# Beyond DRG: The effect of socio-economic indicators on inpatient resource allocation in Australia

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## Abstract

Financing in Australia's public hospital works through the Australian Refined Diagnosis Related Groups (AR-DRGs) with separations to specific DRG groups based on medical diagnosis or surgical procedure, patient's age, mode of separation, clinical complexity and complications. This paper aims at assessing how the AR-DRGs reflect the efficiency and equity of the hospitals resource allocation. Using administrative data of all acute public hospital admissions and length of stay (LOS) as a proxy for hospital costs, this paper showed that patients' socio-economic (SES) characteristics are a strong determinant of health care utilization. Our results revealed that the lower the SES, the longer the LOS and hence more utilization of the inpatient resources. Therefore, omitting SES from the risk adjusters list and solely focusing on DRG- based compensation penalizes hospitals catering to lower SES populations. Our findings further support the idea of smaller/remote hospitals based on block funding.

*Keywords*: Diagnosis related groups (DRG), socio-economic status, length of stay, Australia

## Research highlights

- The main danger of DRG payment to hospitals is selection against high-risk patients.
- Heterogeneity by SES within DRG groups is not accounted by the Australian reform.
- We find significant effects of the SES variables on the use of inpatient resources as the lower the SES the longer the length of stay.
- We recommend that SES variables be included in the hospitals' reimbursement formula

## 1. INTRODUCTION

Risk-adjusted capitated payments to hospital networks create financial and higher-powered incentives to promote allocative and dynamic efficiency. Capitated payments create incentives to provide appropriate array of hospital services to a defined population and also, incentives to liaise with other sectors in particular primary care, (i.e. primary care organizations - see below), in order to provide the most cost-effective continuity of care (Segal et al, 2002). Public hospitals in Australia are paid based on an Activity-based funding (ABF) that largely depends on a refined and tailored version of weighted, capitated and prospective payments, the Diagnosis Related Groups (DRGs) - namely the Australian Refined Diagnosis Related Groups (AR-DRGs). In this paper, we examine to what extent the risk adjustment of the hospital ABF model in Australia, which is solely based on DRGs adjusters, reflects the efficiency and equity of the hospitals resource allocation. Furthermore, we examine the resource allocation efficiency, as approximated by the length of stay, based on the dataset of all publicly admitted patients in Australia in the 2007-08 financial year. Specifically, we argue that allocation of resources based on DRGs alone is not sufficient and other patients' characteristics, socioeconomic status (SES) in particular, explain variations in resource use and must be reflected in the hospitals compensation formula. In this introduction section, we will provide a synopsis of the Australian health financing system, followed by a brief summary of how the DRGs systems work in general and in Australia specifically. Also, key reforms regarding hospital payment methods in Australia will be highlighted.

***The Australian Health Care System***

The Australian health care system has been designed to achieve a high level of equity in treatment. Universal access and coverage are provided through a number of publicly financed programs collectively known as *Medicare*. Introduced in 1984, the Medicare universal arrangements are financed principally out of general taxation and a specific health levy of 1.5% of taxable income (and additional Medicare levy of 2.5% for high income earners who do not take out private health insurance). All Australians are entitled to a level of subsidies for medical services (i.e. privately or publicly provided) such as GP and specialists visits under the Medical Benefits Schedule (MBS) which is funded by the Commonwealth government. Also, under the Medicare arrangements, the Commonwealth provides financial support to state governments to fund public hospital services whereby all Australians are able to access public hospitals free at the point of delivery.

A significant feature of the Australian health system is the division of responsibilities and powers between Commonwealth and State governments in the funding and provision of health care services. The Commonwealth government is directly responsible for financing medical services, and pharmaceutical benefits, as described above, and jointly with State governments funds public hospital services. State and territory governments with varying financial assistance from the Commonwealth have been primarily responsible for the managing of public hospitals, mental health programs and community health services. Since the early 1990s, most state governments have moved towards funding hospitals under a prospective case-mix system based on a classification system of treatment complexity known as Diagnosis-Related Groups (DRGs).

***Diagnosis Related Groups in Australia***

Implementation of a DRG-based payment system requires in brief, four building blocks: (a) a clinical classification system to group patients into similar clinically homogenous characteristics clusters (Kobel, Thuilliez, Bellanger & Pfeiffer, 2011; Klein-Hitpaß and Scheller-Kreinsen, 2015), (b) a pattern of hospitals' cost information to assess the DRGs weights and points (Tan *et al*., 2011; Cots, Chiarello, Salvador, Castells & Quentin, 2011), (c) a conversion of the DRGs points to monetary values that are subject to adjustment according to structural (i.e. location, wages level) and resource-consumption variables (i.e. length of stay, service utilization) (Cots *et al.*, 2011; Klein-Hitpaß and Scheller-Kreinsen, 2015) and finally (d) payment to take place according to the number and weight of DRGs (Busse, 2012). The advantage of the DRG-based payment system stems from reimbursing providers based on prospective inputs, which are required to manage and treat a specific group. Thus, it incentivizes service providers to provide more efficient services and curb unnecessary services (unnecessary long length of stay) (Cylus & Irwin, 2010). Nevertheless, few inadvertent implications result from the scheme such as: cream skimming of low-risk patients (Cylus & Irwin, 2010); DRG creep (i.e. where providers place patients into higher points DRGs (Serdén, Lindqvist & Rosén, 2003; Pongpirul & Robinson, 2013)) and inadequacy in the quality of case management (leading to higher rates of readmission (Kjerstad, 2003)).

