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Differences in waiting times for elective admissions in NSW public hospitals: A decomposition analysis by non-clinical factors

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Abstract

In the Australian public health system, access to elective surgery is rationed through the use of waiting lists. In accord with the national goal of universal and adequate provision of health care services, it is generally assumed that a patient's waiting time reflects his/her medical need with priority given to more urgent patients. However, waiting times exhibit great variation across patients in different socioeconomic groups and locations. In this paper we undertake an Oaxaca-Blinder decomposition and a DiNardo-Fortin-Lemieux reweighting approach to attribute variation in waiting time to a component explained by clinical need and to differential treatment effects. The latter have an interpretation as discrimination, since treatments vary by non-clinical factors such as socioeconomic status. Using data from public patients in NSW public hospitals in 2004-2005, we find evidence that socioeconomically advantaged patients, patients in remote areas, and patients in several Area Health Services have shorter waiting times than their clinically comparable counterparts. Furthermore, the discrimination effect dominates clinical needs among less urgent patients, who are unlikely to develop into an emergency admission if their treatments are delayed. This finding has policy implications for the current operation of waiting lists and for the design of equitable quality targets for public hospitals.

JEL codes: I11, J7, H51

Keywords: Public hospitals, waiting times, discrimination, decomposition analysis

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I. Introduction

In Australia, over half of the population depends on public hospitals for inpatient care. In 2005–2006 there were about 4.5 million patient admissions to Australian public hospitals of which 87% were public patient (non-charge) admissions. Accessing treatment for elective surgery can involve long waiting times and this is a major concern for the delivery of health care and the promotion of health. Delays in medical treatment prolong suffering, decrease earning capacity and cause deterioration of quality of life. For example, Propper (1990, 1995) and Johannesson et al. (1998) find that individuals are willing to pay to avoid waiting for medical treatment, and that willingness to pay varies with income and other socio-economic characteristics. 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.

The Productivity Commission (2008) regarded waiting times for elective surgery as a measure of governments' success in providing accessible health care. At the Council of Australian Governments' meeting in December 20, 2007, the Prime Minister identified the reduction of elective surgery waiting times in public hospitals as a major policy priority and in 2008 $100 million was allocated to reduce waiting lists for people who have been waiting for elective surgery longer than the clinically recommended time. Since then, $200 million has been allocated over two years to increase elective surgery throughput. Financial incentives of up to $300 million are provided to those States and Territories that complete all elective surgery within the clinically recommended time by the end of 2011. The States and Territories are required to create additional capacity within the public hospital system or purchase additional capacity from the private sector.

In Australia, there is very little analysis of waiting times, and in particular identification of the factors determining a patient's waiting time. Waiting time data has been available since the late 1990s but analyses of this data has been limited to summary statistics by medical procedure, surgical specialty, and state. For example, the Australia Institute of Health and Welfare (2007a) reports the number of days waited at the 50th and 90th percentile and the percentage of patients waiting more than a year by state, surgical specialty and procedure. The summary data shows dramatic differences by state. For example, NSW waiting times at the 50th percentile can be about double (ear, nose and throat) or triple (ophthalmology) those in Victoria. For cataract extraction, waiting times at the 50th percentile is 182 days in NSW compared with 44 days in Victoria. While the policy focus is on average waiting times by state and the failure to achieve targets for timely access, there is no detailed reporting of how waiting times are distributed across the population within state. Anecdotal evidence suggests that waiting times may vary by region and socioeconomic status.

The objective of accessible health care for all Australians is compromised if there is an inequitable distribution of public hospital waiting times. To justify the order of admission, a clinical urgency classification system is used which prioritises patients waiting for elective hospital treatment. These urgency categories, assigned by the treating specialist, specify target maximum waiting times for each patient to ensure that priority is given to patients needing more urgent medical attention. For example, a 30 day urgency is assigned to patients with 'a condition that has the potential to deteriorate quickly to the point that it may become an emergency'. In principle, for a given procedure, patients have similar clinical need should experience similar waiting times conditional on diagnosis and urgency class. Indeed, some countries including England have further emphasised the importance of urgency assignment by using it as an explicit target of time to admission and tied it with performance incentives to hospitals. It has been found that explicit targeting can reduce waiting times (Hauck and Street, 2007).

In this paper, we decompose variations in waiting times across patient groups into variations that are due to clinical need and variations that are due to differential treatment of patients in different groups in the waiting list. We examine the impacts of non-clinical factors such as socioeconomic status and location, which should not, in principle, affect waiting time. In addition, we explore heterogeneity in the scope of discrimination at different points of the waiting time distribution. We use data on elective surgery patients in NSW public hospitals who were admitted during the period 2004-2005. Using information on patients' residential postcode, this data is combined with census data on socioeconomic advantage and remoteness. Our aim is to inform improved targeting of health care investments and provide an evidence base for effective policy design.

II. 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 information on patient's age, gender, chronic conditions (diagnoses), and planned procedure. In addition, patient postcodes are recorded and can be linked to information on socioeconomic status and remoteness from census data; postcode information can also be used to identify the Area Health Service (AHS) within which the patient resides. Within NSW, public hospitals are administered by AHSs, which receive annual funding from the NSW government related to the needs of their populations and allocate funding to individual hospitals within their area.

Our analyses use data on all 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 any advantageous treatment associated with private health care (Johar and Savage, 2010). Further, 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 as they are likely to represent quasi emergency admissions especially in areas with no emergency departments.[1] Finally, inter-state patients are excluded since the postcode mapping uses postcodes located within NSW. The final sample size consists of 194,199 patients.

The non-clinical factors that we explore are: (1) the SEIFA quintile of the patient's postcode, to measure socioeconomic status; (2) the ARIA category of the patient's postcode to measure remoteness; and (3) the Area Health Service (AHS) boundaries that existed in 2004-2005 to measure variation in delivery by region. We adopt the ABS SEIFA summary measure of economic advantage and disadvantage (the higher the better off). The ARIA codes summarise an area's remoteness: remote or very remote (ARIA 1), outer regional (ARIA 2), inner regional areas (ARIA 3), and major city (ARIA 4). Within most AHSs, there are multiple ARIA and SEIFA groups. An exception is Far West AHS, which is almost exclusively ARIA 1.

The means of waiting times and some explanatory variables by SEIFA, ARIA and AHS are presented in Appendix Tables 1, 2 and 3.[2] Across SEIFA groups, the age and gender distribution of patients as well as counts of acute conditions are comparable. However, the expected waiting times are markedly shorter for patients in the most advantaged areas (SEIFA 5) with an average waiting time of 75 days, compared with about 100 days in lower SEIFA quintiles. Across ARIA groups, ARIA 3 has slightly longer average waiting time, and ARIA 4 has a lower share of patients assigned urgency levels beyond 90 days. Lastly, there are wide variations of waiting times across AHSs. Northern Sydney has the shortest average wait, which is half the wait of patients in Central Coast, Illawarra and Mid North Coast, and two thirds of the wait of patients in Far West, Greater Murray, and Mid Western.[3]

III. Estimation

The decomposition analysis is conducted using two techniques. The first technique is the conventional Oaxaca-Blinder decomposition, which takes advantage of the additive separability of a linear regression model to decompose the difference in the expected outcomes of two groups. The second technique is that proposed by DiNardo, Fortin and Lemieux (1996; hereafter DFL) which extend the Oaxaca-Blinder's single-point mean-

[1] Patients with zero waiting days make up 5% of admissions, with over three quarters of them being assigned an urgency of less than 7 days and having planned procedure classified as either "other surgical" or "other medical". Cumulatively, 94% were admitted within 30 days.

