Cream skimming and hospital transfers in a mixed public-private system

Terence C. Cheng[a],John Haisken-DeNew[b], Jongsay Yong[b]

[a]School of Economics, University of Adelaide

[b]Melbourne Institute of Applied Economic and Social Research, University of Melbourne

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Abstract

The increasing prominence of the private sector in health care provision has generated considerable interest in understanding its implications on quality and cost. This paper investigates the phenomenon of cream skimming in a mixed public-private hospital setting using the novel approach of analysing hospital transfers.

We analyse hospital administrative data of patients with ischemic heart disease from the state of Victoria, Australia. The data set contains approximately 1.77 million admission episodes in 309 hospitals, of which 132 are public hospitals, and 177 private hospitals. We ask if patients transferred between public and private hospitals differ systematically in the severity and complexity of their medical conditions; and if so, whether utilisation also differs.

We find that patients with higher disease severity are more likely to be transferred from private to public hospitals whereas the opposite is true for patients transferred to private hospitals. We also find that patients transferred from private to public hospitals stayed longer and cost more than private-to-private transfer patients, after controlling for patients' observed health conditions and personal characteristics. Overall, the evidence is suggestive of the presence of cream skimming in the Victorian hospital system, although we cannot conclusively rule out other mechanisms that might influence hospital transfers.

Keywords: Australia; Hospital transfers; Cream skimming; Hospital utilisation; Mixed

public-private system

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- Cream skimming involves selecting patients with lower cost, or for higher profit
- We investigate cream skimming by analysing public and private hospital transfers
- Cream skimming implies specific transfer and resource utilisation patterns
- Patients with more severe conditions are more likely to transfer to public hospitals
- Hospital utilisation is higher for patients transferred to public hospitals

1 Introduction

The role of the private sector in the financing and provision of health care has received much attention in recent years, not least because of the rapid increase in health care costs and constraints on public budgets in many countries. The increasing prominence of the private sector has generated considerable interest in understanding its implications on health care quality and cost; see Barros and Siciliani (2012) for a recent review. A large international literature has investigated whether public and private hospitals differ in their behaviour. Studies in the United States for instance have sought to determine if there are differences in mortality and adverse events (e.g., complications, medical errors) among public, private non-profit and for-profit hospitals (Shen et al., 2007; Eggleston et al., 2008). Recent European studies have also examined if public and private hospitals differ in their efficiency (Barbetta et al., 2007; Herr, 2008; Marini et al., 2008).

In this paper we study an interesting aspect of the public and private interface in health care: the presence of "cream skimming" behaviour in the mixed public and private hospital system of Australia. Cream skimming involves the selection of patients with lower expected cost of treatment by hospitals and health care providers, which stand to gain financially by focusing on patients with less severe medical conditions. A number of reasons have been proposed on why providers may engage in cream skimming. Hospitals remunerated through activity-based funding, and hence receive a fixed price for a given diagnosis-related group (DRG), have the incentive to treat patients with lower

than average costs within the DRG (Ellis, 1998). This behaviour has been referred to as patient selection or "vertical" cream skimming, and is distinguished from "horizontal" cream skimming. The latter exists in the form of treatment selection whereby hospitals and doctors choose to specialise in the provision of certain medical treatments that are deemed profitable (Levaggi and Montefiori, 2003). Public hospitals in many countries, however, are often constrained by their role as the provider of subsidised care. In Australia, for example, public hospitals accept all patients; they are not allowed to turn away patients. Thus there is limited scope for public hospitals to engage in cream skimming.

Providers may also cream skim to achieve higher productive efficiency by focusing on easy to treat patients. Given a fixed capacity, hospitals will be able to treat more patients with less severe conditions and attain higher profits (Friesner and Rosenman, 2009). In health systems where private hospitals coexist with tax-funded public hospitals, cream skimming arises not just because of their different roles but also of differences in how workers in the public and private sectors are remunerated (González, 2005). Public hospital jobs are often salaried appointments and dual practising doctors can supplement their income with private practice which is often remunerated through fee-for-service, and usually more lucrative. The difference in remuneration, combined with long waiting times in the public system, create a situation where dual practice doctors have the incentive to divert easy to treat patients from public waiting lists to their private practice (Barros and Olivella, 2005; see also Biglaiser and Ma, 2007).

The empirical evidence of cream skimming is relatively thin. Duggan (2000), for example, exploits a policy change in Californian hospitals where the reimbursement of poor patients became more generous, and finds evidence that private non-profit and for-profit hospitals cream skim profitable patients, leaving unprofitable patients to public hospitals. In a UK study, Street et al. (2010) investigate whether patients treated in English public hospitals differ in complexity compared to those in treatment centres and find that patients in the former setting are more likely to be from deprived areas, have more diagnoses, and received significantly more medical procedures. Using Italian hospital data, Berta et al. (2010) quantify the extent of treatment selection by developing a cream skim index, and find that private hospitals cream skim at a much higher intensity than public or non-profit hospitals.

Over the past two decades, corporate involvement in the Australian hospital sector has gained prominence with the emergence of for-profit investor-owned hospitals becoming a key provider of hospital care. This is driven by a combination of pro-market policies on privatisation and contracting introduced by governments since the 1980s (Collyer and White, 2001), and the increased subsidisation of private health insurance in the late 1990s. The geographical boundaries of public and private domains of hospital care have also been blurring, with increasingly more private hospitals co-locating alongside public hospitals (Brown and Barnett, 2004). Co-location facilitates medical specialists to combine public sector work with private work (i.e., dual practice). As explained below, the intricate mix of public and private hospitals, combined with physician dual

practice, make the Australian hospital system a fertile ground to study cream skimming.

