%]	0	[0%]	0	[0%]	-3***	[-60%]	-14***	[-280%]	-42***	[420%]	-12.52***	[462%]
	Total	-1.89	[100%]	1	[100%]	2	[100%]	5	[100%]	5	[100%]	-10	[100%]	-1.89	[100%]
Inner	*Explained*	8.76***	[144%]	1 [b]	[100%]	2 [b]	[200%]	7***	[233%]	17***	[155%]	27***	[104%]	8.21***	[135%]
& City^	*Unexplained*	-2.66***	[-44%]	0 [b]	[0%]	-1***	[-100%]	-4***	[-133%]	-6***	[-55%]	-1	[-4%]	-2.11***	[-35%]
	Total	6.10	[100%]	1	[100%]	1	[100%]	3	[100%]	11	[100%]	26	[100%]	6.10	[100%]
Remote	*Explained*	7.70***	[-72%]	1**	n.a.	2***	[67%]	5***	[83%]	12***	[240%]	22***	[-31%]	10.40***	[-98%]
& Inner^	*Unexplained*	-18.36***	[172%]	-1*	n.a.	1	[33%]	1	[17%]	-7	[-140%]	-97**	[131%]	-21.07***	[198%]
	Total	-10.66	[100%]	0	n.a.	3	[100%]	6	[100%]	5	[100%]	-72	[100%]	-10.66	[100%]
Outer	*Explained*	0.27	[-3%]	0	n.a.	0	[0%]	0	[0%]	2*	[-33%]	3	[-8%]	0.15	[-2%]
& Inner^	*Unexplained*	-8.25***	[103%]	0	n.a.	1**	[100%]	2***	[100%]	-8***	[133%]	-39***	[108%]	-8.14***	[102%]
	Total	-7.98	[100%]	0	n.a.	1	[100%]	2	[100%]	-6	[100%]	-36	[100%]	-7.98	[100%]
Remote	*Explained*	4.18***	[-156%]	0	n.a.	2***	[100%]	3***	[75%]	8***	[73%]	7	[-19%]	3.98**	[-149%]
& Outer^	*Unexplained*	-6.86***	[256%]	0	n.a.	0	[0%]	1	[25%]	3	[27%]	-43***	[119%]	-6.66***	[249%]
	Total	-2.68	[100%]	0	n.a.	2	[100%]	4	[100%]	11	[100%]	-36	[100%]	-2.68	[100%]

Note: ^ the reference group. n.a refers to no difference in waiting time. Decomposition of waiting time gap in proportions are in brackets. *, ** and *** indicate 10%, 5% and 1% significance level, respectively, based on bootstrapped standard errors with 200 replications. The test hypothesis is under the null of no difference in waiting times. [a] bootstrap sample is done by group such that the proportion of remote patients are always the same with the original sample. This is because remote patients are very few compared with patients in other areas resulting in bootstrap samples occasionally have very small number of ARIA 1 patients. Detailed 197 dummy variables for procedures are replaced with 27 dummy variables for condition groups because of perfect predictive power of many of the procedure dummy variables. [b] all replications return the same difference. The OB column reports the decomposition results using Oaxaca-Blinder approach with identical specification as the one used in DFL.

Table 5: Patient mobility by ARIA

Patient/Hospital	Remote	Outer	Inner	City	Total
Remote	45.14%	34.51%	10.12%	10.23%	100%
Outer	0.24%	60.65%	26.12%	13.00%	100%
Inner	0.00%	2.21%	62.55%	35.23%	100%
City	0.00%	0.02%	3.56%	96.42%	100%

Note: figures in each cell are shares out of patient location. ‘Movers’ are observations in the off-diagonal and ‘stayers’ are observations in the diagonal terms.

Table 6: Results of DFL reweighting approach by ARIA and mobility (reference group: city stayers)