[2] For conciseness, we suppressed the summary statistics related to procedures because there are close to 200 procedures. In estimation, we use dummy variables to control for each of the planned 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). For the count of diagnoses we obtained clinical advice on mapping ICD10AM codes in the hospital data to condition associated with hospitalisation.

[3] Most patients are treated in facilities within their own AHS: over 90% of patients in non Sydney AHSs and about 60% of patients in Sydney AHSs.

based decomposition to estimate how differences in endowments contribute towards differences in the distribution of waiting time between two groups.

Oaxaca-Blinder decomposition

The Oaxaca-Blinder decomposition technique comes from the labour economics literature where it has been used to examine variation in labour market outcomes that cannot be explained by differences in workers' human capital level (Oaxaca, 1973; Blinder, 1973; Brown and Corcoran, 1997; Oaxaca and Ransom, 1994). In the health economics field, some studies have extended the technique to incorporate the non-linearity of many health variables in studying inequality in health outcomes (Wenzlow, Mullahy and Wolfe, 2004) and insurance coverage (Pylypchuk and Selden, 2008).

Let the expected waiting time for patients in any two distinct groups, A and B, be $E(w^A)$ and $E(w^B)$, respectively. From the standard linear regression model, we can write the expected waiting time as:

$$(1) \qquad E(w^j) = \hat{\alpha}^j + \sum_k \hat{\beta}_k^j E(x_k{}^j), \qquad (j = A, B)$$

where $\hat{\alpha}^j$ is the intercept of group j and $\hat{\beta}_k$ is the OLS slope estimates of variable x_k (k= 1,… K). The covariates are chosen to reflect patients' clinical need as measured by surgical procedure, number of diagnosis, urgency assignment, and the patients' age and gender. All covariates are demand-side variables; theoretically, waiting time equilibrates supply and demand. This implies that, when choosing a hospital (which essentially determine the duration of wait) patients and specialists take the NSW health system in its entirety, which is consistent with the principle that patients can be admitted to any public hospitals they wish. Any supply-side dimension to waiting time variation across clinically comparable patients (as measured by their health and demographics) therefore is regarded as part of discrimination.[4]

The expected waiting time differential between group A and B can be partitioned as:

$$(2) \quad E(w^A) - E(w^B) = \sum_k \hat{\beta}_k^B \left(E(x_k{}^A) - E(x_k{}^B)\right) + \sum_k E(x_k{}^A)\left(\hat{\beta}_k^A - \hat{\beta}_k^B\right) + \left(\hat{\alpha}^A - \hat{\alpha}^B\right)$$

The first term on the right hand side measures the endowment effect. From the viewpoint of patients in the reference group B, the endowment effect measures the change in the expected waiting time of patients in this group were they to have the endowments of patients in group A. The second term measures differences in expected waiting times that are due to differences in covariate parameters, which we refer to as the treatment effect.

[4] One might argue that supply-side control variables, such as hospital characteristics (fixed effects), should also be included as covariates, but this is not done, because doing so would alter the interpretation of results. In particular, hospital fixed-effects model would test discrimination in patients' waiting times *within a public hospital* in a universal public health system. But we are interested in discrimination in patients' waiting times in a universal public health system. A simple ANOVA exercise reveals that the bulk of variations in waiting times are due to within-hospital variations instead of between-hospital variations. So even if there is supply dimension to the waiting time gap, we do not expect it to explain a large part of the discrimination story.

The term ‘treatment’ is often used in the program evaluation literature to indicate a policy or program that affects a particular group of subjects. The average treatment effect (ATE) and the average treatment effect on the treated (ATT) are estimated to analyse the effectiveness of the policy or program. In a decomposition exercise and under certain conditions, differences in covariate parameters can have an ATT interpretation: the ‘treatment effect’ is quicker removal from waiting lists or delayed removal, and the ‘treated’ is group A, whose values are used to calculate the treatment effect.

One of the identifying conditions is exogeneity of covariates (in this case the clinical factors). In labour economics, endogeneity problems complicate the interpretation of wage gap as discrimination, if the effect of unobserved ability on human capital accumulation varies across groups and cannot be controlled for (i.e., this violates the assumption of mean conditional independence). In the current context, it is not clear how socio-economic conditions of a patient or remoteness of residence should affect his/her waiting time for a given procedure, conditional on doctors’ diagnosis and urgency assignment.[5] In principle, the assignment of urgency system should produce a justifiable ordering of admissions that is independent of non-clinical factors.

Another potential problem is non invariance features of the Oaxaca-Blinder technique (Yun, 2003). The first non invariance problem is the sensitivity of treatment effects to the choice of the reference group, which is arbitrary. Several papers have suggested ways to overcome this problem by using the more advantaged group as the reference group (Oaxaca, 1973), estimating a pooled model and using weighted average of both groups (Neuman, 1988), or imposing an identifying restriction in the pooled model so that the advantage of one group equals the disadvantage of another (Fortin, 2006). The last method, which we adopt, avoids the pooled model capturing some of the between group effects.

The expected differences in waiting times in a pooled model can be written as:

$$\text{(3)} \quad \begin{aligned} E(w^A) - E(w^B) = {} & \sum\nolimits_k \hat{\beta}_k^* \left(E(x_k{}^A) - E(x_k{}^B) \right) + \sum\nolimits_k E(x_k{}^A) \left(\hat{\beta}_k^A - \hat{\beta}_k^* \right) + \\ & \sum\nolimits_k E(x_k{}^B) \left(\hat{\beta}_k^* - \hat{\beta}_k^B \right) + \left(\hat{\alpha}^A - \hat{\alpha}^B \right) \end{aligned} .$$

$\hat{\beta}^*$ represents estimates in the absence of discrimination. (3) reduces to (2) if it is assumed that there is no discrimination against the reference group i.e., $\beta^* = \beta^B$. The first term is the variation in waiting time that can be explained by differences in covariates and the remaining terms together comprise the unexplained variation. The explained component is closely related to the endowment effects in the previous approach and the unexplained component is closely related to the treatment effects. To avoid the base group problem, dummy variables for both group A and B are included and the sum of their coefficients are constrained to zero (Fortin, 2006).

[5] It is difficult to identify unobservable factors that would simultaneously increase clinical need and impact on location in terms of SEIFA or ARIA.

The second non invariance problem is caused by the choice of the omitted groups when covariates include categorical variables. This problem is solved by transforming the model such that the estimated coefficients of each variable sum to zero.

The estimation of Oaxaca-Blinder decomposition is implemented in STATA using the *oaxaca* command, which also produces the standard error of the estimates of the decomposition terms (Jann, 2008). The variance of estimates is due to sampling variances of the coefficients and sample means.

DiNardo, Fortin and Lemieux reweighting approach

With the DFL decomposition technique we can analyse how variations in waiting time are explained by differences in endowments at different points of the waiting time distribution, and correspondingly how gaps (between actual and explained) vary along waiting time distributions. This provides extra insights because it is quite possible that in some parts of the waiting time distribution, differences in waiting times across groups are caused mainly by differences in patients' clinical need, whilst in other parts of the distribution, observed waiting time differences are driven by non-clinical factors. For example, clinical factors may be less important drivers of waiting time at the upper end of the waiting time distribution because less urgent cases are associated with lower mortality risk from delayed treatment.