We study cream skimming behaviour by hospitals using the novel approach of analysing transfers between public and private hospitals. A hospital transfer occurs if the patient is discharged from one hospital and immediately admitted into another during a single episode of care. The presence of cream skimming implies specific transfer and resource utilisation patterns along two dimensions. Firstly, patients transferred from private to public hospitals are on average sicker and costlier to treat than patients transferred in the opposite direction. Secondly, for resource utilisation among transferred patients, those transferred from private to public hospitals would on average incur higher utilisation than patients transferred from one private hospital to another private hospitals, after controlling for patients' medical needs (e.g., disease categories) and personal attributes.

This paper seeks to answer two specific questions. First, we ask if there exist systematic differences in patient severity and complexity between private-to-public transfers and public-to-private transfers. Second, we examine the level of hospital utilisation of patients and asks if there exists systematic differences in the post-transfer utilisation pattern of two subsets of transfer patients: (i) utilisation of private-to-public transfers in comparison to that of private-to-private transfers; (ii) utilisation of public-to-private transfers in comparison to that of public-to-public transfers.

Previewing our results, we find that the probability of private-to-public transfers tends to increase with disease severity or complexity, while the opposite is true for public-to-

private transfers. On post-transfers resource utilisation, private-to-public transfers have significantly higher hospital utilisation than private-to-private transfers. This pattern of utilisation does not apply to public-to-private transfers. The observed patterns of transfers and utilisation are consistent with cream skimming behaviour by private hospitals. To our knowledge, this is the first study of cream skimming via examining data on hospital transfers.

This paper is structured as follows. Section 2 describes the institutional context in Australia, including the financing, service provision, and remuneration arrangements. Section 3 describes the data, and Section 4 the methods of investigation. The results are discussed in Section 5, along with robustness and sensitivity checks. The paper concludes with a summary of our main findings in Section 6.

2 Institutional context

Australia has a mixed public and private hospital system. Public hospitals are owned and managed by state governments, and are jointly funded by both state and federal governments. The latter provides approximately half of the funding for public hospitals in the form of block grants to state governments through the National Health Care Agreements which are negotiated every five years. In the state of Victoria on which this study is based, public hospitals are primarily funded via a case-mix payment scheme based on the Australian version of diagnostic-related groups (DRGs). Under this scheme,

each hospital admission episode is assigned a DRG code with an associated cost weight for the purpose of calculating the amount to be reimbursed. Given that public hospitals cannot turn away patients, this payment system forces public hospitals to strive for efficiency improvements, since inefficient operations would result in financial losses and reflect on the performance of the hospital management.

Private hospital are privately owned entities and operate mainly as for-profit and not-for-profit institutions. In 2012-13, private hospitals account for roughly 41 percent of all inpatient separations (or hospital discharges) and 65 percent of elective surgeries in Australia (Australian Institute of Health and Welfare, 2014). Private hospitals operate under a fee-for-service funding model, and derive their revenue predominantly from patients in the form of billings to private health insurance funds, and direct payments by self-funded patients. The cost of private hospital treatment is largely determined through negotiations between private hospitals and health funds; information on payment schedules are not publicly available due to commercial confidence. Anecdotally, private hospitals are increasingly paid in schemes similar to the DRG system. That is, each admission episode is categorised according to the disease class, treatment type and degree of severity or complexity. The payment for each category is by and large a function of the length of stay, with an upper limit beyond which payments will be scaled downward.

Roughly 45 per cent of the Australian population have supplementary private health in-

surance cover, which from 1999 onwards, has been heavily subsidised by the government. Doctors in private practice and private hospitals are free to charge patients according to what the market will bear, with a fixed subsidy payable from Medicare, Australia's tax-funded universal health insurance scheme.

With tight budget constraints, public hospitals have the incentive to encourage patients with private health insurance to elect to be treated as private patients. Doing so generates additional revenue for public hospitals, as it shifts cost onto private health funds, and to the federal government by obtaining fee-for-service payments from Medicare, which is funded from the federal budget. Both public and private hospitals increasingly compete for private patients. To encourage patients to use their private health insurance, a number of public hospitals has undertaken to pay for patients' out-of-pocket co-payments. In response, private hospitals have attempted to differentiate their products to attract patients. For example, a large private hospital group took unprecedented steps in 2011 to reveal its performance on patient outcomes such as infection rates in an attempt to attract private patients.

Australia's hospital system is an interesting environment to study cream skimming. Private hospitals, particularly for-profit institutions, have the incentive to attract patients with easy-to-treat conditions in order to maximise productive efficiency and hence profits. Perceived differences in the quality of care (e.g., waiting times, choice of doctor), reinforced through advertising campaigns, influence private hospital choice by patients

who require for instance elective (non-urgent) care for which public hospital waiting lists can be long. Public hospitals on the other hand are less likely to engage in cream skimming for several reasons. Firstly, public hospitals are required to accept all patients, although this does not rule out the transfer of patients from smaller less well equipped public hospitals to larger better equipped public hospitals. Secondly, public hospitals closures are uncommon, due to their political unpopularity. Historically, budget deficits in public hospitals have been dealt with by temporarily reducing resources (e.g., medical ward/bed closures, reduced staffing), and by reducing the amount of elective care (e.g., surgery). Third, compared to private hospitals, public hospitals operate within a more restrictive regulatory environment with numerous performance indicators. As such public hospital managers might be thought of minimising costs subject to revenue (quantity targets), quality (e.g. hospital acquired infection rates), and access (e.g. elective surgery waiting time) targets, rather than as revenue or profit maximisers.