However, notwithstanding adoption of case-mix classification for funding hospitals, the total funding from which payments are made is still derived from capped budgets. Thus, whilst all hospitals are ostensibly paid the same based on their case-mix complexity of episodes of treatment, the funding pool of State resources (with the exception of NSW, see NSW Health, 2005; Rice and Smith, 2001) is not based on a needs-adjusted capitated basis either at a person-level or at an aggregated regionally-defined population basis.

The complex division of responsibilities in funding and provision of healthcare services between Commonwealth and State governments have resulted in a highly fragmented and uncoordinated health system structure. This fragmented and *ad hoc* approach to health system funding and resource allocation has led to calls over the past decade in Australia to consolidate all public funding into single funding stream; and the adoption of risk-adjusted capitation to allocate funds to area-based purchasing authorities based on the health care needs of the defined population (Podger, 2005; FitzGerald, 2005; Richardson, 2005; Richardson, 2003; Peacock & Segal, 2000). These calls have culminated with the Federal government introducing a number of major reform initiatives to improve efficiency and fairness in the allocation of resources in the public hospital system.

### *Hospital Payment Scheme Reforms in Australia*

In April 2010, the Federal government reached a historic agreement with state governments to adopt key structural reforms to the governance, funding and delivery of health services. Under the National Health and Hospital Network (NHHN) reforms the federal government becomes co-funder (50%) of public hospital services; takes full funding and policy responsibility in primary health care services; and takes full funding and policy responsibilities in aged care services (NHHN, 2010a). A key structural change is the establishment of Local Hospital Networks (LHN) as a separate legal entity, involving the clustering of a small group of public hospitals with defined geographical and functional areas of responsibility. State governments are responsible for system-wide planning and monitoring of public hospitals, but LHN are given flexibility in how to best meet its locally-derived service requirements. LHN funding is based on a nationally consistent approach to activity-based funding (ABF) for public hospital services.

The new national ABF is managed through an inter-governmental agency, with emergency and sub-acute services funded on a similar basis as classifications and costs are finalized overtime (Mihailovic et al., 2016). In terms of funding arrangements, an Independent Hospital Pricing Authority (IHPA) determines the (single) national ‘efficient price’, representing the Australian Government’s payments to public hospital and sub-acute services determined on activity-based funding arrangements across Australia. According to the Report by Health Policy Solutions, Case-mix Consulting & Aspex Consulting (2011), the AR-DRGs (Version 6.Ox) are used for inpatient services classifications. According to the same report, the new prospective payment system with a case-mix basis aims at reducing the in-patient length of stay (LOS) and the subsequent non-medical costs.

The new hospital financing scheme raises some equity concerns related to the emergence of some forms of implicit (or even explicit) selection of patients after the implementation of nationally homogeneous prospective payments systems in other countries (see Perelman, Shmueli & Closon, 2008 and references therein). If hospitals’ decisionmakers can observe heterogeneity in expected costs across patients’ subgroups and within a particular (risk-)group of patients, for which the risk-adjusted payment per admission is the same, selection may occur. Selection is thus a consequence of the imperfect risk adjustment of prospective payments. The implications of imperfect risk adjustment on equity and efficiency are straightforward. Hospitals engaging in selection activities focus on attracting low-cost patients, with high-cost ones facing lower access to (high-quality) care (e.g. increased waiting times). Hospitals not practicing patients’ selection can suffer financial distress and potentially bankruptcy. In the long term, either those hospitals fail and access to care is at risk, or they decrease the quality of treatments and access to quality is at risk (van de Ven and Van Vliet, 1992, Perelman, Shmueli & Closon, 2008).

Furthermore, it is important to note the distinction between public and private hospitals in Australia. One way to make it simple is to differentiate between the accessibility to both types of hospital depending on the type of insurance. For instance, a public insurance holder can access public hospitals as a public patient and receive medical services, free at point if delivery. On the other hand, a private health insurance holder can access private hospitals and also can still access public hospitals as a ‘private’ patient where it is allowed to choose the preferred physician. Generally, private hospitals are characterized with shorter waiting times while public hospitals are usually the first choice for emergency cases and also offer wider basket of services (Shmueli & Savage, 2014).

We should also note that the correlation between patients’ SES and the LOS has been investigated in the body of literature of hospital payment schemes and equity. Many studies have found substantial and significant impact of SES on LOS in other countries include Epstein, Stern, & Weissman (1990); Kominski & Long (1997); Martin & Smith (1996); Picone, Wilson & Chou, (2003); Perelman, Shmueli & Closon (2008); and Moore et al. (2015); Strobel et al. (2017); and Henry et al. (2018).

The paper is structured as follows. Section 2 presents the methods and include two subsections that describe data and analytic methods used in our analysis. Section 3 summarises the results, and Section 4 provides the discussion and concludes.