The DFL reweighting approach relies on construction of a counterfactual distribution of waiting time. From the viewpoint of the reference group B, it estimates the distribution of waiting time had patients in this group had the distribution of covariates of patients in group A. Basically, the approach reweights the group B sample to have the same distribution of characteristics as group A. As well as providing increased information, the DFL approach is more flexible than the Oaxaca-Blinder decomposition, which assumes a waiting time equation that is linear in parameters. The DFL approach does not require any parametric assumption relating waiting time to characteristics.[6]

The distribution of waiting times for group B is the integral over the joint distribution of waiting time and individual characteristics for patients in group B:

(4) $$F_B(w) = \int F_{W^B|X,t=B}(w \mid X) dF_{X|t=B}(X) .$$

The covariates X can be partitioned into various sets (e.g., X_1 and X_2), and the DFL approach allows us to decompose differences in waiting times into variations due to X_1 and X_2. The marginal effect of additional variables however will be sensitive to the order in which the exercise is performed because it relates to the conditioning sets (unless X_1

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[6] Fairlie (2006) discusses an alternative approach which performs a series of non-linear versions of Oaxaca-Blinder decomposition on proportions. Decomposing proportions is not equivalent to estimating a quantile regression because the *k*th percentile of group *A* does not need to be the same that the *k*th percentile of group *B*. It is possible that one group is very under-represented in a particular quantile of another group.

and X_2 are independent). However, as our research question is about non-clinical determinants of waiting times, we treat *X* as the whole conditioning set of clinical factors.[7]

The counterfactual density of waiting time for patients in group B, if they were given the characteristics of patients in group A, can be defined as:

(5) $$F_{B^{CF}}(w) = \int F_{W^B|X,t=B}(w \mid X)dF_{X|t=A}(X) = \int F_{W^B|X,t=B}(w \mid X)\psi(X)dF_{X|t=B}(X)$$

$F_{B^{CF}}$ represent the counterfactual marginal waiting time distribution, which is the distribution of waiting times that would prevail for group A workers if they were treated like group B workers. $F_{X|t=B}$ represent the marginal distribution of *X* in group B and $F_{W|X,t=B}$ represent the conditional distribution of waiting times observed in group B,, and

(6) $$\psi(X) = \frac{dF_{X|t=A}(X)}{dF_{X|t=B}(X)}$$

is a reweighting function. Using Bayes' rule, we obtain

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

To estimate the conditional probabilities in (7), we estimate group membership with logit models as a function of observed covariates. The unconditional probabilities are given by sample proportions of group A and B. We then compute several ordered statistics (waiting times at the 10th, 25th, 50th, 75th and 90th percentiles) and mean waiting times, using group B patients reweighted using (7) (Fortin et al., 2010).[8]

We can then decompose the difference in, say, the mean waiting times of the two groups as:

(8) $$\overline{w}^A - \overline{w}^B = (\overline{w}^A - \overline{\hat{w}}^B_{CF}) + (\overline{\hat{w}}^B_{CF} - \overline{w}^B),$$

where $\overline{\hat{w}}^B_{CF} = 1/N^B \sum_{i \in B} \hat{\psi}_i(T_i, X_i) \cdot w_i$, is the sample mean of the reweighted counterfactual waiting times. The first term parallels the treatment effect in the Oaxaca-Blinder decomposition and indicates the scope of discrimination. That is, discrimination exists if there is a gap in waiting times between patients in different groups, after adjusting for differences in patients' characteristics. Discrimination in favour of group B patients is consistent with $\overline{w}^A$ being larger than $\overline{\hat{w}}^B_{CF}$; after adjusting for patients'

[7] The two most influential predictors of waiting time are urgency and procedure, which is not unexpected. Conditional on urgency assignment and procedures, the role of other patients' characteristics is minor. Hence, if we partitioned X into urgency assignment and procedure and the remaining covariates, the marginal effect of adding variables conditional on urgency and procedure would be small. In addition, the DFL reweighting approach needs to be amended for detailed decomposition by variables (Firpo et al., 2010).

[8] The DFL approach has also been used to decompose differences in waiting time densities across two groups. However, interpretation of densities is more difficult than interpreting statistics of interest which are in the units of waiting times.

characteristics, the waiting time of group B patients is shorter than the waiting time of group A patients. The second term parallels the endowment effect in the Oaxaca-Blinder approach. If there are no group differences in the distribution of the covariates, $\overline{w}^{B} - \overline{\hat{w}}^{B}_{CF} = 0$.

As the DFL technique is essentially a matching technique, the standard matching assumptions apply: mean conditional independence (ignorability) and the presence of common support (i.e., no one covariate can perfectly predict group membership). We use the bootstrap method to obtain the confidence interval for the waiting gap at various points of the waiting time distribution with 200 replications.

IV. Results

Oaxaca-Blinder decomposition

(i) SEIFA

Table 1 presents the Oaxaca decomposition results by SEIFA quintiles. The columns represent the reference group (group B). We report the total (raw) difference, the endowment and treatment effects from the two-way decomposition, the explained and unexplained component from the pooled model, and the size of the treatment and unexplained component as a proportion of the total difference. A share larger than 100% in absolute value indicates that the components move in opposite directions. The dominating component will give the sign of the total difference. A positive (negative) treatment or unexplained component reflects discrimination in favour of (against) the reference group.

All of the endowment effects in Table 1 are positive indicating that patients in less advantaged areas have endowments which predict longer waits than those characterising patients in more advantaged areas. The treatment effects offset the endowment effects in pairs SEIFA 3 and SEIFA 4 compared with lower SEIFA groups, whilst the treatment and the endowment effects are reinforcing in the comparison pair SEIFA 1 and SEIFA 2 and all comparisons with SEIFA 5. The net differences between SEIFA 3 and SEIFA 4 patients and lower SEIFA groups are small as the endowment and treatment effects are similar in magnitude. In the other cases, there is evidence of discrimination in favour of the reference group as the treatment effects dominate the endowment effects. In comparison pair SEIFA 4 and SEIFA 5 for instance, SEIFA 5 patients waited 25 days less than SEIFA 4 patients and 85% of this observed waiting time gap is due to non-clinical factors. The treatment effect shares are positively related to SEIFA.[9]

The pooled model produces consistent results but with smaller (absolute) magnitudes of treatment effects. This difference rejects the hypothesis that the reference group's

[9] Discrimination in favour of high SEIFA patients may be consistent with utilitarian policymakers (who maximise total welfare with zero distributional weights) who give preference to patients whose marginal cost of waiting is higher (Gravelle and Siciliani, 2009).

scenario, which in this case is the more advantaged group, represents the case of no discrimination.

(ii) ARIA

Table 2 shows opposing directions of endowment and treatment effects between any pair of ARIA groups: variations in endowments tend to lengthen the waiting time of patients in more remote areas, but the treatment effects more than offset the endowment effects. Except in one case, the overall effect is longer waiting times for patients in less remote areas. The exception to this is the comparison between patients in inner regions (ARIA 3) and major cities (ARIA 4) where the treatment effect is relatively small resulting in shorter waiting time overall for city (ARIA 4) patients.

If our prior expectation is that patients in ARIA 4 are an advantaged group of patients relative to those in more remote regions, this negative treatment effect is quite unexpected, suggesting that public patients who live in (further away from) major metropolitan areas are disadvantaged (advantaged) in their waiting times for elective treatments at public hospitals. A potential explanation for this result could lie in the willingness to travel of patients in more remote areas.

(iii) AHS

Table 3 presents the decomposition results by AHS. Unlike in the cases of SEIFA and ARIA, there is no obvious ranking of the relative advantage of AHSs. We present the results assuming that group B (column) is the more advantaged group. The endowment and coefficient effects reveal a common pattern: the bulk of the observed gaps in waiting times are not explained by differences in patients' endowments in different areas. In comparison pair Northern Sydney and Illawarra for instance, the total difference in average waiting times is 70 days, but only 2 days is due to differences in patients' characteristics and the remaining 68 days is due to differential treatment. In some comparison pairs, the endowment and treatment effects go in opposite directions, but due to the relatively large treatment effects, the direction of the total differences follows the direction of the treatment effects. In comparison pair New England and Northern Rivers for instance, the total gap is 35 days in the favour of New England patients, despite endowment effects predicting that Northern Rivers' patients should wait 23 days less. In only a handful of cases, such as in the comparison pair Central Coast and South Eastern Sydney, is the endowment effect larger than the coefficients effect.