The incentive for cream skimming is closely related to the policy on dual-practice doctors in public hospitals. Dual-practice medical specialists have the incentive to encourage patients in public hospitals, particularly those with medical conditions for which waiting times are long, to seek care in their private practice. Half of Australian specialists combine both public and private sector work (Cheng et al., 2013).

As described above, the mixed public and private system for hospital care in Australia creates both incentive and mechanism for dual-practice doctors and private hospitals

to engage in cream skimming. The next two section discuss the data and methods of investigation.

3 Data

The data are extracted from the Victorian Admitted Episodes Dataset (VAED), a hospital administrative database containing all hospital admission episodes in the state of Victoria. The database contains information at the level of admission episodes (known as "separations" in the data), and includes information on patient demographics such as age and gender, clinical details such as relevant diagnoses and comorbidity, administrative details such as the date of admission and discharge, and patient type (i.e., private or public).

The extracted data only contain episodes of all patients identified to have ischemic heart diseases (IHD) over the period 1998/99 to 2004/05. IHD is identified using the ICD-10 codes I20 through to I25. A patient is included in the sample if he or she had an IHD episode during the study period, and is known to have survived throughout the sample period, i.e., no death record is registered against the patient. It should be noted that the sample include all admission episodes of the patient, whether the episodes are IHD related or non-IHD admissions. We restrict our sample to patients with IHD as it is a common and widely studied disease.

We divide the data into two sub-samples according to whether the patient was initially

admitted as a public or private patient. Transfer cases are identified using information derived from the variable 'admission source'. This variable records patients' status prior to the commencement of the episode, and among other things shows if the patient was transferred from another hospital. For each sub-sample, we identify three types of transfer possibilities: (i) no transfer; (ii) transfers between the same hospital type (i.e., private-to-private or public-to-public transfers); (iii) transfers across hospital type (i.e., private-to-public and public-to-private transfers).

The sample contains approximately 1.77 million admission episodes in 309 hospitals, of which 132 are public hospitals, and 177 private hospitals. Public hospitals account for approximately 72 per cent of all admission episodes. The majority of episodes do not involve transfers, with 1,248,069 non-transfer public episodes, and 483,039 non-transfer private episodes. There are in total 37,736 transfer episodes. Same-type transfers form the majority (90 percent), with 11,926 private-to-private transfers and 22,021 public-to-public transfers. Cross-type transfers in the form of private-to-public and public-to-private transfers account for respectively 2,180 (5.8 percent) and 1,609 (4.2 percent) episodes.

It should be pointed out that although transfer cases are relatively rare, it does not follow that cream skimming is also rare. In fact, anecdotal evidence suggests that it is more common for patients to be turned away at private hospitals before admission, on the ground that they could be better cared for in public hospitals. These patients will

not appear in our data as transfers, since they were never admitted in private hospitals in the first instance. Hence the prevalence of cream skimming is likely understated in our sample.

4 Methods

4.1 Illness severity/complexity and transfer types

The empirical investigation consists of two parts. The first part investigates whether the probability of cross-type transfers is influenced by patient severity and complexity. The outcome variable of interest is the type of transfer conditional on hospital type at the initial admission. The three transfer types are "no transfer", "same-type transfer" and "cross-type transfer". Given the multinomial outcome, we use separate multinomial logit regressions for each initial admission hospital type. The base outcome is the type "no transfer". The key explanatory variable is the Charlson comorbidity index, which is often used as a measure of the severity and complexity of a patient's condition (Sundararajan et al., 2004). We control for other factors that potentially affect the probability of transfer by including covariates such as patients' personal (e.g., age and gender) and socioeconomic characteristics (e.g., marital status, SEIFA Advantage-disadvantage Index), geographical location (ARIA remoteness index), and measures of patients' medical conditions (e.g., DRG) and hospitalisation type (e.g., emergency department admission).

A summary of key variables used in the estimation is presented in Table 1. Patients in different transfer types differ in illness severity and complexity. Among patients initially admitted to private hospitals, those transferred to public hospitals had higher Charlson index, number of diagnoses, and are older compared with those transferred to other private hospitals. Conversely, among patients initially admitted to public hospitals, those transferred to private hospitals have lower Charlson index and the number of diagnoses compared with those transferred to public hospitals. In other words, patients in private-to-public transfers appear on average to be most severe and complex, while patients transferred in the other direction, i.e., from public to private hospitals, have the opposite pattern. Not surprisingly, non-transfer patients were noticeably lower in severity and complexity than transfer patients.

4.2 Utilisation in post-transfer episode

In the second part of the empirical investigation, we examine the differences in post-transfer hospital utilisation across different types of transfer patients. Hospital utilisation is measured in two ways, by (i) the length of stay, and (ii) cost weighted utilisation. Both are measured for the immediate post-transfer episode. Cost weighted utilisation is measured by an approximate dollar value based on the case-mix payment system used by the state government for the purpose of reimbursing public hospitals.

As discussed in Section 4.1, there are two types of transfer patients. The first is same-

type transfers, i.e., transfers between hospitals *within* the public or the private hospital system. The second is cross-type transfers, that is, transfers of patients *between* the public and private hospital systems. Both types of hospital transfers can arise when hospitals specialise in the treatment of different medical conditions and severities. For example hospitals in the Victorian health system is organised into local hospital networks containing one or more hospitals, usually defined by geography, community, or as a business group. Specialisation by public hospitals are also particularly common in metropolitan areas. Comprehensive public hospitals are generally found in urban centers, so are specialist hospitals such as women's and children's hospitals. In contrast public hospitals in regional and remote areas tend to be less comprehensive. Private hospitals do also specialise, for instance, in the treatment of low-cost diseases such as elective surgeries, and hence might transfer patients requiring more complex care to the public system. This is regarded as a form of cream skimming, and is referred to as treatment selection (Levaggi and Montefiori, 2003).

