# Performance measures, reimbursement and behaviour of public health care providers in New Zealand

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# Abstract

This dissertation contains three empirical studies that examine the performance measures, reimbursement and behaviour of New Zealand public health care providers, the district health boards (DHBs).

The first essay investigates whether highly skilled health care providers are at a disadvantage because they attract difficult cases, by examining over 10 million publicly funded patient discharges in New Zealand during the period from 1999 to 2011. Using a patient's transfer status and the complexity and comorbidity level (CCL) indicator as the measure of task difficulty, I calculate the effects of task difficulty on performance indicators such as the length of hospital stay, and the probabilities of 30-day mortality and readmission while controlling for potential endogeneity. The results confirm that this disadvantage does exist. Transferred patients stay in hospital longer, and have higher probabilities of 30-day mortality and 30-day readmission. Overall, patients assigned to higher level of complexity and comorbidity indicators also have longer hospital stays and higher probabilities of mortality and readmission.

The second essay examines how the public health care providers in New Zealand responded to the system reform that reintroduced a capitation scheme, which pays providers a fixed amount per enrollee, regardless of the actual service usage per enrollee. I find that the new capitation scheme decreased the movement of patients between districts, especially those whose conditions are more severe. The results indicate that sicker patients are less likely to be treated by specialist providers since the reform. Overall, the decrease in inter-district movement seems to have negative effects on health outcomes.

The third essay examines the capitation funding system for New Zealand public health care providers, which allocates funds across districts based on the characteristics of district population. As the first step in understanding the adequacy of this payment system, this research examines how the actual usage by patients is associated with the funding, which is computed based on the characteristics of population. To examine the relation, I regress the government funding received by the DHBs on the characteristics of the population who actually received treatment over the period of 2003 to 2011. I find that the usage of health care services by certain population groups is higher than their population share.

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I dedicate this dissertation to Mom, Dad, my sister and Jeff.

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# Chapter 1 Introduction

## 1.1 Introduction

This dissertation studies the performance measures and reimbursement system of public health care providers in New Zealand and examines whether there are differences in the response to the payment system change between highly skilled and low skilled providers. Providing the correct incentives to induce the optimal performance of the participants is a difficult task for any organisation, especially for health care providers, as a life is at stake.

As Arrow (1963) discusses in his seminal work, the medical care market shows characteristics different from a competitive market. The main reason for the differences is the existence of uncertainty in regards to the occurrence and treatment of disease. There is greater informational inequality between the buyer and seller in the medical care market than in a competitive market. Due to this uncertainty, competitive markets may generate an inefficient allocation of resources, while non-market means may improve the efficiency of the medical care market. This explains the prevalence of the public provision of health care in many countries.

In the past, the public health sector around the world reimbursed care providers based on the costs incurred during the treatment of patients. Faced with rising health expenditure, however, many countries including New Zealand have switched the payment methods to the prospective payment system, which pays health care providers based on the average costs across all providers. A concern surrounding such a system is that the quality of health care may deteriorate because the providers receive a fixed payment regardless of the actual costs incurred. Another problem is that providers may selectively treat more profitable patients. For example, Ellis (1998) shows that a prospective payment system leads providers to undersupply services to more seriously ill patients and to even avoid these patients. Sometimes, a change within the fixed payment system also results in undesirable responses from providers. Dafny (2005) shows that, after a change in the diagnosis-related group (DRG) prices in 1988 in the U.S., hospitals upcoded patients to diagnosis codes with the largest price increases.

As important as the efficient provision of health care is, maintaining high quality care and ensuring access to care for those in need should also be the key objectives of the public health sector. A payment system that provides the correct incentives to the health care provider plays a pivotal role in achieving those objectives. In the New Zealand health care system, access to health care services for its citizens and permanent residents is less of a problem, because public hospitals in general are not able to select which patients to treat. However, ensuring the quality of care, while keeping costs low is still an issue. In particular, under the fixed payment system, it may be harder to provide the correct incentives and compensation for those providing more complex services, such as specialist hospitals. In other markets, the seller of high quality products may be able to demand higher prices. In a market where consumers do not directly pay for the services and the reimbursement providers receive is based on the average costs across all health care facilities, the quality of care the specialist hospitals provide may, however, decline if they do not receive some type of reward.

This dissertation contains three essays. The first essay aims to answer the question of whether highly skilled providers are at a disadvantage due to their expertise; as they possess more complex skills, they receive cases that are more difficult, however, more difficult cases take more effort and time to treat, while having a higher probability of failure. This essay investigates the effects of task difficulty on performance measures, while controlling for potential endogeneity problems between the task difficulty and performance measures. The second essay of the dissertation investigates the response of health care providers in New Zealand to the system reform in 2003, which reintroduced capitation. Under the capitation system, the funder pays providers based on the number of people enrolled to use their services, regardless of the actual usage by the enrolled people. I examine whether the system reform has varying effects on providers with different skill levels and whether it has any effects on health outcomes. Lastly, the third essay examines how the actual usage of health care services by patients is associated with the payment received by providers under the capitation system, which is computed based on the characteristics of population. In addition, I examine the levels of funding for providers treating complex cases under the current funding system.

### 1.2 Contribution to the literature

The general contribution of this dissertation is to provide a comprehensive analysis of the performance and reimbursement of health care providers that have different skill levels, using a rich dataset that includes all the publicly funded health care events in New Zealand over the 12-year period. The number of total observations in the dataset exceeds 10 million discharges and 3 million patients. The publicly funded health care events comprise nearly 80 percent of the total admissions in New Zealand. Therefore, my findings are not specific to certain diseases and facilities, but are more generally applicable across the sector. Below I discuss the contribution of each essay.