The pooled model provides a largely consistent picture, but in many instances, the size of the unexplained component is smaller than coefficient effects. As discussed above, this discrepancy suggests that the reference group's scenario fails to represent the case of no discrimination. In some comparison pairs however, the effects of the coefficients and the unexplained components are close (e.g.., Northern Sydney and Central Coast, or Northern Sydney and Greater Murray). When the coefficient effect is small (e.g., less than

10 days), the pooled model shows high sensitivity of the unexplained component to the selection of the reference group.

DiNardo, Fortin Lemieux reweighting approach

Tables 4, 5 and 6 report the DFL results by SEIFA, ARIA and AHS, respectively. From (8), at each point of the waiting time distribution the explained component is the gap between the counterfactual waiting time and the waiting time of the reference group B, and the unexplained component is the gap between the waiting time of group A and the counterfactual waiting time. Analysis by quantile allows us to examine the behaviour of the discrimination effect across the waiting time distribution.

In the analysis of SEIFA groups, we find that in most cases explained and unexplained components do not switch sign throughout the distribution but they dominate in different parts of the distribution. The explained component tends to dominate in the lower tail of the waiting time distribution whilst the unexplained component dominates the upper tail. This pattern is plausible given that patients in the lower tail of the distribution have relatively urgent medical attention; urgency limits the scope for discrimination. Above the median, which corresponds to a waiting time of 30-40 days (Appendix Table 1), the effects are quite different; by definition, patients who are assigned an urgency of more than 30 days are very unlikely to have conditions that can develop quickly into an emergency.

In the uppermost tail of the distribution, the poorest patients (SEIFA 1) have characteristics that are associated with longer waits; however the unexplained component works in the opposite direction except in the comparison with SEIFA 5. At the 90^{th} percentile, we find that the richest patients are treated at least 2 months earlier than clinically comparable patients in lower SEIFA quintiles. Interestingly, the strength of the unexplained component relative to the explained component in explaining the total waiting time gap is increasing in SEIFA. In comparison with the poorest patients (SEIFA 1), 62% of the total gap is due to discrimination; in comparison with the intermediate income group (SEIFA 3), the corresponding share is 80% and in comparison with the second wealthiest group (SEIFA 4), it is 90%.

At the mean, the richest patients get admitted 2-3 weeks earlier, consistent with the treatment effects found by the Oaxaca-Blinder approach. The DFL analysis however reveals that the source of this positive treatment effect is discrimination in favour of the most socially advantage patients.

Comparing ARIA groups, more remote patients tend to have characteristics resulting in longer waits, however the unexplained components tends to reduce waits, especially in the upper tail of the distribution. The most remote patients get admitted about 3 months earlier than their clinically comparable counterparts in inner regional areas or cities. At the top of the waiting time distribution (P90) there are large unexplained gaps (of between 39 and 97 days) in favour of patients in more remote areas, except when comparing city and inner region patients (ARIA 4 and ARIA 3). On the other hand, at lower points of the waiting time distribution, waiting time gaps are primarily due to unequal distribution of health profiles in different areas.

In general this pattern is consistent with the Oaxaca-Blinder results in Table 2. However DFL analysis reveals that preferential treatments can change direction at different points of the waiting time distribution. In pairs ARIA 1 and ARIA 2, ARIA 1 and ARIA 3 and ARIA 2 and ARIA 3, the unexplained components have positive signs in the lower half of the waiting time distribution and negative signs in the upper half of the waiting time distribution. This pattern reveals that the current health system is favouring more remote patients who are categorised under the lowest urgency class (within 365 days), possibly those who are waiting for procedures with long waits like joint replacements or cataract surgery.

Finally, in Table 6 we provide the DFL analysis by Area Health Service. To keep the discussion tractable, we take Central Sydney as the reference group, and show the waiting time gaps of other AHSs relative to waiting times of patients in Central Sydney. The corresponding results for these comparison pairs by the Oaxaca-Blinder approach can be found in Table 3 where the reference group is the column AHS. By the symmetry of the matrix, the negative of the Central Sydney row entries in Table 3 show the raw difference in waiting times between each AHS and Central Sydney (e.g., the total difference with Far West is 12.57 days).[10] According to the Oaxaca-Blinder estimates, when using Central Sydney as the base group, the unexplained components dominate the explained components in 9 out of the 16 comparison pairs.[11]

The first dramatic finding in Table 6 is that 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, 53 days at the mean and 173 days at the 90th percentile. Similarly in Illawarra, compared with Central Sydney, the total difference in waiting times at the 90th percentile is 153 days. The bulk of these gaps are not due to differences in patient characteristics. For some reasons that are not related to observed clinical needs, treatment of Illawarra patients was delayed for 135 days (4.5 months). Second, we find unexplained components at the left tail of the waiting time distribution. This suggests that urgent patients (e.g., those assigned with urgency of 7 days) are at risk of not being admitted in the clinically recommended time. Third, there are six cases where the unexplained components dominate at the uppermost tail of the waiting time distribution (P90). Fourth, components tend to have consistent sign throughout the waiting time distribution. For instance, the

[10] For the split components in Table 3, except for Central Coast, the omitted Central Sydney column entries would have the opposite sign to the corresponding Central Sydney row entries.
[11] Use of other base groups will alter the unexplained components. For example, when using Central Coast as the base group, the unexplained components are dominant in 12 out of the 16 comparison pairs. In keeping with the theme that base group is the more advantaged group however we decided that Central Sydney, which consists of entirely city postcodes (ARIA 4) and 4 hospitals, two of which are principal referrals hospitals, is an appropriate base group.

distribution of health profiles in Hunter, Macquarie, New England, North Sydney and Southern tend to increase their waiting times but patients in these areas are admitted earlier than their comparable counterparts in Central Sydney. Health profiles and unexplained components 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. Large discriminatory effects are found even among Sydney-based AHSs (North Sydney, South Eastern Sydney and South Western Sydney compared with Central Sydney). Less urgent patients in North Sydney were admitted 3 weeks faster at P75 and 12 weeks faster at P90 than their counterparts living in Central Sydney. In contrast, less urgent patients in South Eastern Sydney and South Western Sydney waited 3-13 weeks longer.

V. Discussion

Waiting time is the rationing device used to equate supply and demand the NSW 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. We find, however, that waiting times are largely influenced by non-clinical factors. Variations in waiting times unexplained by clinical factors can be interpreted as discrimination against clinically comparable patients. The size of the unexplained differences in waiting time can be very large, over 2 weeks for patients assigned a 30 day category and over 3 months for less urgent cases.

The distributional analysis reveals that the direction of discrimination is often not monotonic along the waiting time distribution. Discrimination works in favour of the most advantaged group (SEIFA 5) compared with all less advantaged groups, with delays of 2 to 3 months for those in the very top end of the waiting time distribution. For patients below the top quintile, discrimination favours those less well off who are admitted 20 to 30 days faster in the top tail of the distribution. Contrary to expectations, there is discrimination in favour of patients living in more remote areas, again with the largest impact in the top tail of the distribution.