## 2. METHODS

The data provided all hospitalization episodes during the financial year 2007-08 and was obtained from the Australian Institute of Health and Welfare (AIHW). Our study focused on the following variables: length of stay (LOS) as the outcome variable, the Australian refined DRGs, number of affected systems, and socioeconomic and demographic factors. We worked on two frameworks to model the LOS, where the difference between the two frameworks was based on the type of treatment and number of days in hospital before discharge. Both approaches as well as the data will be described in full in the below subsections. Subsection 2.1 will present the data used in this study while subsection 2.2 will describe the analytical methods.

### 2.1. DATA

The data came from AIHW and covered all hospitalization episodes in Australia for the 2007-08 financial year with a total of 7.02 million observations.[1] The study concentrated on the acute care episodes only: 6.75 million observations, or 96.2 percent of all data. We further limited the analysis to the publicly admitted patients which gives overall sample size of 3.65 million observations (approximately 47% of acute care episodes were classified as private patients).

The originally available information is at the episode level only and includes some of the patient demographic, socio-economic and admission related characteristics. Demography covers *age* (in 5-year group brackets) and *gender,* while the first set of the socio-economic (SES) variables includes place of *birth* (Australia or overseas), whether a patient is of *Aboriginal or Torres Strait Islander* (ATSI) background and *remoteness* indicator (major city, inner-region, outer-region and remote/very remote). Available admission characteristics included *length of stay* (LOS), *same-day discharge*, *Diagnosis Related Group* (DRG) assigned for admission as well as a list of all (up to 50) accompanying *diagnoses*.

The first set of the SES variables above was clearly limited. To expand the set, we utilized information from the diagnostic factors – the details are discussed below – and supplemented the patients' SES characteristics with the second set based on the *Z-codes* from the diagnosis information: the latter identified whether there were any social and/or economic characteristics accompanying patient's admission. The diagnoses information was also used to classify inpatients according to the number of affected systems.

The data also completely lacked any hospitals identifiers and did not distinguish if an individual was hospitalized more than once (i.e. the data are effectively at the episode level). The first limitation constrained the possibility to control for the hospital-level fixed effects and the second limited the possibility to control for readmissions.

[1] Difficulties in securing access to administrative data precludes us from updating to a more recent version of the dataset. However, given that neither the system nor the mechanisms within it have changed over time, the importance and relevance of the research question remains irrespective of the period examined.

Below we provide a brief description of the main variables in the analysis. Table 1 summarizes the descriptive information for all variables.

***Length of Stay (LOS)***

The Length of Stay (LOS) was measured in number of nights and maximum LOS in the original dataset is truncated at 35. The average LOS is 2.36 with the standard deviation of 5 nights where same-day discharge is included. For overnight or longer separations, the LOS increases to 4.92 with the standard deviation of 6.28 nights. These numbers are not substantially different from the total hospital system where the average LOS was 2.18 (4.8) and 4.95 (6.21) including (excluding) the same-day discharge respectively.

Same day discharge constituted a major bulk of all hospitalization episodes: 52.1 percent for publicly admitted patients and 56 percent for all hospital admissions, including private patients in 2008. The high proportion of same-day admissions required a careful approach to how to model LOS behavior – the details are discussed in the next section.

***Australian Refined Diagnosis-Related Group (DRG)***

The complexity of admission episodes was measured by the DRG cost weights, which was calculated as a relative measure relating specific $DRG_i$ average cost to the average costs of all *DRGs*. The average cost of all *DRGs* was normalized to unity. In general, the higher the DRG cost-weight the more complex the medical conditions associated with the episode and the higher the intensity of hospital resource use. The 2008 hospital admissions were based on a version 5.1 of the AR-DRG classification system with individual AR-DRGs grouped under 23 Major Diagnostic Categories (the latter is mostly defined by body system or disease type). According to the Productivity Commission Report (2009):

> Each separation is assigned to an AR-DRG mainly on the basis of the medical diagnosis or surgical procedure involved, but also according to a patient's age, length of stay, mode of separation, the level of clinical complexity and the existence of complicating diagnoses or procedures. (p. 32)

The summary statistics of the DRG cost weights is given in Table 1: given the average normalized cost-weight of 1, the range of DRG cost weights was between 0.13 and 46.05 with standard deviation of 1.55. A number of similar admission types were grouped into separate DRGs depending on whether the admission was classified as same-day or longer. Out of 665 individual DRGs there were ten DRG groups specifically assigned for the same-day discharge and there were 40 DRG groups where admissions were always longer than overnight. The remaining DRG groups did not explicitly distinguish between same-day and longer admissions.

***Number of Affected Systems***

The dataset contained the information for up to 50 diagnoses for each hospitalization episode. Given that less than 10 percent of the sample had more than 7 diagnoses, both SES and number of affected systems extraction were based on a truncated at seven diagnoses dataset– this did not reduce the efficiency of new variables creation since most of diagnoses beyond 7 belong to the same code group.

We distinguished between *one*-, *two*- and *three*-(*or-more*) affected systems. This aggregation was derived from the list of diagnoses and based on the ICD-10 coding system (WHO, 2008). As an illustration, if an admission episode included codes *I00-I99* which refer to the *diseases of the circulatory system*, *J00-J99 - respiratory system* and *K00-K99 - digestive system*, this episode was classified as *three (-or more)* affected systems. Overall, 63 percent of admissions were with *one* affected system, 19.1 with *two* affected systems and remaining 17.8 were complicated cases with *three* affected systems. As expected, for overnight admissions and longer, the proportion of episodes with *two*- and *three* affected systems increased and accounted for more than 50 percent. In the ICD-10 classification the codes *R00-R99* '*symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified*' and *S00-T98* '*injury, poisoning and certain other consequences of external causes*' refer to the causes of illness rather than bodily systems involved and hence could affect any part of human anatomy. The sub-codes in each category were used to assign the information contained in the *R-T* classifications in order to reflect the number of systems affected with more accuracy.