### 1.2.1 Expertise: Is it a gift or curse? Evidence from the health care sector

In the first essay, I examine the effects of case complexity as measured by the transfer status and complications/comorbidity levels on the performance measures commonly used in practice; length of stay in hospital, 30-day mortality, and 30-day readmission. The findings of the essay show that overall there are negative effects of complex cases on these performance measures. To my knowledge, this is the first study that addresses the issue of potential simultaneity bias between the complexity indicators and performance measures. The findings that transfer increases the length of hospital stay, mortality and readmission are prone to simultaneity bias, as a hospital that initially receives patients may transfer them to another provider because it anticipates a longer length of stay and/or higher probabilities of mortality and readmission. Therefore, the positive relations found in the previous literature between transfer or other indicators of the severity of illness, and performance measures[1] may simply reflect the simultaneity bias.

In this essay, I use the Instrumental Variable (IV) approach to accurately measure the effects of complex cases on performance measures. As instruments, I use the exogenous variation of transfer due to variation on the number of people eligible for the publicly funded health care, which is the focus of this study. The change in the eligibility is measured by the change in the level of net permanent migration. The increase in transfer due to the increase in the number of people eligible for public health care is exogenous, since the health status of the net immigrants is, on average, similar to the people already

[1] See, for example, Bernard, Hayward, Rosevear, Chun and McMahon (1996), Combes, Luyt, Trouillet, Chastre and Gibert (2005), Gordon and Rosenthal (1996) and Rosenberg, Hofer, Strachan, Watts and Hayward (2003).

living in New Zealand. The results from the IV models suggest that endogeneity is not an issue in the regressions on the length of stay, mortality and readmission.

### 1.2.2 Health care provider response to system reform: Effects of capitation on the inter-district movement of patients and health outcomes

The second essay of this dissertation investigates the effects of the system reform in New Zealand in 2003, which reintroduced capitation, on inter-district patient flows and health outcomes. The findings show that patients are less likely to receive treatment in a district outside their residence since the system reform. The decline is more notable among those patients with more severe illnesses. Highly skilled providers are also less likely to receive patients from another district. The results indicate that sicker patients are less likely to be treated by specialist providers since the reform. Nevertheless, the reform has actually increased the transfer of patients with diagnoses where the probability of mortality is high. Therefore, the finding suggests that non-specialist providers are selectively treating patients in more severe, but less fatal, conditions. Overall, the decrease in inter-district movement seems to have negative effects on health outcomes.

A number of past studies examine how the diagnosis related group (DRG) based payment system affects the transfer decision of hospitals[2], however, few report the impact of capitation on patient flow between hospitals, even though many countries use capitation to reimburse their health care providers. Some studies examine the impact of a capitation scheme on referrals, which are the patient flows between primary care

[2] See, for example, Eze and Wolfe (1993), Newhouse (1989) and Sloan, Morrisey and Valvona (1988).

providers and specialists[3]. The studies on physician referral under capitation, however, are not directly comparable to this essay because there are notable differences between physician referral and hospital transfer. For instance, non-tertiary and tertiary DHBs perform more similar work than do general practitioners and specialists. Most importantly, hospitals transferring patients need to pay the receiving hospital out of the capitation payment, whereas general practitioners generally do not pay for the patient's specialist care. Furthermore, this essay investigates how the change in transfer patterns due to the system reform affects health outcomes.

Lastly, the previous literature reports that fixed payment systems, such as the DRG based payment system, increases transfer rates, but this essay shows that the direction of the impact is less clear under capitation, which is another type of fixed payment system. Capitation may increase the inter-district patient flow if the prices for the treatment of patients from another district are set too low. More interestingly, however, hospitals may be discouraged from transferring patients to another district in order to retain the funds received from the government. Although this study uses data from New Zealand hospitals, its findings are applicable to the health sector in other countries where capitation and universal coverage are in place.

### 1.2.3 Public health care provider reimbursement in New Zealand

The third essay examines how the usage of health care services by patients is associated with the level of government funding, computed based on the characteristics of population regardless of actual usage. To examine the relation, I regress the government

[3] An example is Allard, Jelovac and Leger (2011).

funding received by public health care providers on the characteristics of those patients who receive treatment. I find that some population groups are associated with lower levels of funding, although they receive higher weights under the current funding system. This is because the usage of health services by these groups exceeds their population share. Maori and Pacific Island patients, for instance, receive higher levels of funding, as they are considered as high-risk ethnic groups. The finding of this essay shows, however, that the level of funding for providers treating a higher proportion of these ethnic groups is lower, suggesting that the rates of usage by these groups are higher than their population share in districts that treat a higher proportion of them.

To the best of my knowledge, this study is the first to examine the relation between the patients' actual usage of hospital services and the level of funding computed based on the regional population under the New Zealand capitation system. Since the capitation system was reintroduced in July 2003, it has received much attention from the health sector, however, no studies have yet to analyse the relation between the actual usage by population and the level of funding, or the adequacy of payment. There are past studies that examine similar payment systems that are based on the average costs across providers. Most of these studies, however, use observations from U.S. Medicare patients, who only account for less than 15 percent of the nation's population and have different demographics than the general public.

In New Zealand, Penno, Audas and Gauld (2012) provide an excellent review of the new funding system that was introduced in 2003, however, they note that whether the funding allocations are adequate, and whether the methods could be improved, are further issues to be investigated. My essay provides the first step in understanding the adequacy of payment by examining how the actual usage of health services relates to the government funding.

### 1.3 Organisation of dissertation

The remainder of the dissertation is organised as follows. Chapter 2 examines the effects of complex cases on performance measures in the New Zealand health care sector. Chapter 3 studies how the health system reform introduced in 2003 in New Zealand has affected health care providers. Chapter 4 examines the reimbursement system for public health care providers in New Zealand. Chapter 5 summarises the key findings from the three essays.