While the decomposition exercise indicates the size of discriminatory components it cannot tell us how these arise. The order of treatment is largely determined by urgency assignment by the treating specialists. Our results by SEIFA suggest that preferential treatment is given to economically advantaged patients in the lowest urgency category where there is more scope to give preferential treatment to patients in higher SEIFA categories. "Gaming" behaviour of doctors has been recognised in the literature (MacCormick et al., 2004). However, the incentives for doctors to discriminate between non-paying public hospital 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

There might be other explanations for the observed pattern of discrimination. Corner-Spady *et al*. (2007) focus on patients waiting for hip and knee replacements in Canada and find that patient's expectation of waiting times influences their behaviour; the majority of patients do not switch surgeons even when faced with long waiting times. Our results find discrimination in favour of more rural and remote areas. This might suggest factors such as different expectations by location, more searching behaviour and willingness to travel in more remote areas, or closer patient-doctor relationships outside cities that reduce waiting times.

We find that the discriminatory effects by AHSs, which are responsible for the delivery of care in their area, can be extremely large. These large unexplained differential times to treatment may result from differences in resourcing that may warrant further study of the funding procedures. Political factors may also be influential if waiting times relate to funding rules. We conduct an additional exercise to highlight the importance of AHS boundaries utilising a natural experiment soon after the period of the data used in this study. In 2005, the 17 AHSs in NSW were amalgamated into 8 AHSs. The pairing rule appears to group together AHSs with short and long waiting times, e.g., North Sydney which has the shortest average waiting time of all AHSs was paired with Central Coast which has the longest average waiting time. Under the new boundaries and using the 2004-05 data, the amalgamated North Sydney – Central Coast AHS has the second longest waiting time of the 8 new AHSs. The shortest waiting time is in the Greater Western AHS, which amalgamates the Far West, Macquarie and Mid Western AHSs, all of which were in the middle of the previous waiting time distribution. Using the new boundaries, pair-wise raw differences in average waiting times never exceed 30 days. Not surprisingly, the new AHS boundaries conceal much of the discriminatory effects by AHS revealed in our analysis.

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Table 1: Decomposition by SEIFA quintile

Total difference	SEIFA 1	SEIFA 2	SEIFA 3	SEIFA 4	SEIFA 5						
SEIFA 1	0	2.01*	0.12	2.09*	27.48***						
SEIFA 2		0	-1.86*	0.08	25.48***						
SEIFA 3			0	1.96*	27.36***						
SEIFA 4				0	25.40***						
SEIFA 5					0						
Endowment effect	SEIFA 1	SEIFA 2	SEIFA 3	SEIFA 4	SEIFA 5	*Pooled: Explained*	SEIFA 1	SEIFA 2	SEIFA 3	SEIFA 4	SEIFA 5
SEIFA 1	0	0.87	3.11***	10.38***	10.35***	SEIFA 1	0	1.51**	2.96***	9.85***	14.34***
SEIFA 2		0	2.58***	9.92***	9.82***	SEIFA 2		0	1.32**	7.82***	12.94***
SEIFA 3			0	7.27***	7.61***	SEIFA 3			0	6.85***	12.97***
SEIFA 4				0	3.86***	SEIFA 4				0	7.40***
SEIFA 5					0	SEIFA 5					0
Treatment effect	SEIFA 1	SEIFA 2	SEIFA 3	SEIFA 4	SEIFA 5	*Pooled: Unexplained*	SEIFA 1	SEIFA 2	SEIFA 3	SEIFA 4	SEIFA 5
SEIFA 1	0	1.14	-2.99***	-8.29***	17.14***	SEIFA 1	0	0.50	-2.83***	-7.77***	13.14***
[*%Treatment*]		[57%]	[-2492%]	[-397%]	[62%]	[*%Unexplained*]		[25%]	[-2358%]	[-372%]	[48%]
SEIFA 2		0	-4.46***	-9.84***	15.66***	SEIFA 2		0	-3.20***	-7.74***	12.54***
[*%Treatment*]			[-240%]	[-12300%]	[61%]	[*%Unexplained*]			[-172%]	[-9675%]	[49%]
SEIFA 3			0	-5.30***	19.75***	SEIFA 3			0	-4.89***	14.38***
[*%Treatment*]				[-270%]	[72%]	[*%Unexplained*]				[-249%]	[53%]
SEIFA 4				0	21.54***	SEIFA 4				0	18.00***
[*%Treatment*]					[85%]	[*%Unexplained*]					[71%]
SEIFA 5					0	SEIFA 5					0

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. SEIFA 1 if the least advantaged and SEIFA 5 is the most advantaged. Pooled model has linear restriction that the gain from one group = loss to another. *%Unexplained* = 100*(*Treatment effect* / *Total difference*) and *%Treatment* = 100*(*Unexplained* / *Total difference*).

Table 2: Decomposition by ARIA

Total difference	ARIA 1	ARIA 2	ARIA 3	ARIA 4
ARIA 1	0	-2.68	-10.66***	-4.57*
ARIA 2		0	-7.98***	-1.89*
ARIA 3			0	6.10***
ARIA 4				0

Endowment effect	ARIA 1	ARIA 2	ARIA 3	ARIA 4
ARIA 1	0	3.98**	10.40***	19.71***
ARIA 2		0	0.15	10.63***
ARIA 3			0	8.99***
ARIA 4				0

Pooled: Explained	ARIA 1	ARIA 2	ARIA 3	ARIA 4
ARIA 1	0	8.06***	13.19***	21.02***
ARIA 2		0	-0.01	7.59***
ARIA 3			0	6.86***
ARIA 4				0

Treatment effect	ARIA 1	ARIA 2	ARIA 3	ARIA 4
ARIA 1	0	-6.66***	-21.07***	-24.28***
[*%Treatment*]		[-249%]	[-198%]	[-531%]
ARIA 2		0	-8.13***	-12.52***
[*%Treatment*]			[-102%]	[-662%]
ARIA 3			0	-2.89***
[*%Treatment*]				[-47%]
ARIA 4				0

Pooled: Unexplained	ARIA 1	ARIA 2	ARIA 3	ARIA 4
ARIA 1	0	-10.70***	-23.85***	-25.58***
[*%Unexplained*]		[-399%]	[-224%]	[-560%]
ARIA 2		0	-8.01***	-9.52***
[*%Unexplained*]			[-100%]	[-504%]
ARIA 3			0	-0.77
[*%Unexplained*]				[-13%]
ARIA 4				0

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. ARIA 1 is remote or very remote, ARIA 2 is outer regions, ARIA 3 is inner region and ARIA 4 is major city. Pooled model has linear restriction that the gain from one group = loss to another. *%Unexplained* = 100*(*Treatment effect* / *Total difference*) and *%Treatment* = 100*(*Unexplained* / *Total difference*).