***Geographical and Demographic Variables***

Males accounted for 47.5 percent of the admitted public patients and 44.4 percent for overnight and longer discharges. The patients were grouped in five-year brackets according to their age, with the exception of less than one year old and patients older than 65 years old. It is interesting that the proportion of younger patients (< 40 years old) increased in longer hospital stays compared to older population.

Most of the patients were born in Australia (70.9 percent) and were admitted in the hospitals at *major cities* (61.7 percent); followed by *inner regions* (21.8) and *outer region* (12.5) admissions. Patients with *ATSI* background constituted approximately 6 percent of the sample.

***Additional SES Variables***

To supplement the existing SES characteristics, we used the admission information where admission episodes include the *Z-codes* (Chapter XXI of the ICD-10 classification – Factors influencing health status and contact with health services, WHO, 2008). These *Z-codes*, if present, point to economic and/or social background of patients. For instance, code *Z56* lists problems associated with employment or unemployment, while code *Z59* includes 'housing and economic circumstances' problems and/or complications. This information was utilized to create an extra set of the SES variables: *homeless & housing problems*, *low income* and *unemployed.* Table 1 lists the number of episodes associated with each SES characteristic. Even though the proportion of episodes with these characteristics was rather small (less than 1 percent of the overall sample), it is based on the whole population of hospitalized public patients in Australia in 2008. Note that proportion of patients with adverse SES characteristics increased somewhat where admissions are longer than overnight.

It is quite plausible that not all admission episodes were accurately and completely recorded. Additionally, if a list of diagnoses did not include the Z code, the structure of the data would not allow identifying unambiguously if the admission episode was not complicated by adverse SES characteristics. We suspected that episodes with adverse SES characteristics were underreported. As a quick check, a low proportion of identified episodes with adverse SES characteristics was substantially lower than corresponding counterparts for the Australian population especially taking into account that the data do not control for readmissions. For example, the average unemployment rate for 2007-08 financial year was around 4.2 percent (Australian Bureau of Statistics, 2008) while the proportion of patients reporting issues related to unemployment was less than 0.2 percent of all patients. Therefore, we estimated the models with and without the second set of SES characteristics which allows to check the sensitivity of results. Based on the diagnosis information it is also possible to identify a wider range of SES characteristics which can reflect *adverse lifestyle,* exposure to *stress,* various *employment issues,* and exposure to *environmental &occupational risks.* Compared to the three chosen SESs, the latter were more subjective and ambiguous, thus were not considered in the current version.

## 2.2. ANALYTIC METHODS

Given the nature of the dependent variable *LOS* – count data truncated at 35 nights with high proportion of the same day discharge (0 nights) – there were two frameworks to model its behavior. The first approach was to treat the length of stay as a uniform process – one-part modeling (1-PM) framework – where no specific treatment was given to the same-day discharges. For this type, either Poisson or Negative Binomial (NegBin) family of estimators can be applied. In turn, two-part modeling approach (2-PM) treated same day discharges and length of stay (for episodes longer than one night) as two separate processes, each being affected differently by the explanatory variables. In this case, either Probit or Logit estimators can be used to estimate the probability of being discharged on the same day of admission and zero-truncated Poisson and NegBin family of estimators can further be applied to the second part of the model to analyze the determinants of the *LOS* (more than one night). In this paper we used both approaches to assess the impact of *SES* to the *LOS*.

Turning to the Poisson versus NegBin estimations: the results presented in this paper were based on the NegBinI specification. The Poisson distribution was based on the attractive but unlikely applicable to the current data property that variance of the data distribution was equal to its mean. While the logarithmic or square-root transformation of the LOS could reduce the variance and hence satisfy the assumptions of the Poisson model more fully, we did not proceed with the *ln(LOS)* in this analysis due to a number of reasons including the issues of retransformation (see Duan, 1983, Mullahy, 1998, Manning, 1998) and excessive same-day discharge in the LOS.

In turn, the Negative Binomial framework addressed the issue of overdispersion. In the empirical literature there are two main specifications applied– NegBinI and NegBinII. The main difference between the two is the assumption of the relationship between variance and mean of the distribution: NegBinI assumes that the variance is linearly proportional to the mean and NegBinII further inflates the variance as a quadratic function of the mean (which in turn implies that variance is increasing as mean is increasing). According to Cameron & Trivedi (1986), if $E[LOS] = \mu(X, \beta)$, then Poisson distribution requires $var[LOS] = \mu$, while for the NegBin family $var[LOS] = \mu + \delta \cdot \mu^{2-k}$. NegBinI is obtained when $k = 1$ and NegBinII with $k = 0$.
The test of the coefficient $\delta$ allowed to discriminate between Poisson ($\delta = 0$) and NegBin distributions, where $\delta > 0$ captures overdispersion. In all estimations, the Poisson model for either 1-PM or 2-PM specifications has been rejected with the *p-value=0.000*. Comparing the NegBinI and the NegBinII models – we favor NegBinI with NegBinII overinflating the variance and resulting in a very wide range of predicted values.