# Chapter 2 Expertise: Is it a gift or a curse? Evidence from the health care sector

## 2.1 Introduction

The problem with being better at something than others is that you might end up taking on the most difficult tasks, but not receiving recognition for doing so. One of the reasons for this lack of recognition may be psychological. A common finding in psychology literature (Gilbert & Malone, 1995; Heider, 1958; Ichheiser, 1949; Jones & Harris, 1967) suggests that people take insufficient consideration of situational constraints, such as task difficulty and role assignment, when determining the causes of a person's behaviour, or assessing the performance of others[4]. Another explanation may be that, due to the complexity of the task, a more difficult task is harder to evaluate and compensate accordingly. In general, more difficult tasks take longer to complete, so the person or organisation working on it may appear inefficient if the level of difficulty is not taken into account. The health care sector may be an example of this issue. Those in the industry often argue that the common performance measures currently used cast hospitals treating complex cases in an unfair light. If performance measures do not accurately reflect the complexity of cases, hospitals dealing with difficult cases are likely to appear inefficient, as complex cases require longer hospital stays and higher levels of resources, often with unfavourable results, such as death.

This study investigates whether more highly skilled organisations are at a disadvantage because they attract difficult cases, by examining all the publicly funded

[4] For more on these studies, see Jones and Harris (1967), Ross, Amabile and Steinmetz (1977), Weber, Camerer, Rottenstreich and Knez (2001), Mayo and Tinsley (2009) and Moore, Swift, Sharek and Gino (2010).

hospital events in New Zealand during the period of July 1999 to June 2011. The dataset includes more than 10 million patient discharges and about 3 million patients. As the Ministry of Health in New Zealand keeps records on all of the publicly funded hospital admissions, which comprise nearly 80 percent of the total admissions, my results are not specific to a few diagnoses, or hospitals, but apply generally to all of them. I use a patient's transfer status and the complication/co-morbidity class level (CCL) indicator to measure the difficulty of a case and calculate their effects on performance indicators, such as the length of hospital stay, 30-day mortality and readmission.

The disadvantage faced by highly skilled people, or organisations, has two components. First, they are given the most difficult tasks, which take longer and/or require greater effort, but have lower success rates. Second, the payment they receive for a difficult task may not adequately compensate them for the level of difficulty. The problem is more serious when these two components co-exist. Receiving a more difficult case on its own will not necessarily be a problem if you receive higher payment that compensates for the complexity. If a hospital receives a premium for a complex case, the negative effects may not be as large as they first appear, although an unfavourable impact will remain, as bad performance in the quality and/or efficiency measures will make the hospital look bad in the public eye, causing disruptions to the organization, such as changes of the board. This study intends to provide evidence on the first type of disadvantage. The third essay of the dissertation will provide the first step in answering the question of whether the compensation given to highly skilled hospitals is sufficient.

My findings confirm that the disadvantage to highly skilled hospitals does exist. In the base models, transfer leads to an increase in the length of hospital stay by approximately 22 days, in the probability of mortality by 5 percentage points and in the probability of readmission by 0.04 percentage points. Higher levels of complexity and comorbidity also have negative effects on performance measures, in general. As endogeneity between transfer and the dependent variables may cause the models to fail, I further estimate the models by using instrumental variable (IV) methods. Endogeneity may be present if hospitals transfer a patient because they expect her to stay longer, or have a higher chance of mortality, or readmission.

The instrument used in this study is the changes in the monthly level of net permanent migration, which will measure the change in the number of people eligible for the publicly funded health care. As the hospital admissions studied in this essay are publicly funded, permanent residency or citizenship is required in general for a patient to be eligible for the service. The increase in transfer due to the increase in the number of people eligible for public health care is exogenous, since the health status of the net immigrants is, on average, similar to that of people already living in New Zealand.

In the models controlling for potential endogeneity, the effects of transfer on the length of hospital stay and readmission are statistically insignificant. In the regression on mortality, the effect of transfer is slightly smaller than the base model estimated by Probit. However, the test for endogeneity does not find that endogeneity is present in any of the IV models. Thus, the negative effects of transfer on the performance measures found in the base models still hold.

To the best of my knowledge, this study is the first to provide comprehensive analysis of the effects of task difficulty on performance in hospitals using extensive data. Several medical studies examine the effects of transfer, or severity of illness, on performance measures and costs in hospitals (Combes, et al., 2005; Gordon & Rosenthal, 1996; Hall, Willis, Medvedev, & Carson, 2012; Kahn, Kramer, & Rubenfeld, 2007; Munoz, et al., 1988; Rosenberg, et al., 2003); however, their data include only a limited number of hospitals, diagnoses and/or years. While these studies provide valuable insights, in order to obtain accurate results a variety of conditions need to be included in the analysis. My finding that the effects of complex cases on the performance measures vary across different diagnoses confirms the importance of examining a broad set of patient discharges. Another contribution of this study is that I address the issue of endogeneity between transfer and the performance measures. If providers are more likely to transfer a patient because they anticipate a longer length of hospital stay, or higher probabilities of mortality and readmission, the estimates obtained ignoring such a relation will be biased. I use the IV approach to control for the potential endogeneity.

I believe that transfer is a good indicator of task difficulty, because the hospital to which a patient is originally admitted will transfer the patient to another facility if her condition is too complex for it to treat[5]. Thus, I define highly skilled hospitals as those equipped with facilities and staff that can treat complex conditions. Along with a patient's transfer status, I use the complication/co-morbidity class level (CCL) as difficulty measures. Ranging from 0 to 4, a CCL is assigned to each case and indicates the level of complexity. My results suggest that the common performance measures may not adequately represent the true quality and efficiency of hospitals, if they are used without the indicators of case complexity.