Table 3: Decomposition by Area Health Service (Column group is the reference group)

Total difference

	CC	CS	FW	GM	Hunter	Illawarra	Macquarie	MNC	MW	NE	NR	NS	SES	SWS	Southern	Wentworth	WS
Central Coast	0	53.00***	40.42***	37.23***	53.27***	-0.21	43.79***	13.12***	46.57***	59.67***	24.67***	69.32***	22.59***	18.16***	48.82***	25.46***	41.07***
Central Sydney		0	-12.57***	-15.76***	0.28	-53.20***	-9.20***	-39.87***	-6.42***	6.68***	-28.32***	16.33***	-30.40***	-34.84***	-4.17**	-27.53***	-11.92***
Far West			0	-3.19	12.85***	-40.63***	3.37	-27.30***	6.15***	19.25***	-15.75***	28.91***	-17.82***	-22.26***	8.41***	-14.96***	0.65
Greater Murray				0	16.04***	-37.44***	6.56***	-24.11***	9.34***	22.44***	-12.56***	32.09***	-14.64***	-19.07***	11.59***	-11.77***	3.84**
Hunter					0	-53.48***	-9.48***	-40.15***	-6.71***	6.39***	-28.60***	16.05***	-30.68***	-35.12***	-4.45***	-27.81***	-12.21***
Illawarra						0	44.00***	13.33***	46.78***	59.88***	24.88***	69.53***	22.80***	18.37***	49.03***	25.67***	41.28***
Macquarie							0	-30.67***	2.77	15.88***	-19.12***	25.53***	-21.20***	-25.64***	5.03**	-18.33***	-2.73
Mid North Coast								0	33.44***	46.54***	11.55***	56.20***	9.47***	5.03**	35.70***	12.34***	27.94***
Mid Western									0	13.10***	-21.89***	22.76***	-23.97***	-28.41***	2.26	-21.11***	-5.50***
New England										0	-35.00***	9.66***	-37.07***	-41.51***	-10.84***	-34.21***	-18.60***
Northern Rivers											0	44.65***	-2.08	-6.52**	24.15***	0.79	16.39***
Northern Sydney												0	-46.73***	-51.17***	-20.50***	-43.86***	-28.26***
South Eastern Sydney													0	-4.44**	26.23***	2.87	18.47***
South Western Sydney														0	30.67***	7.30***	22.91***
Southern															0	-23.36***	-7.76***
Wentworth																0	15.61***
Western Sydney																	0

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 3: Decomposition by Area Health Service (cont)

Endowment effects

	CC	CS	FW	GM	Hunter	Illawarra	Macquarie	MNC	MW	NE	NR	NS	SES	SWS	Southern	Wentworth	WS
Central Coast	0	24.00***	-0.47	16.09***	12.56***	31.78***	12.58***	3.76***	27.13***	5.83***	33.26***	20.68***	24.34***	12.30***	6.89***	32.58***	19.60***
Central Sydney		0	-23.46***	-13.95***	-11.69***	-10.30***	-12.12***	-24.60***	-3.80***	-13.38***	-5.42**	-2.80***	-7.80***	-18.37***	-16.71***	-3.16	-8.13***
Far West			0	7.52**	9.26***	24.18***	1.08	-5.20*	19.73***	1.33	13.29***	10.47***	18.58***	12.87***	-2.66	30.49***	17.71***
Greater Murray				0	1.54	16.96***	-2.89	-8.25***	10.54***	-1.30	21.19***	9.23***	9.27***	1.63	-6.16***	16.10***	7.74***
Hunter					0	14.02***	-14.78***	-12.70***	-0.15	-6.68***	2.67***	-1.81*	6.24***	-6.47***	-10.09***	5.40***	0.56
Illwara						0	-12.73***	-19.63***	1.90	-6.16***	8.10***	1.36	-3.17**	-12.35***	-14.14***	5.69**	-1.48
Macquarie							0	5.80***	25.28***	9.18***	28.94***	15.76***	27.48***	18.06***	5.61***	33.13***	22.58***
Mid North Coast								0	22.65***	4.34***	35.33***	15.17***	16.70***	8.38***	-0.59	25.29***	13.50***
Mid Western									0	-2.43**	18.03***	1.07	5.11***	-4.41***	-10.04***	11.09***	5.21***
New England										0	23.49***	10.41***	15.85***	6.03***	-1.42	23.59***	11.14***
Northern Rivers											0	0.38	3.27	-1.46	-13.63***	10.53***	-0.07
Northern Sydney												0	-0.78	-10.47***	-11.41***	3.31	-3.04***
South Eastern Sydney													0	-10.90***	-10.98***	6.33***	-0.78
South Western Sydney														0	-5.82***	10.63***	4.71***
Southern															0	28.19***	14.27***
Wentworth																0	-2.41*
Western Sydney																	0

Coefficient effects

	CC	CS	FW	GM	Hunter	Illawarra	Macquarie	MNC	MW	NE	NR	NS	SES	SWS	Southern	Wentworth	WS
Central Coast	0	29.00***	40.89***	21.14***	40.71***	-31.99***	31.21***	9.36***	19.44***	53.83***	-8.59**	48.64***	-1.74	5.85***	41.93***	-7.12***	21.46***
Central Sydney		0	10.88***	-1.81	11.98***	-42.90***	2.91	-15.27***	-2.62	20.06***	-22.90***	19.13***	-22.60***	-16.47***	12.54***	-24.37***	-3.80***
Far West			0	-10.71***	3.59	-64.80***	2.29	-22.09***	-13.58**	17.92***	-29.04***	18.43***	-36.41***	-35.13***	11.07***	-45.45***	-17.06***
Greater Murray				0	14.50***	-54.40***	9.45***	-15.85***	-1.21	23.74***	-33.75***	22.86***	-23.91***	-20.70***	17.76***	-27.87***	-3.90**
Hunter					0	-67.50***	5.30***	-27.45***	-6.56***	13.07***	-31.27***	17.86***	-36.92***	-28.65***	5.64***	-33.21***	-12.77***
Illwara						0	56.73***	32.96***	44.88***	66.04***	16.78***	68.17***	25.97***	30.71***	63.17***	19.98***	42.76***
Macquarie							0	-36.47***	-22.51***	6.70***	-48.07***	9.77***	-48.68***	-43.69***	-0.58	-51.47***	-25.31***
Mid North Coast								0	10.79***	42.21***	-23.79***	41.03***	-7.23***	-3.35*	36.29***	-12.95***	14.44***
Mid Western									0	15.53***	-39.93***	21.67***	-29.08***	-24.00***	12.30***	-32.19***	-10.71***
New England										0	-58.49***	-0.76	-52.93***	-47.54***	-9.43***	-57.80***	-29.74***
Northern Rivers											0	44.28***	-5.35*	-5.06*	37.78***	-9.74***	16.46***
Northern Sydney												0	-45.95***	-40.70***	-9.09***	-47.17***	-25.22***
South Eastern Sydney													0	6.46***	37.21***	-3.47	19.25***
South Western Sydney														0	36.49***	-3.32	18.20***
Southern															0	-51.55***	-22.03***
Wentworth																0	18.02***
Western Sydney																	0

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 3: Decomposition by Area Health Service (cont)

Pooled - Explained

	CC	CS	FW	GM	Hunter	Illwara	Macquarie	MNC	MW	NE	NR	NS	SES	SWS	Southern	Wentworth	WS
Central Coast	0	20.24***	-15.14***	12.31***	8.21***	19.67***	-10.13***	0.14	12.24***	2.10	13.89***	20.38***	18.46***	2.48***	3.84**	25.81***	9.19***
Central Sydney		0	-27.95***	-11.34***	-14.32***	-8.03***	-24.05***	-22.39***	-7.91***	-15.35***	-9.11***	-0.90	-3.62	-19.54***	-18.35***	-10.21***	-13.75***
Far West			0	16.00***	11.20***	29.09***	1.27	-0.25	22.04***	7.02***	22.71***	21.15***	28.72***	13.99***	5.77***	24.86***	15.27***
Greater Murray				0	-3.28***	9.42***	-14.59***	-10.93***	4.33***	-3.72***	12.28***	8.51***	9.47***	-5.12***	-8.07***	4.72***	-2.75**
Hunter					0	12.17***	-17.36***	-7.13***	2.47**	-2.32**	11.05***	7.12***	12.82***	-4.83***	-4.18***	2.90***	-1.62**
Illwara						0	-29.55***	-25.37***	-7.73***	-15.51***	5.46***	4.57***	6.26***	-16.19***	-25.69***	0.92	-8.27***
Macquarie							0	5.08***	18.78***	9.02***	22.64***	19.08***	23.81***	15.60***	7.60***	24.18***	17.31***
Mid North Coast								0	13.07***	2.87***	20.80***	16.32***	24.63***	4.69***	-3.10**	16.14***	7.24***
Mid Western									0	-6.10***	4.45**	3.64***	4.84***	-8.27***	-10.41***	2.53	-4.69***
New England										0	14.31***	9.84***	14.43***	0.88	-2.03***	8.29***	2.68***
Northern Rivers											0	-1.22	5.59***	-6.96***	-16.90***	2.95	-6.57***
Northern Sydney												0	-4.00***	-13.92***	-10.29***	-5.27***	-9.95***
SES													0	-16.70***	-20.59***	-4.14**	-11.25***
SWS														0	-4.99***	10.62***	3.25***
Southern															0	13.76***	4.68***
Wentworth																0	-4.40***
WS																	
Inter state/uni																	