We estimated and reported ***average marginal effects (AME).*** Those were reasonably straightforward for the 1-PM: denoting $m_{k,1PM} = \frac{\partial E[LOS]}{\partial x_k}$ as a marginal effect with respect to the variable $x_k$, average marginal effects were evaluated at each value of $x_k$ and then averaged out. Extra steps needed to be taken to obtain AME for the 2-PM. Following the literature (Dow and Norton (2003)) the conditional mean for the 2-PM was then $E[LOS|x] = \Pr[ON = 1|x_1] \times E[LOS|LOS > 0, x_2]$, where $x_1$ and $x_2$ are the sets of explanatory variables for staying overnight or longer (*ON=1*) and *LOS*. In our case these sets were the same so $x_1$=$x_2$=$x$. Total ME from the two-part model were then calculated as $m_{k,2PM} = \frac{\partial E[LOS]}{\partial x_k} = \frac{\partial \Pr[ON=1]}{\partial x_k} \times E[LOS|LOS > 0] + \frac{\partial E[LOS]}{\partial x_k} \times \Pr[ON = 1]$ and standard errors need to be bootstrapped.

To summarize, 1-PM is estimated with the NegBinI distribution specification. The first part of the 2-PM (for the probability to stay longer than overnight) was estimated with Probit and the second part of the 2-PM is estimated with truncated (at unity) NegBin1 distribution. All calculations were done using STATA/MP version 12. Standard errors for the total average marginal effects in 2-PM are bootstrapped, where the STATA code was based on Deb, Manning, & Norton, 2010.

## 3. RESULTS

As was presented in the Methods section above, we estimated the marginal effects of the socio-economic (SES) characteristics of the hospitalized patient on the length of stay (LOS), controlling for age, gender, DRG-cost weight and the number of physiological systems affected by the condition, using two specifications: in the first we assume that the LOS decision (the number of inpatient days) is taken in one stage. This translates into a 1-PM where "same-day" separations are considered as zero inpatient nights. Alternatively, one can think on a two-stage decision, where first a binary decision is made whether it is a same-day or over-night separation, and for over-night separations, the LOS (hospitalization nights) is determined in a second stage. This leads to a 2-PM where we first estimate the probability for zero nights, and second – the number of nights conditional on its being positive.

We focused on two sets of SES variables. The basic set includes three characteristics: ATS, Australian-born, and remoteness. The enlarged set includes, in addition, three types of problems which, we argue, affect length of stay and represent specific SES indicators: homelessness – including various housing - problems, low income problems and unemployment problems.

Table 2 presents the marginal effects computed for all – *Medical* (columns 1-4), *Base* (columns 5-8) and *SES* (columns 9-12) - specifications. For brevity, we discuss the results based on 2-PM estimations and reference to 1-PM is made where the results differ between the two approaches.

The clinical variables have, clearly, a major effect on LOS. Every additional DRG-weight point increases the probability for over-night separations by 0.37. Among over-night separations, every additional point increase LOS by 0.26 days. In total, an additional DRG-weight point increases the expected LOS by almost 2 nights. The 1-PM, imposing a constant coefficient for the DRG-weight throughout the range of inpatient nights, results in a marginal effect of 0.26 days. The main difference in the results is the estimated total marginal effect of the DRG as reflected in the relative cost weights: 1-PM specification substantially underestimates this effect; while in the 2-PM the main impact is absorbed in the probability equation. This does make an intuitive sense: in the 2-PM specification the complexity of the admission is accounted for by both the probability equation (the more complicated the case, the greater is the probability to stay for longer than overnight) and in the LOS equation; here the probability equation serves as a screening device separating same day discharge from the length of stay. In turn, 1-PM restricts DRG coefficient to be the same across same day discharge and longer: given high proportion of short stays that reduces the effect. Notice that individual marginal effects are not substantially different between the 1-PM results and second equation for the LOS in the 2-PM as shown in Table 2.

Similarly, the number of systems affected by the condition, which has led to the hospitalization, exercises a sizeable effect on LOS. When two systems are affected, relative to the case when only one system is affected, the probability of an over-night separation increases by 0.12, and when three systems are affected – by 0.22. The marginal effect of the second system affected on LOS among the over-night separation is 1.6 days, and that of the third system reaches 4.4 days. The total marginal effects on LOS are 1.3 and 3.1 days respectively. We note that the 1-PM marginal effects – 1.3 and 3.9 days respectively – are quite close to the two-part effects.

Furthermore, Table 2 shows that Aboriginal and Torres Strait Island individuals have, on average and controlling for the clinical profile, lower LOS. Their probability to be hospitalized over-night is lower by 0.04, and if hospitalized overnight, their average LOS is shorter by 0.3 days. In total, ATSI individuals have 0.3 (in the 2-PM) and 0.6 (in the 1-PM) less inpatient days. This is a quite unexpected effect, since we anticipated the ATSI individuals to use more inpatient resources when hospitalized due to worse health state. A careful look at the data reveals that ATSI individuals dominate same day discharge: while 57.4% of ATSI patients were discharged on the same day, the corresponding number for non-ATSI patients was lower at 51.9%. This phenomenon is largely attributed to a single DRG group (i.e. L61Z *Admission for Renal Dialysis*) with 41.2% of all ATSI patients being admitted under L61Z DRG classification compared to 15.9% for non-ATSI. This would explain lower probability for ATSI patients of staying longer than overnight.