		Mean		**P10**		**P25**		**P50**		**P75**		**P90**	
Movers													
Remote	*Explained*	16.83***	[-117%]	2***	[200%]	4***	[400%]	13***	[1300%]	29***	[-126%]	45***	[-78%]
	Unexplained	-31.53***	[217%]	-1*	[-100%]	-3***	[-300%]	-12***	[-1200%]	-52***	[226%]	-103***	[178%]
	Total	-14.69	[100%]	1	[100%]	1	[100%]	1	[100%]	-23	[100%]	-58	[100%]
Outer	*Explained*	7.06***	[-122%]	0	n.a.	0	[0%]	2**	[-100%]	11***	[550%]	31***	[-207%]
	Unexplained	-12.84***	[222%]	0	n.a.	-1*	[100%]	-4***	[200%]	-9***	[-450%]	-46***	[307%]
	Total	-5.78	[100%]	0	n.a.	-1	[100%]	-2	[100%]	2	[100%]	-15	[100%]
Inner	*Explained*	-7.63***	[68%]	0	n.a.	-1***	[100%]	-2***	[100%]	-10***	[91%]	-31***	[65%]
	Unexplained	-3.56***	[32%]	0	n.a.	0	[0%]	0	[0%]	-1	[9%]	-17***	[35%]
	Total	-11.20	[100%]	0	n.a.	-1	[100%]	-2	[100%]	-11	[100%]	-48	[100%]
Stayers													
Remote	*Explained*	14.95***	[236%]	2***	[67%]	3***	[33%]	10***	[45%]	25***	[42%]	47***	[-152%]
	Unexplained	-8.62***	[-136%]	1	[33%]	6***	[67%]	12***	[55%]	35***	[58%]	-78***	[252%]
	Total	6.33	[100%]	3	[100%]	9	[100%]	22	[100%]	60	[100%]	-31	[100%]
Outer	*Explained*	12.64***	[2030%]	2***	[100%]	4***	[80%]	12***	[150%]	26***	[325%]	34***	[-425%]
	Unexplained	-12.01***	[-1930%]	0	[0%]	1*	[20%]	-4***	[-50%]	-18***	[-225%]	-42***	[525%]
	Total	0.62	[100%]	2	[100%]	5	[100%]	8	[100%]	8	[100%]	-8	[100%]
Inner	*Explained*	18.72***	[114%]	2 [b]	[200%]	5***	[250%]	14***	[200%]	36***	[129%]	54***	[89%]
	Unexplained	-2.27***	[-14%]	-1 [b]	[-100%]	-3***	[-150%]	-7***	[-100%]	-8***	[-29%]	7**	[11%]
	Total	16.45	[100%]	1	[100%]	2	[100%]	7	[100%]	28	[100%]	61	[100%]

Note: n.a refers to no difference in waiting time. Decomposition of waiting time gap in proportions are in brackets. *, ** and *** indicate 10%, 5% and 1% significance level, respectively, based on bootstrapped standard errors with 200 replications. The test hypothesis is under the null of no difference in waiting times. [b] all replications return the same difference. The sample size is 194,198.

Table 7: Results of the DFL reweighting approach by AHS (reference group: Central Sydney AHS)

		Mean		P10		P25		P50		P75		P90	
Central Coast	*Explained*	21.02***	[40%]	1***	[100%]	5***	[83%]	12***	[80%]	37***	[41%]	72***	[42%]
	Unexplained	31.97***	[60%]	0	[0%]	1**	[17%]	3***	[20%]	53***	[59%]	101***	[58%]
	Total	52.99	[100%]	1	[100%]	6	[100%]	15	[100%]	90	[100%]	173	[100%]
Far West	*Explained*	26.32***	[209%]	2***	[66%]	6***	[60%]	15***	[75%]	4***	[7%]	84***	[-840%]
	Unexplained	-13.75***	[-109%]	1*	[34%]	4***	[40%]	5**	[25%]	57***	[93%]	-85**	[850%]
	Total	12.57	[100%]	3	[100%]	10	[100%]	20	[100%]	61	[100%]	-1	[100%]
Greater Murray	*Explained*	16.19***	[103%]	1 [b]	[100%]	4***	[67%]	10***	[91%]	32***	[97%]	51***	[93%]
	Unexplained	-0.43	[-3%]	0	[%]	2***	[33%]	1	[9%]	1	[3%]	4	[7%]
	Total	15.76	[100%]	1	[100%]	6	[100%]	11	[100%]	33	[100%]	55	[100%]
Hunter	*Explained*	12.24***	[4371%]	2***	[100%]	6***	[120%]	12***	[170%]	22***	[244%]	31***	[-182%]
	Unexplained	-12.52***	[-4271%]	0	[0%]	-1**	[-20%]	-5***	[-70%]	-13***	[-144%]	-48***	[282%]
	Total	-0.28	[100%]	2	[100%]	5	[100%]	7	[100%]	9	[100%]	-17	[100%]
Illawarra	*Explained*	3.94***	[7%]	0	[0%]	1**	[17%]	3***	[12%]	9***	[8%]	18***	[12%]
	Unexplained	49.25***	[93%]	1**	[100%]	5***	[83%]	22***	[88%]	111***	[92%]	135***	[88%]
	Total	53.19***	[100%]	1	[100%]	6	[100%]	25	[100%]	120	[100%]	153	[100%]
Macquarie	*Explained*	30.74***	[334%]	2***	[100%]	7***	[117%]	21***	[191%]	60***	[600%]	91***	[-433%]
	Unexplained	-21.55***	[-234%]	0	[0%]	-1*	[-17%]	-10***	[-91%]	-50***	[-500%]	-70***	[333%]
	Total	9.20	[100%]	2	[100%]	6	[100%]	11	[100%]	10	[100%]	21	[100%]
Mid North Coast	*Explained*	20.87***	[52%]	2***	[50%]	7***	[58%]	15***	[52%]	40***	[51%]	65***	[53%]
	Unexplained	19.00***	[48%]	2***	[50%]	5***	[42%]	14***	[48%]	39***	[49%]	57***	[47%]
	Total	39.87	[100%]	4	[100%]	12	[100%]	29	[100%]	79	[100%]	122	[100%]
Mid Western	*Explained*	15.23***	[237%]	2***	[100%]	7***	[350%]	13***	[1300%]	29***	[967%]	41***	[124%]
	Unexplained	-8.81***	[-137%]	0	[0%]	-5***	[-250%]	-12***	[-1200%]	-26***	[-867%]	-8	[-24%]
	Total	6.42	[100%]	2	[100%]	2	[100%]	1	[100%]	3	[100%]	33	[100%]
New England	*Explained*	19.80***	[-296%]	1**	[100%]	6***	[120%]	14***	[175%]	38***	[271%]	66***	[-194%]
	Unexplained	-26.48***	[396%]	0	[0%]	-1*	[-20%]	-6***	[-75%]	-24***	[-171%]	-100***	[294%]
	Total	-6.68	[100%]	1	[100%]	5	[100%]	8	[100%]	14	[100%]	-34	[100%]
Northern Rivers	*Explained*	16.39***	[58%]	0	[0%]	1*	[25%]	6***	[54%]	22***	[79%]	58***	[47%]
	Unexplained	11.93***	[42%]	1***	[100%]	3***	[75%]	5***	[46%]	6	[21%]	66***	[53%]
	Total	28.32	[100%]	1	[100%]	4	[100%]	11	[100%]	28	[100%]	124	[100%]