Pooled - Unexplained

	CC	CS	FW	GM	Hunter	Illwara	Macquarie	MNC	MW	NE	NR	NS	SES	SWS	Southern	Wentworth	WS
Central Coast	0	32.75***	55.56***	24.92***	45.06***	-19.88***	53.92***	12.98***	34.33***	57.57***	10.77***	48.94***	4.13**	15.68***	45.07***	11.65***	31.87***
Central Sydney		0	15.38***	-4.42**	14.61***	-45.17***	14.85***	-17.48***	1.48	22.03***	-19.21***	17.23***	-26.78***	-15.30***	14.28***	-17.32***	1.82
Far West			0	-19.19***	1.65	-69.72***	2.11	-27.05***	-15.90***	12.23***	-38.46***	7.76***	-46.55***	-36.26***	2.73	-39.82***	-14.62***
Greater Murray				0	19.33***	-46.87***	21.16***	-13.18***	5.00***	26.16***	-24.84***	23.59***	-24.11***	-13.96***	19.75***	-16.49***	6.59***
Hunter					0	-65.66***	7.88***	-33.02***	-9.18***	8.72***	-39.65***	8.93***	-43.50***	-30.29***	-0.18	-30.71***	-10.58***
Illwara						0	73.56***	38.70***	54.50***	75.39***	19.42***	64.96***	16.55***	34.56***	74.81***	24.75***	49.55***
Macquarie							0	-35.75***	-16.00***	6.85***	-41.77***	6.45***	-45.01***	-41.24***	-2.48	-42.52***	-20.04***
Mid North Coast								0	20.37***	43.68***	-9.25***	39.88***	-15.16***	0.34	38.90***	-3.81	20.70***
Mid Western									0	19.20***	-26.35***	19.12***	-28.81***	-20.14***	12.76***	-23.64***	-0.81
New England										0	-49.30***	-0.19	-51.50***	-42.39***	-8.72***	-42.50***	-21.28***
Northern Rivers											0	45.87***	-7.67***	0.45	41.14***	-2.17	22.97***
Northern Sydney												0	-42.73***	-37.24***	-10.12***	-38.59***	-18.31***
SES													0	12.26***	46.91***	7.00***	29.73***
SWS														0	35.75***	-3.31	19.66***
Southern															0	-37.22***	-12.53***
Wentworth																0	20.01***
WS																	0

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Pooled model has linear restriction that the gain from one group = loss to another.

Table 4: DFL reweighting approach by SEIFA

		Mean		P10		P25		P50		P75		P90	
SEIFA 1 & 2^	*Explained*	0.82	(41%)	0	n.a	0	n.a	1*	(50%)	1	(17%)	5*	n.a
	Unexplained	1.19	(59%)	0	n.a	0	n.a	1	(50%)	5***	(83%)	-5	n.a
	Total	2.01	(100%)	0	n.a	0	n.a	2	(100%)	6	(100%)	0	n.a
SEIFA 1 & 3^	*Explained*	3.14***	n.a.	0	n.a	0	n.a	1**	(50%)	5***	(63%)	12***	(150%)
	Unexplained	-3.02***	n.a.	0	n.a	0	n.a	1*	(50%)	3	(37%)	-20***	(-250%)
	Total	0.123	n.a.	0	n.a	0	n.a	2	(100%)	8	(100%)	-8.00	(-100%)
SEIFA 1 & 4^	*Explained*	10.33***	(494%)	1 [a]	(100%)	2***	(100%)	7***	(100%)	20***	(125%)	29***	(414%)
	Unexplained	-8.24***	(-394%)	0	(0%)	0	(0%)	0	(0%)	-4*	(-25%)	-36***	(-314%)
	Total	2.09	(100%)	1	(100%)	2	(100%)	7	(100%)	16	(100%)	-7	(-100%)
SEIFA 1 & 5^	*Explained*	10.46***	(38%)	1***	n.a.	4***	(67%)	7***	(47%)	14***	(29%)	36***	(38%)
	Unexplained	17.02***	(62%)	1***	n.a.	2***	(33%)	8***	(53%)	35***	(71%)	59***	(62%)
	Total	27.48	(100%)	0	n.a.	6	(100%)	15	(100%)	49	(100%)	95	(100%)
SEIFA 2 & 3^	*Explained*	2.59**	(137%)	0	n.a	0	n.a	1**	n.a	5***	(250%)	10***	(125%)
	Unexplained	-4.47***	(-237%)	0	n.a	0	n.a	-1	n.a	-3**	(-150%)	-18***	(-225%)
	Total	-1.88	(-100%)	0	n.a	0	n.a	0	n.a	2	(100%)	-8	(-100%)
SEIFA 2 & 4^	*Explained*	9.60**	n.a.	1 [a]	(100%)	3***	(150%)	8***	(160%)	19***	(190%)	25***	(357%)
	Unexplained	-9.52**	n.a.	0	(0%)	-1*	(-50%)	-3***	(-60%)	-9***	(-90%)	-32***	(-457%)
	Total	0.08	n.a.	1	(100%)	2	(100%)	5	(100%)	10	(100%)	-7	(-100%)
SEIFA 2 & 5^	*Explained*	9.65***	(38%)	1***	(50%)	5***	(83%)	8***	(62%)	13***	(30%)	32***	(34%)
	Unexplained	15.83***	(62%)	1***	(50%)	1***	(17%)	5*	(38%)	30***	(70%)	63***	(66%)
	Total	25.48	(100%)	2	(100%)	6	(100%)	13	(100%)	43	(100%)	95	(100%)
SEIFA 3 & 4^	*Explained*	6.99***	(355%)	1 [a]	(100%)	2***	(100%)	6***	(120%)	13***	(163%)	17***	(1700%)
	Unexplained	-5.03***	(-255%)	0	(0%)	0	(0%)	-1	(-20%)	-5***	(-63%)	-16***	(-1600%)
	Total	1.97	(100%)	1	(100%)	2	(100%)	5	(100%)	8	(100%)	1	(100%)
SEIFA 3 & 5^	*Explained*	7.51***	(27%)	1 [a]	n.a.	4***	(67%)	7***	(54%)	11***	(27%)	21***	(20%)
	Unexplained	19.86***	(63%)	1 [a]	n.a.	2***	(33%)	6***	(46%)	30***	(73%)	82***	(80%)
	Total	27.36	(100%)	0	n.a.	6	(100%)	13	(100%)	41	(100%)	103	(100%)
SEIFA 4 & 5^	*Explained*	3.70***	(15%)	1**	(100%)	2***	(50%)	2***	(25%)	5***	(15%)	10***	(10%)
	Unexplained	21.70***	(85%)	0	(0%)	2***	(50%)	6***	(75%)	28***	(85%)	92***	(90%)
	Total	25.40	(100%)	1	(100%)	4	(100%)	8	(100%)	33	(100%)	102	(100%)

Note: ^ the reference group. n.a refers to no difference in waiting time. Decomposition of waiting time gap in proportions are in parentheses. *, ** 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] all replications return the same difference.