[5] The health care sector in the U. S. is likely to be an exception to this argument because the country does not have the wide coverage of publicly funded health care systems. For instance, some U. S. studies (Himmelstein et al., 1984; Schiff et al., 1986) report that many transfers during the period of their studies are due to economic reasons, such as the lack of insurance. In most developed countries, however, publicly funded health care events comprise the majority of total health care expenditure, so the decision to transfer a patient is mostly based on medical conditions, rather than economic ones.

## 2.2 Related literature

The disadvantages faced by high skilled hospitals due to imperfect performance measures have received relatively little attention in the economic literature. Cutler, Huckman and Landrum (2004) and Dranove, Kessler, McClellan and Satterthwaite (2003) point out that hospitals treating sicker patients may appear to have low quality if the quality reporting system in the health care markets does not adjust for the differences in levels of sickness. The focus of the study by Cutler et al. (2004), however, is on the impact of the quality reporting system on the volumes and future quality of hospitals, while Dranove et al. (2003) focus on the selection of patients by hospitals.

Evans and Walker (1972) examine 90 hospitals in British Columbia, Canada and show that case-mix complexity increases costs. A decade later, Barer (1982) confirms Evans and Walker's findings, using a panel dataset containing 87 acute care hospitals in the same region. The literature on non-health care markets also provides some evidence on the impact of complexity on costs. In the electronics industry, Miller and Vollmann (1985) claim that transactions which occur due to the complexity of the production process drive up overhead costs. Banker and Johnston (1993) find production process complexity and product diversity to be a significant cost driver in the airline industry. On the other hand, Foster and Gupta (1990) examine the effects of volume, complexity and efficiency on overhead costs and find no significant effects of complexity and efficiency. Despite the finding, they believe that complexity and efficiency affect overhead costs, and argue that the insignificant results must have arisen from the difficulty of selecting appropriate proxies for complexity and efficiency, and the lack of consistent measures.

The studies similar to this essay are mostly found in the medical field. These studies examine the effects of transfer, or severity of illness, on costs or other performance measures, such as the ones used in my study. Although these studies provide valuable insights into the effects of case complexity on hospitals, their results are hard to generalise because most of them use data from a single hospital, a limited number of diagnoses and/or relatively short time periods. A study by Rosenberg et al. (2003) is closest to this essay, as it examines the impact of transfer on benchmark measures, such as length of stay (LOS), readmission and mortality rates. Using data on 4,579 admissions to the medical intensive care unit (MICU) at a tertiary care university hospital in the U.S. from 1994 to 1998, they show that transfer patients have a 40 percent longer hospital stay and two times higher mortality rates. The authors acknowledge that the results are hard to generalise, as the sample is from a single hospital and the reasons for transfer are unclear. My study improves on these points, as I have an extensive data set that includes every hospital and nearly 80 percent of all the hospital admissions in a country. Also, in my sample the reason for transfer is most likely to be the inability of the transferring hospital to treat the patient because New Zealand hospitals are not able to select which patients to treat, whereas in the U.S. transfer often occurs due to financial reasons (Himmelstein, et al., 1984; Schiff, et al., 1986). Moreover, I control for the endogeneity between transfer rates and the performance measures.

Bernard et al. (1996), by examining about 85,000 patients admitted to the University Hospital at the University of Michigan, show that transfer patients are more likely to stay in hospital for longer, die in the hospital and consume more resources. They do not control for the severity of illness in the study, however, so it is difficult to measure the true effects of transfer on the outcomes. Gordon and Rosenthal (1996) examine 40,820 patients at University Hospitals in Cleveland from 1988 to 1991 and show that transfer patients have higher hospital mortality, LOS and charges, even after adjusting for the severity of illness. Their findings indicate that hospitals where transfer patients account for 20 percent of admissions would appear to have higher mortality and LOS of 17 percent and 8 percent, respectively, compared with hospitals where transfer comprises only 2 percent of the patients. Combes et al. (2005) use data from the intensive care unit (ICU) of a tertiary care centre to measure the differences between transfers from another hospital's ICU. The database includes 3,416 patients from 1995 to 2001. Their findings show that not only does transfer have negative effects on the length of stay and mortality rates, but that the negative effects are stronger for ICU transfer than non-ICU transfer. This study suggests that classifying transfers based on the characteristics of the sender may provide further insights into the analysis.

Munoz et al. (1988) analyse the lengths of stay and costs related to 3,073 general surgical patients in Long Island Jewish Medical Center in New York during the period of January 1985 to December 1986. Of these patients, 97 were transferred from another acute care hospital. They find that transferred patients cost twice as much to treat as non-transferred patients and have longer hospital stays. Transferred patients also generated a yearly deficit of US$238,717 during the study period. Jencks and Bobula (1988), using Medicare data for 1984 to 1985, also find that costs per case at hospitals receiving more transfers and referrals are higher. The transferred patients, however, account for only one-third of the higher costs, while referred patients do not have effects on costs. They note that the possible reasons for these high costs may be that those hospitals have higher admission thresholds of complexity, or assume roles as centres of excellence and use more expensive treatment methods than other hospitals.

Dormont and Milcent (2004) investigate how much unobservable, as well as observable, hospital heterogeneity can explain hospital cost variability, using 7,314 stays for acute myocardial infarction in 36 French public hospitals during the period of 1994 to 1997. They point out that, although cost variability may result from inefficiency, it can also be the result of unobservable differences among hospitals, such as long-term moral hazard, infrastructure and care quality. Their findings suggest that transitory unobservable heterogeneity plays a large role in cost variability. In addition, hospitals that receive a higher number of transfers have higher costs.