The presence of specialisation creates a situation where the technological possibilities of hospitals in the public and private systems are different, which can result in a pattern of hospital transfers that is consistent with cream skimming. To account for the effects of specialisation, we used matching methods to separate the analysis sample into two groups given patient type (public or private) in the initial hospitalisation episode. The objective of matching is to identify patients who are similar in terms of their medical conditions and other observable characteristics ('matched patients'), and those who are

dissimilar ('unmatched patients'). Because patients are matched based on a detailed set of variables describing their medical conditions (e.g. 3-digit DRG, DRG class) and their personal characteristics, conceptually we expect that matched patients have medical conditions for which both public and private hospital systems are equally capable of treating. In addition to matching, we further control for variations in resource utilisation from specialisation using an extensive set of covariates.

For matched patients, cream skimming takes the form of patient selection in that private hospitals select patients requiring low-cost care, while on the other hand transfer similar patients requiring high-cost care to public hospitals. Hence private-to-public transfer patients are expected to have higher utilisation than private-to-private transfer patients if private hospitals avoid serving patients with high degrees of severity or complexity. For unmatched patients, cream skimming takes the form of treatment selection in that private hospitals specialise in the treatment of diseases that require low-cost care. Therefore among patients of different medical conditions, public-to-private transfer patients are expected to have lower resource use compared with public-to-public transfer patients. The opposite result is expected for unmatched patients initially admitted to private hospitals.

For the matching, we employ a recently developed matching methodology known as coarsened exact matching (CEM); see Iacus et al. (2011; 2012); Stata implementation of the algorithm is described in Blackwell et al. (2009). The covariates used in matching

are as follows: age, gender, Charlson comorbidity index, number of diagnoses, number of procedures, same-day separation dummy, DRG Class dummies, ED admission dummy, and 14 disease groups constructed using three-digit DRGs. All covariates are taken from the pre-transfer episode.

We investigate differences in resource utilisation by estimating ordinary least squares regressions, separately for the matched and unmatched samples where the dependent variables are the logarithms of length of stay and cost weighted utilisation. The key explanatory variable of interest is the transfer type binary variables. Another variable of interest is the DRG Class designation. The DRG classification is a four-digit classification system under which the fourth digit is an alphabetical designation of "A," "B," "C," or "Z." Class A indicates catastrophic or severe complication or comorbidity, while B and C indicate respectively lesser and no complication or comorbidity, and Z denotes a miscellaneous class. However, not all DRG codes have a "C" or "Z" designation, and for these cases usually class "B" designates no complication or comorbidity. To further control for patient heterogeneity, covariates such as age, gender, Charlson comorbidity index, number of diagnoses and procedures are also included in the utilisation regressions. The set of explanatory variables are taken from the post-transfer episode.

Table 2 presents the means and standard deviations of resource use and the frequency count of DRG classes by transfer groups. Summary statistics from Panel A indicate that regardless of hospital type in the initial admission, patients transferred to public hos-

pitals have higher resource use compared to those transferred to private hospitals. For instance, private-to-public transfer patients have higher levels of length of stay and cost weighted utilisation (26 days and A$12,046) compared to private-to-private transfers (14 days and A$9,207). Public-to-private transfer patients have lower levels of resource utilisation compared with public-to-public transfer patients. Panel B shows that a higher proportion of transfers to public hospitals involve patients with catastrophic complications. For example, the percentage of class A DRGs for private-to-public transfer patients is 42.7 per cent, as compared to 38.4 per cent for private-to-private transfer patients.

5 Results

5.1 Predicted probability of transfer types

As mentioned in section 4.1, we estimate separate multinomial logit regressions of hospital transfer types for each patient type at the initial admission. The average predicted probability of cross-type transfers, and marginal effects given an incremental change of the Charlson index are given in Table 3. The full regression estimates are shown in Table S1 in the online supplementary material. [Insert link to online supplementary file A]

The estimates in Table 3 indicate that patients with more severe medical conditions are more likely to be transferred from private to public hospitals. The average predicted

probability of a private-to-public transfer is increasing with the Charlson index, rising from 0.0036 to 0.0044 and then 0.0066 as the Charlson index increases from 0 to 1 or 2, and to 3 or greater. The corresponding marginal effects, computed as the change in the predicted probabilities, are 0.0008 and 0.0030, and both are highly statistically significant. The estimates, though appearing to be small in magnitude, are economically significant. To put these figures in perspective, the marginal effect of varying the Charlson index from 1 or 2 to 3 or above is roughly the same as the effect of varying the age of a patient from 50 to 80 years.

In contrast, patients with more severe medical conditions are less likely to be transferred from public to private hospitals. From Table 3, the average predicted probabilities are *decreasing* with the Charlson index, falling from 0.0015 to 0.0012 and then to 0.0011. The marginal effects, i.e., the decreases in probabilities, are highly statistically significant. Hence the probability of a patient transferred from private to public hospitals increases as the patient's severity and complexity rises, whereas the opposite is true for patients transferred from public to private hospitals. These results taken together suggest a pattern that is consistent with cream skimming by private hospitals. However, our results do not rule out alternative hypotheses to cream skimming, such as private hospitals choosing different areas of specialisation from public hospitals.