Table 5: DFL reweighting approach by ARIA

		Mean		P10		P25		P50		P75		P90	
ARIA 1 & 2^ [b]	*Explained*	4.18***	(156%)	0	n.a.	2***	(100%)	3***	(75%)	8***	(73%)	7	(19%)
	Unexplained	-6.86***	(-256%)	0	n.a.	0	(0%)	1	(25%)	3	(27%)	-43***	(-119%)
	Total	-2.68	(100%)	0	n.a.	2	(100%)	4	(100%)	11	(100%)	-36	(-100%)
ARIA 1 & 3^ [b]	*Explained*	7.70***	(72%)	1**	n.a.	2***	(67%)	5***	(83%)	12***	(240%)	22***	(31%)
	Unexplained	-18.36***	(-172%)	-1*	n.a.	1	(33%)	1	(17%)	-7	(-140%)	-97**	(-131%)
	Total	-10.66	(-100%)	0	n.a.	3	(100%)	6	(100%)	5	(100%)	-72	(-100%)
ARIA 1 & 4^ [b]	*Explained*	16.42***	(359%)	2***	(200%)	4***	(100%)	12***	(133%)	28***	(175%)	47***	(102%)
	Unexplained	-20.99***	(-459%)	-1*	(-100%)	0	(0%)	-3**	(-33%)	-12***	(-75%)	-93***	(-202%)
	Total	-4.57	(-100%)	1	(100%)	4	(100%)	9	(100%)	16	(100%)	-46	(-100%)
ARIA 2 & 3^	*Explained*	0.27	(3%)	0	n.a.	0	(0%)	0	(0%)	2*	(33%)	3	(8%)
	Unexplained	-8.25***	(-103%)	0	n.a.	1**	(100%)	2***	(100%)	-8***	(-133%)	-39***	(-108%)
	Total	-7.98	(-100%)	0	n.a.	1	(100%)	2	(100%)	-6	(-100%)	-36	(-100%)
ARIA 2 & 4^	*Explained*	10.19***	(539%)	1 [a]	(100%)	2***	(100%)	8***	(160%)	19***	(380%)	32***	(320%)
	Unexplained	-12.08***	(-639%)	0	(0%)	0	(0%)	-3***	(-60%)	-14***	(-280%)	-42***	(-420%)
	Total	-1.89***	(-100%)	1	(100%)	2	(100%)	5	(100%)	5	(100%)	-10	(-100%)
ARIA 3 & 4^	*Explained*	8.76***	(144%)	1 [a]	(100%)	2 [b]	(200%)	7***	(233%)	17***	(155%)	27***	(104%)
	Unexplained	-2.66***	(-44%)	0 [a]	(0%)	-1***	(-100%)	-4***	(-133%)	-6***	(-55%)	-1	(-4%)
	Total	6.10	(100%)	1	(100%)	1	(100%)	3	(100%)	11	(100%)	26	(100%)

Note: ^ the reference group. n.a refers to no difference in waiting time. Decomposition of waiting time gap in proportions are in parentheses. *, ** 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] all replications return the same difference. [b] bootstrap sample is done by group such that the proportion of ARIA 1 patients are always the same with the original sample. This is because ARIA 1 patients are very few compared with patients in other areas (10%, 4% and 2% of patients in ARIA 1, ARIA 3 and 4, respectively) 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.

Table 6: DFL reweighting approach by AHS (Central Sydney as reference group)

		Mean		P10		P25		P50		P75		P90	
Central Coast (CC)	*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		1	(100%)	6	(100%)	15	(100%)	90	(100%)	173	(100%)
Far West (FW)	*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 (GM)	*Explained*	16.19***	(103%)	1 [a]	(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 (MNC)	*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 (MW)	*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 (NE)	*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 6 (continued)

		Mean		P10		P25		P50		P75		P90	
North Sydney (NS)	*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		0	n.a.	0	n.a.	-2	(100%)	-15	(-100%)	-66	(-100%)
South Eastern Sydney (SES)	*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 (SWS)	*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 (WS)	*Explained*	11.03***	(93%)	1 [a]	n.a.	4***	(80%)	8***	(80%)	3***	(60%)	27***	(135%)
	Unexplained	0.89	(7%)	1 [a]	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: ^ the reference group. n.a refers to no difference in waiting time. Decomposition of waiting time gap in proportions are in parentheses. *, ** 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] all replications return the same difference.

Appendix Table 1: Variable means by SEIFA quintile

Variable	SEIFA 1	SEIFA 2	SEIFA 3	SEIFA 4	SEIFA 5
Waiting time	102.12	100.11	102.00	100.03	74.63
(std.dev)	(149.91)	(149.48)	(157.26)	(165.46)	(136.48)
P10 waiting time	5	5	5	4	3
P25 waiting time	14	14	14	12	8
P50 waiting time	42	40	40	35	27
P75 waiting time	121	115	113	105	72
P90 waiting time	295	295	303	302	200
Demographics					
0 to 4	3.05%	3.39%	3.81%	3.95%	3.83%
5 to 9	3.65%	3.68%	4.17%	3.77%	2.92%
10 to 14	2.16%	2.09%	2.41%	2.12%	1.76%
15 to 19	2.38%	2.54%	2.55%	2.31%	1.90%
20 to 24	2.87%	3.05%	3.35%	2.97%	3.11%
25 to 29	3.37%	3.42%	3.91%	3.75%	4.46%
30 to 34	4.32%	4.60%	5.18%	5.17%	5.46%
35 to 39	5.13%	5.13%	5.49%	5.29%	5.42%
40 to 44	5.79%	6.16%	6.22%	6.35%	6.47%
45 to 49	6.42%	6.59%	6.57%	6.35%	6.40%
50 to 54	6.85%	6.59%	6.32%	6.45%	6.20%
55 to 59	7.95%	7.72%	7.52%	7.06%	6.93%
60 to 64	8.74%	7.89%	7.64%	7.48%	6.87%
65 to 69	10.55%	10.12%	8.89%	8.61%	7.92%
70 to 74	10.28%	10.16%	9.20%	9.14%	9.10%
75 to 79	8.98%	9.17%	9.25%	9.85%	9.59%
80 to 84	4.75%	4.86%	4.64%	5.78%	6.63%
85+	2.76%	2.84%	2.86%	3.60%	5.05%
male	46.43%	46.50%	45.32%	47.73%	48.12%
Urgency					
urgency < 7 days	10.86%	10.22%	11.00%	13.93%	16.98%
urgency < 30 days	31.17%	31.53%	31.22%	34.86%	34.19%
urgency < 90 days	31.48%	32.74%	32.21%	29.25%	28.25%
urgency < 1 year	26.49%	25.51%	25.57%	21.96%	20.58%
Number of acute conditions					
0 condition	4.70%	5.76%	5.19%	4.77%	5.12%
1 condition	29.47%	31.76%	30.43%	28.52%	32.14%
2 conditions	30.15%	29.68%	29.92%	29.37%	28.11%
3 conditions	20.54%	19.01%	19.66%	20.76%	19.35%
4 conditions	10.71%	9.80%	10.41%	11.76%	10.79%
5 or more conditions	4.42%	4.00%	4.39%	4.82%	4.48%
Number of observations	27,273	38,262	60,909	40,317	27,438

Appendix Table 2: Variable means by ARIA

Variable	ARIA 1	ARIA 2	ARIA 3	ARIA 4
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	2,796	27,505	69,828	94,070

Appendix Table 3: Variable means 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	11,914	5,017	9,182	10,643	9,529	4,294	13,687	16,302	25,222	6,847	6,918	21,517