In the U.S., the transferring hospital receives a per diem payment, which is the diagnosis-related group (DRG) weight divided by the geometric mean of LOS, for transfer cases staying shorter than the geometric mean of LOS, whereas the receiving hospital receives a fixed payment and any outlier adjustments. A transfer with longer than, or equal to, the geometric mean of LOS receives a full DRG payment (Carter & Rumpel, 1993). The differences in payment to the sending hospital and receiving hospital are most likely to recognise differences in the pattern of transfer between the earlier days and the later days of the stay. For example, Buczko (1993) reports that initial stays of transfer episodes are slightly less severe and less costly than the average Medicare discharge, but that final stays are much more severe and costly.

Such differences in payment for transfers have generated interest among researchers in the effects of transfer on sending hospitals, as well as receiving ones. The study by Hall et al. (2012) is similar to this essay, but it examines the impact of transfer on hospitals that send patients to another facility. Hall et al. (2012) measure the effects of transfer rates to long-term acute care hospitals on in-hospital mortality and ICU length of stay, the new quality indicators endorsed by the National Quality Forum in the U.S.

at the time of their research. If a transferred patient dies in hospital, mortality for that patient will not be recorded in the hospital that sent the patient; therefore, there is incentive for hospitals to increase transfers. Using 137 teaching and affiliated non-profit hospitals in the U.S., Hall et al. (2012) show that increasing a transfer rate from the 25th percentile to the 75th percentile will improve the transferring hospital's mortality index from 0.97 to 0.83, and its LOS index from 1.28 to 1.

Buczko (1997) tests whether the percentage of transfers received and sent in a hospital has an effect on costs per case, using U.S. hospital-level data for 1987. His findings suggest that transfers sent, as well as received, increase costs, although their effects are much smaller than case-mix, wages and the resident/bed ratio. Using Medicare data for the financial years 1990 and 1991, Carter and Rumpel (1993) examine the costs of transfer cases to the sending hospital and test alternative payment formulas. In their study, transfer cases at the sending hospital cost more than both the amount received from the existing payment method and the average costs incurred by the corresponding DRGs. Kahn et al. (2007) perform a cohort study and Monte Carlo simulation using 120,475 patients at 85 ICUs in U.S hospitals. They show that increasing transfer rates can significantly improve a potential quality measure for ICUs, the standardised mortality ratio (SMR), which is the observed mortality divided by the expected mortality adjusting for severity of illness and case mix. The authors argue that hospitals can easily manipulate this measure by transferring critically ill patients to other facilities. Transferring only one patient can improve the SMR measure in many ICUs.

I believe that the negative effects of transfer on receiving hospitals are likely to be greater than those on transferring hospitals; therefore, more analysis of the effects on the receiving hospital is required than is currently available. This is because the sending side can respond to the unfavourable compensation by increasing transfer rates, whereas the receiving hospital often does not have any other choice than to treat the patients. This is especially true in the New Zealand health care sector, but also applies to a country such as the U.S. For instance, in a study that analyses the characteristics of transfers in the U.S., Buczko (1993) shows that small and/or rural hospitals are the major senders, whereas large urban hospitals receive a large percentage of transfers. Newhouse (1989) also tests whether unprofitable patients are more likely to be transferred and end up in hospitals of last resort, which he describes as city and county hospitals. These studies support my argument that certain hospitals do not have choice on whether to accept, or transfer a patient, and always treat the patients they receive. My study contributes to the literature, as none of the studies reviewed above explore the issue of endogeneity between transfer rates and the performance measures.

## 2.3 Data

Analytical Services at the Ministry of Health in New Zealand provide patient discharge data for all the publicly funded hospital events in New Zealand for the period 1 July 1999 to 30 June 2011. The earliest year for which I can obtain data with all the required information is 1999. This is a large dataset, with more than 10 million observations. Each record in the dataset contains information such as the age, gender and ethnicity of a patient, the facility in which the patient was treated, a diagnosis type and severity, lengths of stay, transfer status, admission type (e.g. elective, or acute) and event end type (e.g. death, self-discharge, or routine discharge)[6]. Each patient in the dataset has a unique identification number, so I can check the patient's admission and discharge history during my research period.

The dataset includes 3,243,791 patients and 555 facilities. Transferred patients comprise approximately 6 percent of total admissions[7]. The complication/co-morbidity class level (CCL), which ranges from 0 to 4, indicates the severity of illness. CCLs range from 0 to 4 for surgical and neonate episodes, and from 0 to 3 for medical episodes. Each patient is also assigned a cost-weight, which is used to compute the costliness of treatment based on factors that will affect costs, such as DRG codes and length of stay. The length of stay ranges from 0 to 4,220 days[8]. There are 21 district health boards (DHBs), which oversee the facilities in their districts and provide funding and care for all the admissions in the dataset. Diagnosis-related Groups (DRGs)[9], which classify diagnosis types into 667 groups, code the patients' diagnosis types. The Major Diagnostic Category (MDC) provides another method of classifying diagnoses. The MDC divides all the diagnoses into 25 groups, based mainly on an organ system. Table 2.1 provides the description of MDC codes and the number of observations in the dataset that belong to each code.

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[6] For more detailed description of this dataset, see New Zealand Health Information Service (2008).

[7] I exclude transfers from a highly skilled provider to a low skilled one, which typically occurs when patients are transferred back to the facility in their own districts, because this type of transfer is not a good measure of case complexity.

[8] The patient with the longest hospital stay in the dataset is a 91 year-old (at the time of discharge) female diagnosed with dementia and global disturbances of cerebral function.