5.2 Post transfer resource utilisation

We next examine the utilisation of different groups of transferred patients on the premise that cream skimming is reflected in the utilisation pattern. However, patients in different disease groups and of different severity or complexity are expected to have different levels of utilisation. We control for heterogeneity in severity and complexity by making use of the rich diagnostic and clinical information in the data. For this purpose, in addition to the usual variables such as age and gender, we also include the Charlson co-morbidity index, number of diagnoses, number of procedures performed, same-day separation, DRG classification, ED admission dummy, and hospitals' lagged IHD volume as covariates.

As described in Section 4.2, we first match cross-type transfer patients to the corresponding same-type transfers (i.e., private-to-public transfers are matched with private-to-private transfers; public-to-private transfers are matched to public-to-public transfers) using CEM matching. The matching outcomes are summarised in Table 4. Of the 2,180 private-to-public transfer patients, 1,340 patients or 61 per cent have found a match, 840 patients or 39 per cent could not be matched; the former were matched to 3,130 out of 11,926 private-to-private transfer patients. Similarly, of the 1,609 public-to-private transfer patients, 1,233 or 77 per cent could be matched, 376 or 23 per cent could not find a match; the former were matched to 6,030 public-to-public transfer patients. Matched patients are patients with similar attributes, notably of similar illness severity or complexity, hence cream skimming, if present, would take the form of patient selection.

Unmatched patients have different patient characteristics, hence cream skimming, if it occurs, would take the form of treatment selection.

Selected estimates of the regression results on the utilisation of unmatched patients are presented in Table 5. The results indicate that private-to-public transfer patients' stayed 21.8 per cent longer and incurred 11.2 per cent higher level of cost-weighted utilisation than patients in private-to-private transfers and both are statistically significant at the one per cent significance level. In contrast, patients in public-to-private transfers had similar length of stay and 8.2 per cent lower cost-weighted utilisation than patients in public-to-public transfers. This pattern of utilisation is consistent with cream skimming in the form of treatment selection—patients transferred from private to public hospitals registered higher utilisation than the corresponding private-to-private transfers, while transfers in the other direction register no difference in length of stay and lower cost.

For matched patients, the estimates in Table 6 show that private-to-public transfer patients have higher levels of utilisation than their private-to-private counterparts—patients in private-to-public transfers stayed in hospitals 16.5 per cent longer and had 7.3 per cent higher cost-weighted utilisation than patients in private-to-private transfers. In contrast, public-to-private transfer patients have 5.8 per cent shorter length of stay and marginally lower levels of cost-weighted utilisation compared with patients in public-to-public transfers.

The above results from matched patients suggest that, even among patients with similar

ailments and attributes, those in private-to-public transfers incurred on average longer stay and higher costs than those in private-to-private transfers. Thus private hospitals appear to engage in patient selection by retaining patients who were low in severity and complexity and transferring those with high care needs to the public sector. This selection is likely based on illness severity or complexity not captured by covariates in the regressions.

5.3 Further examination using DRG classification

We hypothesize that patient selection will be more prevalent among patients with more severe complication or comorbidity than otherwise. To investigate this, we introduce into the regression a series of dummy variables that represent patients' DRG classes using the four-digit DRG classification system where class A typically indicates catastrophic or severe complication or comorbidity. We extend the regression model shown in Table 6 to include interaction terms involving DRG class A and B dummies, with the other classes (C and Z) serving as the reference.

$$\begin{aligned} use_i =& \beta_0 + \beta_1 prv\_pub_i + \beta_2 DRG\_Cls\_A_i + \beta_3 DRG\_Cls\_B_i + \\ & \beta_{12} prv\_pub \times DRG\_Cls\_A_i + \beta_{13} prv\_pub \times DRG\_Cls\_B_i + \gamma Z_i + \epsilon. \end{aligned}$$

The interaction coefficients, β_{12} and β_{13}, capture the effect of patient selection for classes A and B DRGs respectively. If cream skimming is present, we expect hospitals and doc-

tors to engage in more stringent patient selection in class A DRGs than in other DRGs, thus the interaction coefficient on class A DRGs is expected to be positive and statistically significant while the coefficient on class B is not. The results, presented in Table 7, show that the interaction coefficient on class A DRGs is positive and statistically significant at five and ten per cent levels respectively for length of stay and cost-weighted utilisation. In contrast, the interaction coefficient on class B DRGs is not statistically significant. This is thus further evidence that private hospitals engage in patient selection, especially on patients diagnosed with severe complication or comorbidity.

5.4 Efficiency differences

Our finding that private-to-public transfer patients had higher levels of utilisation could be due to the efficiency difference between public and private hospitals, i.e., if private hospitals are more efficient than public hospitals (Siciliani et al., 2013). To determine the extent to which efficiency differences are driving our results, we investigate if resource utilisation is different in public and private hospitals. To do so, we focus on admission episodes not involving any transfers and match patients of private and public hospitals on their clinical and personal attributes using CEM. The matching variables used are similar to those described in Section 4.2. We estimate the following log-linear utilisation model using data from the matched non-transfer patients:

$$\log(use)_i = \lambda_0 + \lambda_1 Private_i + \sum_k \delta_k DRG\ dummies_{ik} + \epsilon_i.$$

A priori, the coefficient λ_1 would be negative if private hospitals were indeed more efficient than public hospitals. This is however not the case. As shown in Table 8 there is no difference in utilisation between patients of private and public hospitals, whether utilisation is measured by length of stay or cost-weighted utilisation. Thus the efficiency difference between private and public hospitals is not likely to be driving the differences in resource use of different transfer types.