Individuals living (and hospitalized) in more remote areas stay longer in hospitals. Relative to the base category “major city”, individuals in the more remote “inner-region” have a higher probability for an overnight separation by 0.04, and although their LOS is lower by 0.1 days if assigned to an overnight stay, the total effect is 0.14 days (0.25 using the 1-PM). On the other hand, individuals in the more remote “outer regions” have a higher probability (by 0.07) – and hospitalized individuals in “remote areas” have a higher probability by 0.1 – to stay overnight. If staying overnight, individuals from “remote regions” stay 0.1 more days on average than those from “major city”. The total effects of “outer regions’ and ‘remote areas” relative to “major city” are 0.31 and 0.55 days respectively, which is slightly lower compared to the one-part effects (0.47 and 0.76 respectively).

Finally, individuals born in Australia experience shorter LOSs, but albeit statistically significant effects magnitude is negligible (0.06-0.08 days in total).

Columns 9-12 in Table 2 present the marginal effects of the clinical and the expanded set of the SES characteristics on LOS. Comparing the effects of the overlapping variables, we see that the effects are very similar. So, we’ll focus now on the effects of the three additional SES characteristics indicating the existence of specific types of socio-economic problems.

In general, the marginal effects of the additional variables on LOS are very strong – 2.2 to 3 days- and comparable to the effects of the clinical variables discussed above. Homelessness (and housing) problems, low income problems and problems related to unemployment increase the probability of overnight stay by 0.15, 0.19 and 0.10 respectively. Once admitted to an overnight stay, the existence of these factors increases LOS by 3.5, 2.7, and 5.3 days respectively with the total effects on LOS being 2.3, 2.2 and 3 days respectively. The 1-PM marginal effects are of similar magnitude – 2.6, 2.3 and 2.7 days respectively.

The diagnostics suggest that two-part model is superior to the one-part as evidenced by the BIC and AIC criteria, and the pseudo R-squared for the probability equation is about

0.37. Information criteria also agree with the inclusion of additional, both base and extended, SES variables.

## 4. DISCUSSION

This paper examines whether allocation of resources to hospitals based on DRGs alone is sufficient and whether patients' characteristics, socioeconomic status (SES) in particular, explain variations in resource use that should be reflected in the hospitals compensation formula. Associations between length of stay (as a proxy for resource use) and patient characteristics and DRGs are modelled using a two-part model. The results point to the net effect of SES characteristics beyond that of the DRG weights which are traditionally used as a measure of inpatient resource use. All SES effects are both economically and statistically significant. With the exception of ATSI background, all effects are positive suggesting longer hospital stay and hence more intense use of hospital resources. Patients with ATSI background tend to stay 0.3 day less on average than other patients. Not surprisingly, patients coming from remote areas tend to stay longer, while patients in the major cities exhibit the shortest LOS. Notice that this effect mostly comes from the lower probability in staying overnight in the major cities, rather than from the length of stay itself. While the effect of being born overseas is statistically significant, the impact on the LOS as measured in days is not substantial. The greatest effects are observed for socially disadvantaged groups of patients in the extended model. Homeless patients or patients with housing problems will stay 2.3-2.6 days longer on average. Perhaps the most significant impact is estimated in case of unemployed patients who will extend their stay by almost 2.7 – 3 days on average.

Although our estimates offer interesting insights into the Australian health system and the hospitals compensation formula we must acknowledge the lack of causal estimates from our analysis and the need for caution in putting forward policy recommendations. Nevertheless, these effects indicate challenges to both the efficiency and the equity of the public inpatient system. From the equity perspective, the existence of an SES gradient in the use of public inpatient resources indicates that different segments of the Australian population have different use of inpatient resources beyond (accepted) variation in clinical conditions. On the efficiency side, allocation of resources among the hospitals, which is based on DRGs alone, penalizes hospitals, which serve low SES populations, since their expenditures are higher than expected by clinical case-mix. These results point to a SES-related heterogeneity within DRGs, which creates incentives to the hospitals to select against the high-cost population. This selection might be explicit or implicit and might lead to low quality of care and to the under provision of inpatient care.

From a policy perspective, these results indicate that the current allocation mechanism cannot solely provide the silver bullet for efficient and equitable hospital funding schemes. As all SES effects are statistically significant, the need to improve the allocation mechanism, and to include SES variables as risk adjusters together with the DRG traditional adjustment is conspicuous and requisite to achieve better health outcomes. Given that patients in the remote areas tend to use more of hospital resources, this finding supports the Federal government intention to fund remote hospitals on a separate (and not purely DRG based) block funding.