[9] More than one version of the DRG code is available, as the code is constantly updated. I use DRG code version 3.1, because the current code is not available for earlier admissions.

**Table 2.1 Major Diagnostic Category (MDC)**

| MDC code | Description | *N* |
|---|---|---|
| 0 | Pre-MDC[a] | 888 |
| 1 | Diseases and disorders of the nervous system | 595,401 |
| 2 | Diseases and disorders of the eye | 251,536 |
| 3 | Diseases and disorders of the ear, nose, mouth and throat | 565,275 |
| 4 | Diseases and disorders of the respiratory system | 733,787 |
| 5 | Diseases and disorders of the circulatory system | 1,044,025 |
| 6 | Diseases and disorders of the digestive system | 1,071,630 |
| 7 | Diseases and disorders of the hepatobiliary system and pancreas | 177,973 |
| 8 | Diseases and disorders of the musculoskeletal system and connective tissue | 1,061,873 |
| 9 | Diseases and disorders of the skin, subcutaneous tissue and breast | 532,166 |
| 10 | Endocrine, nutritional and metabolic diseases and disorders | 127,425 |
| 11 | Diseases and disorders of the kidney and urinary tract | 552,027 |
| 12 | Diseases and disorders of the male reproductive system | 96,651 |
| 13 | Diseases and disorders of the female reproductive system | 287,815 |
| 14 | Pregnancy, childbirth and the puerperium | 1,270,323 |
| 15 | Newborn and other neonates | 881,203 |
| 16 | Diseases and disorders of blood, blood-forming organs and immunological disorders | 132,832 |
| 17 | Neoplastic disorders | 210,581 |
| 18 | Infectious and parasitic diseases | 178,141 |
| 19 | Mental diseases and disorders | 183,309 |
| 20 | Alcohol/drug use and alcohol/drug-induced organic mental conditions | 34,299 |
| 21 | Injuries, poisoning and toxic effects of drugs | 312,395 |
| 22 | Burns | 15,334 |
| 23 | Factors influencing health status and other contacts with health services | 460,641 |
| 99 | Error DRGs | 0 |
| Total | | 10,777,536 |

[a] Pre-MDC is assigned to cases that require intensive resources, such as organ transplants, before assigning MDC.

I use a subset of the main dataset that excludes the observations from the last month when estimating the effects of task difficulty on mortality, because my mortality variable measures death within 30 days of discharge. Using the records on the event end type, I create an in-hospital mortality dummy variable, which equals 1 if the patient's discharge type is 'died', or 'died while still in emergency department acute facility'. In-hospital mortality comprises about 2 percent of total admissions in this subset. I also count mortality outside hospital within 30 days of discharge at 0.6 percent. In addition, I create a 30-day readmission dummy variable, which equals 1 if a patient is admitted to any hospital in the dataset within 30 days of the previous discharge date, or 0 otherwise. In some cases, patients with more complex conditions may appear to have lower readmission rates because they died since the previous visit to hospital. Therefore, I exclude patients who died in the hospital, or within 30 days of the last discharge date, and compute the readmission variable. The subsample comprises about 96 percent of the full dataset and includes 3,191,519 patients and 546 facilities. Table 2.2 presents the descriptive statistics of the entire dataset, as well as the subsample.

**Table 2.2 Descriptive statistics**

| | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| | A. Entire dataset (*N*=10,777,536) | | | |
| Transfer | 0.06 | 0.24 | 0 | 1 |
| CCL | 0.94 | 0.90 | 0 | 4 |
| Length of stay | 4.92 | 40.74 | 0 | 4,220 |
| Gender (Female dummy) | 0.56 | 0.50 | 0 | 1 |
| Age | 42.73 | 27.93 | 0 | 112 |
| Cost-weight | 1.12 | 3.59 | 0 | 292.33 |
| Small | 0.06 | 0.24 | 0 | 1 |
| Medium | 0.30 | 0.46 | 0 | 1 |
| Large | 0.64 | 0.48 | 0 | 1 |
| Rural | 4.45 | 3.67 | 0.02 | 11.21 |

| | | | | |
|---|---|---|---|---|
| Tertiary | 0.58 | 0.49 | 0 | 1 |
| Teaching | 0.72 | 0.45 | 0 | 1 |
| European | 0.68 | 0.47 | 0 | 1 |
| Maori | 0.16 | 0.37 | 0 | 1 |
| Pacific Islander | 0.07 | 0.25 | 0 | 1 |
| Asian | 0.05 | 0.21 | 0 | 1 |
| Others | 0.05 | 0.21 | 0 | 1 |
| Average no. of admission per patient | 3.32 | 7.46 | 1 | 2,144 |
| Net permanent migration | 1,025 | 1,800 | -2,808 | 6,692 |
| Unemployment rate | 0.05 | 0.02 | 0.02 | 0.09 |
| Median weekly income (NZ$, 2011 price) | 1,086.96 | 195.40 | 594 | 1,423 |
| | B. Mortality dataset (*N*=10,673,877) | | | |
| Transfer | 0.06 | 0.24 | 0 | 1 |
| CCL | 0.94 | 0.90 | 0 | 4 |
| Length of stay | 4.92 | 40.72 | 0 | 4,220 |
| 30 day mortality | 0.03 | 0.17 | 0 | 1 |
| In-hospital mortality | 0.02 | 0.12 | 0 | 1 |
| Gender (Female dummy) | 0.56 | 0.50 | 0 | 1 |
| Age | 42.72 | 27.93 | 0 | 112 |
| Cost-weight | 1.12 | 3.60 | 0 | 292.33 |
| Small | 0.06 | 0.24 | 0 | 1 |
| Medium | 0.30 | 0.46 | 0 | 1 |
| Large | 0.64 | 0.48 | 0 | 1 |
| Rural | 4.45 | 3.67 | 0.02 | 11.21 |
| Tertiary | 0.58 | 0.49 | 0 | 1 |
| Teaching | 0.72 | 0.45 | 0 | 1 |
| European | 0.67 | 0.47 | 0 | 1 |
| Maori | 0.16 | 0.37 | 0 | 1 |
| Pacific Islander | 0.07 | 0.25 | 0 | 1 |
| Asian | 0.04 | 0.20 | 0 | 1 |
| Others | 0.05 | 0.21 | 0 | 1 |
| Average no. of admission per patient | 3.31 | 7.43 | 1 | 2,128 |
| Net permanent migration | 1,031 | 1,807 | -2,808 | 6,692 |
| Unemployment rate | 0.05 | 0.02 | 0.02 | 0.09 |
| Median weekly income (NZ$, 2011 price) | 1,085.38 | 194.88 | 594 | 1,423 |
| | C. Surviving patients at 30 days of discharge (*N*=10,358,815) | | | |
| Transfer | 0.06 | 0.24 | 0 | 1 |
| CCL | 0.92 | 0.87 | 0 | 4 |