5.5 Robustness

We have investigated the robustness of our results against a number of alternative specifications. First, as an alternative to the estimation of the multinomial logit estimation presented in Table 3, we have used the number of diagnoses as an alternative measure of illness severity and complexity. As shown in Table A1 in Appendix A, our results remain unchanged.

Second, our results on hospital utilisation are robust against several alternatives on how the sample is constructed. Specifically, the same qualitative results are obtained whether we exclude private patients in public hospitals and whether we exclude patients admitted through the emergency department in the sample. These results are presented in Tables A2 and A3 in Appendix A.

6 Conclusion

This paper investigates the presence of cream skimming behaviour using the novel approach of analysing hospital transfers. Driven by the profit motive, private hospitals have an incentive to transfer patients with severe or complex conditions to public hospitals. Moreover, dual-practice doctors who work in both public and private hospitals have an incentive to transfer less severe and complex patients from the public to private hospitals, where doctors are able to charge higher fees than in the public sector.

Using administrative data from the state of Victoria, Australia, we examine whether patients transferred between public and private hospitals differ systematically in the severity and complexity of their medical conditions. We find that patients with higher disease severity are more likely to be transferred from private to public hospitals, whereas the opposite is true for patients transferred to private hospitals. We also find that patients transferred from private to public hospitals stayed longer and cost more than private-to-private transfer patients, after controlling for patients' observed health conditions and personal characteristics. The observed patterns of transfers and utilisation are consistent with cream skimming behaviour by private hospitals. This paper is, to our knowledge, the first empirical investigation of cream skimming using hospital transfers.

The lack of supply-side information, particularly on private hospitals and their pricing and costing, is a key limitation of the study. Unfortunately this data limitation cannot be circumvented; our data access agreement explicitly prohibits identifying private hos-

pitals (hospitals are de-identified with random identifers), and linkage to other external data sources is not permitted. Thus attempting to identify cream skimming by using pricing and costing data of private hospital providers is not possible. Anecdotal evidence suggests that although the pricing between private hospitals and health insurance funds varies, it broadly follow the casemix funding principle. These provide incentives for private hospitals to cream skim less complex and severe patients. A related consideration is the effective use of hospital beds—given that capacity is limited, turning over patients by treating those with less complex or severe conditions is usually an effective use of capacity.

While the study has been carefully designed to isolate and identify the effects of cream skimming behaviour, it is important to highlight that the study cannot conclusively rule out other mechanisms that might influence hospital transfers. Indeed, hospital transfers can occur for a variety of reasons other than the intent to cream skim. For example, hospitals may have reached full capacity and hence transfer patients to other hospitals. In addition, patients could also initiate transfers, perhaps due to preferences for hospital location, doctors, and facilities. However, in these situations one has no reason to expect that transfers are correlated with patient severity and complexity.

It is also possible that transfers from private hospitals occur because these hospitals are not as well equipped or staffed in medical specialties as public hospitals, such that patients with complex needs may best be cared for in public hospitals. Observationally,

the relationship between illness severity and the occurrence of transfers of this nature is similar to that expected under cream skimming. However, this still begs the question of why private hospitals are less well equipped or staffed than public hospitals. One may ask why private hospitals specialise in treating less sick patients. If, as set out in the theory model of Levaggi and Montefiori (2003), specialisation is a choice made by hospitals through e.g., investment in equipment and personnel, then it can be argued that this behaviour is a manifestation of cream skimming behaviour.

In conclusion, the overall evidence is suggestive of the presence of cream skimming in the Victorian hospital system. This has implications on the financing and operations of public hospitals. In particular, the practice of cream skimming by private hospitals implies that public hospitals will be saddled with difficult and high-cost patients, who are adding strain on an increasingly limited budget. The practice of cream skimming also calls into question the subsidisation of duplicate private health insurance coverage in Australia, and other policy issues such as physician dual-practice and the partial financing of treatment in private hospitals through the public budget.

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Table 1: Sample characteristics by hospital transfer types

	Initial admission: Private			Initial admission: Public		
Variable	No transfer	To Private	To Public	No transfer	To Public	To Private
Charlson index	0.86	1.13	1.50	1.25	1.45	1.68
No. of diagnoses	3.21	6.01	7.39	3.34	6.87	7.92
Same-day separation	0.50	0.02	0.03	0.63	0.03	0.02
ICU hours	2.23	21.20	22.64	2.43	27.06	31.20
Age	70.34	75.84	78.48	67.30	75.04	74.95
Male	0.58	0.44	0.39	0.61	0.48	0.46
Aria remoteness index (quintile)	1.56	1.58	1.75	1.77	1.84	1.83
SEIFA adv.-disadv. index (decile)	7.25	7.44	6.96	5.93	6.65	5.96
N	483,039	11,926	2,180	1,248,069	1,609	22,021

Note: Hospital transfer types are identified using information from the field 'admission source' in the administrative data. There are three transfer types for each hospital type at initial admission (public or private): "no transfer", "same transfer" and "cross transfer".

Table 2: Summary statistics of resource utilisation and frequency of DRG classes by transfer types

	Initial admissions			
	Private		Public	
Variable	To Public	To Private	To Public	To Private
Panel A: Means and standard deviation of utilisation				
Utilisation–LOS	25.9	14.1	22.7	17.1
std. dev.	26.5	15.3	24.3	17.8
Utilisation–Cost weighted	12,046.2	9,206.7	11,274.6	10,645.0
std. dev.	14,143.5	8,084.7	10,520.1	9,950.3
Panel B: Frequency count of DRG classes				
DRG Class A	930	4,579	10,612	741
per cent	42.7	38.4	48.2	46.1
DRG Class B	725	4,962	7,363	611
per cent	33.3	41.6	33.4	38.0
DRG Class C or Z	525	2,385	4,046	257
per cent	24.0	20.0	18.4	16.0

Note: Class A indicates catastrophic or severe complication or comorbidity; Classes B and C indicate respectively lesser and no complication or comorbidity; Z denotes a miscellaneous class. These class designations are taken from the post-transfer episode.