Table 7 (continued)

		Mean		P10		P25		P50		P75		P90	
Northern Sydney	*Explained*	5.94***	[-36%]	0	n.a.	0	n.a.	3***	[150%]	8***	[53%]	20***	[-30%]
	Unexplained	-22.27***	[136%]	0	n.a.	0	n.a.	-5***	[-250%]	-23***	[-153%]	-86***	[130%]
	Total	-16.33	[100%]	0	n.a.	0	n.a.	-2	[100%]	-15	[-100%]	-66	[100%]
South Eastern Sydney	*Explained*	5.13***	[17%]	0	n.a.	0	[0%]	2***	[29%]	7***	[20%]	26***	[22%]
	Unexplained	25.27***	[83%]	0	n.a.	2***	[100%]	5***	[71%]	28***	[80%]	90***	[78%]
	Total	30.40	[100%]	0	n.a.	2	[100%]	7	[100%]	35	[100%]	116	[100%]
South Western Sydney	*Explained*	16.15***	[46%]	2***	[67%]	6***	[67%]	11***	[55%]	28***	[57%]	40***	[34%]
	Unexplained	18.68***	[54%]	1***	[33%]	3***	[33%]	9***	[45%]	21***	[43%]	79***	[66%]
	Total	34.83	[100%]	3	[100%]	9	[100%]	20	[100%]	49	[100%]	119	[100%]
Southern	*Explained*	24.71***	[593%]	3***	[100%]	8***	[67%]	18***	[106%]	46***	[159%]	78***	[-975%]
	Unexplained	-20.54***	[-493%]	0	[0%]	4***	[33%]	-1	[-6%]	-17***	[-59%]	-86***	[1075%]
	Total	4.17	[100%]	3	[100%]	12	[100%]	17	[100%]	29	[100%]	-8	[100%]
Wentworth	*Explained*	10.02***	[36%]	0	n.a.	3***	[75%]	7***	[50%]	21***	[60%]	29***	[48%]
	Unexplained	17.51***	[64%]	0	n.a.	1*	[25%]	7***	[50%]	14***	[40%]	32***	[52%]
	Total	27.53***	[100%]	0	n.a.	4	[100%]	14	[100%]	35	[100%]	61	[100%]
Western Sydney	*Explained*	11.03***	[93%]	1 [b]	n.a.	4***	[80%]	8***	[80%]	3***	[60%]	27***	[135%]
	Unexplained	0.89	[7%]	1 [b]	n.a.	1**	[20%]	2**	[20%]	2	[40%]	-7	[-35%]
	Total	11.92	[100%]	0	n.a.	5	[100%]	10	[100%]	5	[100%]	20	[100%]

Note: see note for Table 6.