| | | | | |
|---|---|---|---|---|
| Length of stay | 3.68 | 22.82 | 0 | 3,889 |
| 30-day readmission | 0.24 | 0.43 | 0 | 1 |
| Gender (Female dummy) | 0.56 | 0.50 | 0 | 1 |
| Age | 41.78 | 27.66 | 0 | 112 |
| Cost-weight | 1.00 | 2.72 | 0 | 292.33 |
| Small | 0.06 | 0.24 | 0 | 1 |
| Medium | 0.30 | 0.46 | 0 | 1 |
| Large | 0.64 | 0.48 | 0 | 1 |
| Rural | 4.44 | 3.67 | 0.02 | 11.21 |
| Tertiary | 0.58 | 0.49 | 0 | 1 |
| Teaching | 0.72 | 0.45 | 0 | 1 |
| European | 0.67 | 0.47 | 0 | 1 |
| Maori | 0.17 | 0.37 | 0 | 1 |
| Pacific Islander | 0.07 | 0.26 | 0 | 1 |
| Asian | 0.05 | 0.21 | 0 | 1 |
| Others | 0.05 | 0.21 | 0 | 1 |
| Average no. of admission per patient | 3.25 | 7.38 | 1 | 2,128 |
| Net permanent migration | 1,030 | 1,806 | -2,808 | 6,692 |
| Unemployment rate | 0.05 | 0.02 | 0.02 | 0.09 |
| Median weekly income (NZ$, 2011 price) | 1,085.38 | 194.88 | 594 | 1,423 |

## 2.4 Methodology

Equation (1) below measures the effects of transfer and clinical complexity on length of stay in hospital. As the base model, I estimate Equation (1) with ordinary least squares (OLS). Since Equation (1) has the count outcome variable *length of hospital stay,* I also present models estimated by Poisson and negative binomial regressions. I use standard errors clustered by patient. Equation (1) takes the following form:

$$L_{it} = \beta_0 + \beta_1 T_{it} + \sum_{j=1}^{4} \beta_{j+1} C_{ijt} + \beta_6 \boldsymbol{X}_{it} + \beta_7 Y_t + \varepsilon_{it} \quad (1)$$

where $L_{it}$ is the length of stay (LOS) for patient *i* at a facility where she receives treatment; $T_{it}$ is a dummy variable, which equals 1 if the patient is transferred from another facility and 0 otherwise; $C_{ijt}$ is CCL, which takes the value of 0 to 4 and indicates the severity of illness; and $\boldsymbol{X_{it}}$ is a vector of control variables indicating patient characteristics, such as age, gender, ethnicity and diagnoses types (MDC codes[10]), facility characteristics, such as size, location, teaching status and tertiariness[11], and regional economic indicators, such as employment rates and median weekly income of the district patient *i* resides in[12]. $Y_t$ indicates year dummies.

Equation (2) measures the effects of transfer and clinical complexity on mortality:

$$\text{Prob}(M_{it}) = \beta_0 + \beta_1 T_{it} + \sum_{j=1}^{4} \beta_{j+1} C_{ijt} + \beta_6 \boldsymbol{X}_{it} + \beta_7 Y_t + \varepsilon_{it} \qquad (2)$$

where $M_{it}$ is a dummy variable, which equals 1 if patient *i* dies in hospital, or within 30 days of the discharge date, and 0 otherwise. The other variables are as described in Equation (1). Last, Equation (3) measures the effects of task difficulty on the probability of 30-day readmission:

$$\text{Prob}(R_{it}) = \beta_0 + \beta_1 T_{it} + \sum_{j=1}^{4} \beta_{j+1} C_{ijt} + \beta_6 \boldsymbol{X}_{it} + \beta_7 Y_t + \varepsilon_{it} \qquad (3)$$

where $R_{it}$ is a dummy variable, which equals 1 if the patient *i* is readmitted to any facility in the dataset within 30 days of the previous discharge date and 0 otherwise. $T_{it}$, $C_{ijt}$, $\boldsymbol{X}_{it}$ and $Y_t$ are as described above. I estimate Equations (2) and (3) below with probit

[10] I do not include MDC codes 0 and 99, as the number of observations for those two categories is too small. Also, I use MDC codes, instead of DRG codes, to control for diagnoses due to the high number of DRG codes. I perform robustness checks with a subsample of data by including DRG codes. Section 2.6.1 reports the results.
[11] I include 21 DHB dummy variables instead of the characteristics of DHBs and re-estimate the equations. The coefficients and significance of the key variables remain qualitatively unchanged.
[12] Some of the observations do not have records on the district of residence. I exclude these from the analysis.

regression. Table 2.3 shows the summary statistics for the dependent variables and key independent variables by MDC code.