Table 3: Estimates of average predicted probability of cross-type transfers, and marginal effects by Charlson index

	Average predicted probability	s.e.	Marginal effects	s.e. s.e.
Private-to-public transfers				
Charlson index $= 0$	0.0036**	0.00013	–	–
Charlson index $= 1, 2$	0.0044**	0.00015	0.0008**	.00021
Charlson index ≥ 3	0.0066**	0.00033	0.0030**	.00038
Public-to-private transfers				
Charlson index $= 0$	0.0015**	0.00007	–	–
Charlson index $= 1, 2$	0.0012**	0.00005	-0.0003**	0.00009
Charlson index ≥ 3	0.0011**	0.00007	-0.0004**	0.00011

Note: Average predicted probabilities are computed from estimated multinomial logit model with three outcomes: no transfer, transfer to hospital of the same type, transfer to hospital of a different type; covariates include: age, gender, marital status, area characteristics, same-day separation dummy, ED admission dummy, DRG class dummies, and three-digit DRG dummies are fixed at their sample means. Marginal effects are computed as the discrete change in the average predicted probabilities as the Charlson index is varied with reference to the first category while holding all other covariates at their sample means. Standard errors are obtained via delta method.

Significance levels: †: 10% *: 5% **: 1%

Table 4: Coarsened exact matching summary

	Private admissions		Public admissions	
	to private (control)	to public (treatment)	to public (control)	to private (treatment)
All	11,926	2,180	22,021	1,609
Matched	3,130	1,340	6,030	1,233
Unmatched	8,796	840	15,991	376

Note: Matched by pre-transfer variables: Charlson co-morbidity index, no. of diagnoses, no. of procedures, same-day separation, ICU stay, emergency admission,. age, male, disease groups

Table 5: Utilisation of unmatched transferred patients, selected coefficients, log-linear regressions

	Dependent variable	
	log(LOS)	*log(COST)*
	Initial admission private	
Private to public	0.218**	0.112**
s.e.	0.028	0.022
(Ref: private to private)		
N	8,389	8,388
	Initial admission public	
Public to private	-0.086	-0.082*
s.e.	0.047	0.036
(Ref: public to public)		
N	14,182	14,181

Note: Covariates used in regression are Charlson index, no. of diagnoses, no. of procedures, same-day dummy, admitted via ED, age, gender, marital status, Aria remoteness index, SEIFA adv-disadv index, lagged IHD volume, DRG class A dummy, DRG dummies (2-digit); all covariates are post-transfer variables.

Significance levels: †: 10% *: 5% **: 1%

Table 6: Utilisation of matched transferred patients, selected coefficients, log-linear regressions

	Dependent variable	
	log(LOS)	*log(COST)*
	Initial admission private	
Private to public	0.165**	0.073**
s.e.	0.028	0.022
(Ref: private to private)		
N	3,903	3,903
	Initial admission public	
Public to private	-0.058*	-0.030
s.e.	0.029	0.022
(Ref: public to public)		
N	6,507	6,507

Note: Covariates used in regression are Charlson index, no. of diagnoses, no. of procedures, same-day dummy, admitted via ED, age, gender, marital status, Aria remoteness index, SEIFA adv-disadv index, lagged IHD volume, DRG class dummies, DRG dummies (2-digit); all covariates are post-transfer variables.

Significance levels: †: 10% *: 5% **: 1%

Table 7: Utilisation of matched transferred private patients, log-linear regressions with interaction terms, selected estimates

	Initial admission private			
	log(LOS)		*log(COST)*	
	Coeff.	s.e.	Coeff.	s.e.
prv_pub	-0.038	0.110	-0.097	0.089
(Ref: *prv_prv*)				
DRG CLS A	0.006	0.091	0.088	0.073
DRG CLS B	-0.128	0.091	-0.145*	0.073
(Ref: *DRG CLS C, Z*)				
prv_pub × *DRG Cls A*	0.226*	0.114	0.181*	0.092
prv_pub × *DRG Cls B*	0.190	0.119	0.175†	0.096
N	3,903		3,903	

Note: Additional covariates include: Charlson index, no. of diagnoses, no. of procedures, same-day dummy, admitted via ED, age, gender, marital status, SEIFA adv-disadv index, lagged IHD volume, DRG dummies (2-digit).

Significance levels: †: 10% *: 5% **: 1%

Table 8: Resource utilisation and efficiency differences in public and private hospitals

	Coeff.	Std. err.
Dep var = log(*LOS*)		
Private	0.004	0.016
(Ref: *Public*)		
Dep var = log(*Cost*)		
Private	0.026	0.019
(Ref: *Public*)		
N	917,342	

Note: Included are covariates are 79 two-digit DRG dummies.