Data limitations force the analysis to be carried at the episode level omitting controls for any hospital- and individual- level fixed effects pushing all such time-invariant unobserved factors to the error term. Further, low SES categories could be under-represented in our dataset implying measurement error for admission episodes. From a statistical point of view, non-random measurement error problems (e.g. over- and under- reporting problems do occur similarly across the SES distribution) result in problematic regression estimates and marginal effects. From an economic perspective, if under-reporting is a feature of the system rather than the dataset, it would imply differential access to health care resources in the system or possible selection against high-cost patients. Unfortunately, this study cannot distinguish between the two but whatever the causes, such issues reinforce the message that caution is needed when putting forward policy recommendations based on non-causal estimates. Future research must look into the replication of such results and their generalizability in other contexts (i.e. mixed versus public health care systems) or countries (i.e. evaluation of different hospital reimbursement strategies). Most importantly, future work should focus on the causal evaluation of the contribution of patient SES characteristics towards resource utilization possibly using panel datasets and controlling for selection.

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**Table 1 Summary Statistics: Public Patients, Australian Hospitals, acute episodes, 2008**

| | **Same-Day discharge included** | | | **Overnight or Longer** | | |
|---|---|---|---|---|---|---|
| | N | Mean or %[a] | sd[a] | N | Mean or %[a] | sd[a] |
| ***Admission Characteristics*** | | | | | | |
| LOS (nights) | 3,648,764 | 2.36 | 5.00 | 1,748,405 | 4.92 | 6.28 |
| Same day discharge | 1,900,359 | 52.08 | | | | |
| DRG cost weight | 3,645,985 | 0.98 | 1.55 | 1,746,469 | 1.59 | 2.03 |
| *Min* | | *0.13* | | | *0.15* | |
| *Max* | | *46.05* | | | *46.05* | |
| ***Demographic Characteristics*** | | | | | | |
| Male | 1,732,271 | 47.48 | 49.94 | 775,824 | 44.37 | 49.68 |
| Age | | | | | | |
| <1 year old | 60,999 | 1.68 | | 41,605 | 2.40 | |
| 1-4 | 119,545 | 3.30 | | 68,609 | 3.96 | |
| 5-9 | 83,077 | 2.29 | | 43,099 | 2.49 | |
| 10-14 | 72,669 | 2.01 | | 41,234 | 2.38 | |
| 15-19 | 121,548 | 3.36 | | 70,699 | 4.08 | |
| 20-24 | 182,272 | 5.03 | | 108,019 | 6.23 | |
| 25-29 | 218,183 | 6.02 | | 129,745 | 7.49 | |
| 30-34 | 242,947 | 6.71 | | 138,647 | 8.00 | |
| 35-39 | 209,045 | 5.77 | | 104,061 | 6.01 | |
| 40-44 | 207,629 | 5.73 | | 90,364 | 5.22 | |
| 45-49 | 211,860 | 5.85 | | 85,038 | 4.91 | |
| 50-54 | 225,537 | 6.23 | | 85,400 | 4.93 | |
| 55-59 | 251,448 | 6.94 | | 93,115 | 5.37 | |
| 60-64 | 251,318 | 6.94 | | 95,263 | 5.50 | |
| 65+ | 1,164,776 | 32.15 | | 537,569 | 31.03 | |
| ***SES Characteristics*** | | | | | | |
| Aboriginal or Torres Strait Islander (ATSI) | 216,229 | 5.93 | 23.61 | 92,580 | 5.30 | 22.39 |
| Australian born | 2,586,036 | 70.87 | 45.43 | 1,288,552 | 73.70 | 44.03 |
| Major city | 2,234,616 | 61.68 | 48.62 | 1,018,782 | 58.81 | 49.22 |
| Inner region | 788,520 | 21.77 | 41.26 | 401,830 | 23.19 | 42.21 |
| Outer region | 454,422 | 12.54 | 33.12 | 235,524 | 13.59 | 34.27 |
| Remote region | 145,304 | 4.01 | 19.62 | 76,334 | 4.41 | 20.52 |
| One affected system | 2,299,070 | 63.01 | 48.28 | 796,558 | 45.56 | 49.80 |
| Two affected systems | 698,136 | 19.13 | 39.34 | 425,416 | 24.33 | 42.91 |
| Three+ affected sys. | 651,558 | 17.86 | 38.30 | 526,431 | 30.11 | 45.87 |
| Homeless & house problems | 6,159 | 0.17 | 4.11 | 5,139 | 0.29 | 0.00 |
| Low income | 7,321 | 0.20 | 4.47 | 6,379 | 0.36 | 6.03 |
| Unemployed | 2,740 | 0.08 | 2.74 | 2,323 | 0.13 | 3.64 |
| Total | 3,648,764 | | | 1,748,405 | | |

Notes:
[a] mean and standard deviation is reported for LOS and DRG cost weight; % of total sample observations for all other variables

**Table 2 Average Marginal and Total Average Marginal Effects**

| | Medical | | | | Base | | | | SES | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One-part modelling approach (1-PM) | Two-part modelling approach (2-PM) | | | 1-PM | 2-PM | | | 1-PM | 2-PM | | |
| | Total AME | Prob | LOS | Total AME | Total AME | Prob | LOS | Total AME | Total AME | Prob | LOS | Total AME |
| | | Eq-n | Eq-n | | | Eq-n | Eq-n | | | Eq-n | Eq-n | |
| | * In days | | | | * In days | | | | * In days | | | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Male | -0.295 | -0.271 | -0.175 | -0.209 | -0.300 | -0.028 | -0.173 | -0.213 | -0.307 | -0.028 | -0.183 | -0.215 |
| | (0.005) | (0.001) | (0.010) | (0.005) | (0.004) | (0.001) | (0.0101) | (0.005) | (0.004) | (0.001) | (0.010) | (0.005) |
| DRG cost weight | 0.261 | 0.382 | 0.255 | 1.987 | 0.260 | 0.373 | 0.255 | 1.942 | 0.260 | 0.372 | 0.258 | 1.969 |
| | (0.002) | (0.001) | (0.001) | (0.015) | (0.002) | (0.001) | (0.001) | (0.005) | (0.002) | (0.001) | (0.001) | (0.015) |
| 2 affected systems | 1.346 | 0.114 | 1.611 | 1.335 | 1.343 | 0.124 | 1.612 | 1.388 | 1.338 | 0.123 | 1.569 | 1.315 |
| | (0.005) | (0.001) | (0.013) | (0.028) | (0.004) | (0.001) | (0.013) | (0.028) | (0.005) | (0.001) | (0.0133) | (0.028) |
| 3 or more affected sys | 3.905 | 0.205 | 4.405 | 3.071 | 3.927 | 0.219 | 4.407 | 3.152 | 3.917 | 0.218 | 4.352 | 3.058 |
| | (0.0109) | (0.001) | (0.017) | (0.037) | (0.010) | (0.001) | (0.017) | (0.036) | (0.010) | (0.001) | (0.017) | (0.037) |
| Aboriginal or Torres Strait Islander (ATSI) | | | | | -0.616 | -0.040 | -0.282 | -0.332 | -0.632 | -0.041 | -0.329 | -0.344 |
| | | | | | (0.007) | (0.001) | (0.026) | (0.014) | (0.007) | (0.001) | (0.026) | (0.014) |
| Inner-region | | | | | 0.250 | 0.038 | -0.106 | 0.142 | 0.254 | 0.038 | -0.103 | 0.142 |
| | | | | | (0.006) | (0.001) | (0.012) | (0.006) | (0.0056 | (0.001) | (0.012) | (0.006) |
| Outer-region | | | | | 0.465 | 0.066 | -0.0395 | 0.305 | 0.472 | 0.066 | -0.0329 | 0.307 |
| | | | | | (0.007) | (0.001) | (0.015) | (0.008) | (0.007) | (0.001) | (0.0152) | (0.008) |
| Remote-region | | | | | 0.786 | 0.104 | 0.158 | 0.581 | 0.760 | 0.103 | 0.104 | 0.548 |
| | | | | | (0.013) | (0.001) | (0.030) | (0.015) | (0.013) | (0.001) | (0.0306) | (0.015) |
| Australian born | | | | | 0.079 | 0.005 | 0.0833 | 0.063 | 0.077 | 0.005 | 0.0803 | 0.060 |
| | | | | | (0.005) | (0.001) | (0.010) | (0.0052 | (0.005) | (0.0011) | (0.010) | (0.005) |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Homeless and house problems | | | | | | | | | 2.627 | 0.151 | 3.455 | 2.348 |
| | | | | | | | | | (0.086) | (0.007) | (0.200) | (0.100) |
| Low income | | | | | | | | | 2.326 | 0.187 | 2.745 | 2.200 |
| | | | | | | | | | (0.063) | (0.006) | (0.153) | (0.078) |
| Unemployed | | | | | | | | | 2.701 | 0.102 | 5.273 | 2.957 |
| | | | | | | | | | (0.125) | (0.010) | (0.329) | (0.160) |
| N (in 1000s) | 3,620 | 3,620 | 1,731 | 3,623 | 3,620 | 3,620 | 1,731 | 3,623 | 3,620 | 3,620 | 1,731 | 3,623 |
| δ | 5.4208 | | 5.6884 | | 5.4118 | | 5.6883 | | 5.3907 | | 5.6307 | |
| se(δ) | (0.010) | | (0.015) | | (0.010) | | (0.015) | | (0.010) | | (0.014) | |
| χ2 | 845,562 | 383,268 | 230,447 | | 861,312 | 414,224 | 230,087 | | 867,627 | 415,821 | 240,384 | |
| p-value | 0.000 | 0.000 | 0.000 | | 0.000 | 0.000 | 0.000 | | 0.000 | 0.000 | 0.000 | |
| AIC (in 1000s) | 12,244 | 3,143 | 7,971 | 11,115 | 12,227 | 3,126 | 7,971 | 11,097 | 12,220 | 3,124 | 7,968 | 11,093 |
| BIC (in 1000s) | 12,245 | 3,144 | 7,972 | 11,116 | 12,228 | 3,126 | 7,971 | 11,098 | 12,220 | 3,125 | 7,969 | 11,094 |
| Pseudo R2 | | 0.373 | | | | 0.376 | | | | 0.377 | | |
| No. of coefficients | 34 | 33 | 34 | 67 | 39 | 38 | 39 | 77 | 42 | 41 | 42 | 83 |

Notes:

- AME: Average marginal effects
- Number of observations for the four columns of each specification are: 3,620,044; 3,620,044; 1,730,513 and 3,622,862, respectively
- Standard errors are in brackets. Standard errors for total Average Marginal Effects (columns 4, 8 and 12) are obtained from bootstrapping (with 200 replications)