A Appendix

Table A1: Multinomial logit estimation with no. of diagnoses as explanatory variables, marginal effect estimates

	Average predicted probability	s.e.	Marginal effects	s.e. s.e.
Private-to-public transfers				
No. diagnoses ≤ 2	0.0020**	0.0001	–	–
No. diagnoses $= 3, 4$	0.0031**	0.0002	0.0011**	0.00021
No. diagnoses $= 5, 6$	0.0043**	0.0002	0.0022**	0.00025
No. diagnoses $=$ 7 to 10	0.0061**	0.0003	0.0041**	0.00032
No. diagnoses ≥ 11	0.0107**	0.0006	0.0087**	0.00064
Public-to-private transfers				
No. diagnoses ≤ 2	0.0010**	0.00009	–	–
No. diagnoses $= 3, 4$	0.0013**	0.00007	0.0003*	0.00010
No. diagnoses $= 5, 6$	0.0012**	0.00006	0.0002†	0.00011
No. diagnoses $=$ 7 to 10	0.0013**	0.00006	0.0002*	0.00011
No. diagnoses ≥ 11	0.0018**	0.00012	0.0007**	0.00016

Average predicted probabilities are computed from estimated multinomial logit model with three outcomes: no transfer, transfer to hospital of the same type, transfer to hospital of a different type; covariates include: age, gender, marital status, area characteristics, same-day separation dummy, ED admission dummy, DRG class dummies, and three-digit DRG dummies are fixed at their sample means.

Significance levels: †: 10% *: 5% **: 1%

Table A2: Utilisation of matched transferred patients (excluding private patients in public hospitals), selected coefficients, log-linear regressions

	Dependent variable	
	log(LOS)	*log(COST)*
	Initial admission private	
Private to public	0.248**	0.153**
s.e.	0.033	0.027
(Ref: private to private)		
N	2,615	2,615
	Initial admission public	
Public to private	-0.058*	-0.030
s.e.	0.029	0.022
(Ref: public to public)		
N	6,507	6,507

Covariates used in regression are Charlson index, no. of diagnoses, no. of procedures, same-day dummy, admitted via ED, age, gender, marital status, Aria remoteness index, SEIFA adv-disadv index, lagged IHD volume, DRG class dummies, DRG dummies (2-digit); all covariates are post-transfer variables.

Significance levels: †: 10% *: 5% **: 1%

Table A3: Utilisation of matched transferred patients (excluding admissions via ED), selected coefficients, log-linear regressions

	Dependent variable	
	log(LOS)	*log(COST)*
	Initial admission private	
Private to public	0.225**	0.131**
s.e.	0.034	0.027
(Ref: private to private)		
N	2,632	2,632
	Initial admission public	
Public to private	0.040	0.025
s.e.	0.111	0.090
(Ref: public to public)		
N	416	416

Covariates used in regression are Charlson index, no. of diagnoses, no. of procedures, same-day dummy, admitted via ED, age, gender, marital status, Aria remoteness index, SEIFA adv-disadv index, lagged IHD volume, DRG class dummies, DRG dummies (2-digit); all covariates are post-transfer variables.

Significance levels: †: 10% *: 5% **: 1%

Supporting Materials

Table S1: Multinomial Logit Regression Coefficients and Marginal Effect Estimates

	Private-to-public transfers Base: no transfer		Public-to-private transfers Base: no transfer	
	Coeff.	M.E.	Coeff.	M.E.
Charlson index category 1 (index = 1,2)	0.2269**	0.0008	-0.2343**	0.0005
	(0.0553)	(0.0002)	(0.0672)	(0.0005)
Charlson index category 2 (index $\geq$ 3)	0.6754**	0.0030	-0.2577**	0.0030
	(0.0713)	(0.0004)	(0.0859)	(0.0008)
(Ref: Charlson index = 0)				
Same-day separation	-1.1538**	-0.0028	-2.1718**	-0.0199
	(0.1421)	(0.0003)	(0.1725)	(0.0005)
Admitted via ED	0.5168**	0.0023	0.6391**	-0.00001
	(0.0516)	(0.0003)	(0.0840)	(0.0005)
DRG class A	0.9113**	0.0038	0.5717**	0.0126
	(0.0833)	(0.0005)	(0.1212)	(0.0010)
DRG Class B	0.1799*	0.0006	0.2007†	0.0028
	(0.0786)	(0.0003)	(0.1174)	(0.0008)
Age	0.0404**	0.0001	0.0243**	0.0005
	(0.0026)	(0.00001)	(0.0025)	(0.00002)
Male	-0.3178**	-0.0011	-0.2275**	-0.0068
	(0.0499)	(0.0002)	(0.0548)	(0.0004)
Divorced	-0.3134**	-0.0010	-0.6582**	-0.0036
	(0.0840)	(0.0003)	(0.1013)	(0.0007)
Married	-0.1416**	-0.0006	0.6052**	-0.00006
	(0.0507)	(0.0002)	(0.0564)	(0.0005)
Aria Remoteness index (quintile)	-0.0851**	-0.0003	0.1539**	-0.0004
	(0.0259)	(0.0001)	(0.0248)	(0.0002)
SEIFA adv.-disadv. index (decile)	-0.0497**	-0.0002	0.1012**	0.0004
	(0.0096)	(0.00004)	(0.0111)	(0.00009)
No. private hospitals within 5 km	-0.0062**	-0.00003	0.0091**	0.00003
	(0.0011)	(0.000005)	(0.0021)	(0.00001)
Specialisation (prop. IHD to all separations)	12.1392**	0.0391	18.9165**	0.2896
	(0.4232)	(0.0018)	(0.4623)	(0.0042)
Intercept	-7.7294**	–	-9.6695**	–
	(0.2341)	–	(0.2567)	–

Also included as covariates in the regression are 62 two-digit DRG dummies.
Figures in parentheses are standard errors; standard errors of marginal effects are obtained via delta method.
Significance levels: †: 10% *: 5% **: 1%