I use the characteristics of DHBs to which each facility belongs, such as size, location, teaching status and tertiariness, to control for the facility characteristics. Using DHBs to proxy for the facility is a reasonable regrouping, as DHBs are in charge of funding and providing care for all the admissions in the dataset. For size, I use the grouping used by the Ministry of Health (2010) (small, medium, or large). Location addresses how rural the district is. To control for location, I use the share of rural adjuster, which is included in the population-based funding formula, to compensate DHBs for extra costs incurred due to how rural the region is (Ministry of Health, 2004). The teaching variable is a dummy, which equals 1 if the DHB has a teaching hospital(s) and is 0 otherwise. Of the 21 DHBs, 9 run teaching hospitals, while one DHB has more than one teaching hospital.  The tertiary variable is a dummy, which equals 1 if the DHB operates a tertiary hospital(s), with 7 of the DHBs being classified as tertiary. Information on teaching hospitals is drawn from the Australian Society of Otolaryngology Head and Neck Surgery (ASOHNS) (ASOHNS, 2010).

**Table 2.3 Summary statistics by MDC**

| | Mean | | | | |
|---|---|---|---|---|---|
| MDC[a] | Transfer | CCL | LOS | Mortality | Readmission |
| 1 | 0.08 | 1.09 | 19.97 | 0.06 | 0.27 |
| | (0.27) | (0.90) | (124.81) | (0.23) | (0.44) |
| 2 | 0.01 | 0.57 | 0.70 | 0.00 | 0.10 |
| | (0.09) | (0.66) | (16.67) | (0.03) | (0.30) |
| 3 | 0.01 | 0.61 | 0.95 | 0.00 | 0.09 |
| | (0.10) | (0.70) | (11.29) | (0.04) | (0.28) |
| 4 | 0.04 | 1.22 | 6.07 | 0.04 | 0.21 |
| | (0.19) | (0.96) | (44.88) | (0.20) | (0.41) |
| 5 | 0.07 | 1.35 | 5.59 | 0.03 | 0.25 |

| | | | | | |
|---|---|---|---|---|---|
| | (0.25) | (0.92) | (43.29) | (0.17) | (0.43) |
| 6 | 0.02 | 0.98 | 2.87 | 0.02 | 0.17 |
| | (0.13) | (0.94) | (17.00) | (0.13) | (0.38) |
| 7 | 0.03 | 1.21 | 4.33 | 0.03 | 0.25 |
| | (0.17) | (1.03) | (16.75) | (0.18) | (0.43) |
| 8 | 0.02 | 0.84 | 4.07 | 0.01 | 0.18 |
| | (0.15) | (0.94) | (28.57) | (0.08) | (0.38) |
| 9 | 0.01 | 0.86 | 2.41 | 0.01 | 0.12 |
| | (0.12) | (0.84) | (17.86) | (0.09) | (0.33) |
| 10 | 0.04 | 1.33 | 7.69 | 0.02 | 0.25 |
| | (0.18) | (0.97) | (57.64) | (0.14) | (0.43) |
| 11 | 0.02 | 1.13 | 2.13 | 0.01 | 0.53 |
| | (0.15) | (0.79) | (21.22) | (0.11) | (0.50) |
| 12 | 0.03 | 0.83 | 3.14 | 0.02 | 0.16 |
| | (0.17) | (0.91) | (27.28) | (0.15) | (0.37) |
| 13 | 0.01 | 0.88 | 1.70 | 0.00 | 0.12 |
| | (0.11) | (0.76) | (11.50) | (0.07) | (0.32) |
| 14 | 0.11 | 0.96 | 2.02 | 0.00 | 0.25 |
| | (0.32) | (0.50) | (4.22) | (0.01) | (0.43) |
| 15 | 0.15 | 0.00 | 3.13 | 0.00 | 0.20 |
| | (0.36) | (0.00) | (7.03) | (0.05) | (0.40) |
| 16 | 0.03 | 0.95 | 2.05 | 0.01 | 0.41 |
| | (0.12) | (0.96) | (18.82) | (0.08) | (0.49) |
| 17 | 0.03 | 0.98 | 2.36 | 0.03 | 0.68 |
| | (0.16) | (0.74) | (17.42) | (0.16) | (0.46) |
| 18 | 0.03 | 1.19 | 3.85 | 0.03 | 0.18 |
| | (0.17) | (1.07) | (22.95) | (0.17) | (0.39) |
| 19 | 0.07 | 0.93 | 24.76 | 0.00 | 0.35 |
| | (0.26) | (0.70) | (85.07) | (0.06) | (0.48) |
| 20 | 0.02 | 0.94 | 6.24 | 0.00 | 0.19 |
| | (0.15) | (0.68) | (39.71) | (0.05) | (0.39) |
| 21 | 0.03 | 0.99 | 2.23 | 0.01 | 0.19 |
| | (0.16) | (0.87) | (7.63) | (0.08) | (0.39) |
| 22 | 0.06 | 1.29 | 4.61 | 0.01 | 0.22 |
| | (0.23) | (0.73) | (8.82) | (0.10) | (0.41) |
| 23 | 0.30 | 1.53 | 11.57 | 0.02 | 0.21 |
| | (0.46) | (1.13) | (43.98) | (0.13) | (0.41) |

NOTE. – Standard deviations are in parentheses.
[a] For full description of MDC codes, see Table 2.1.

Endogeneity between transfer and the dependent variables may cause the models to fail because hospitals may transfer a patient as they expect her to stay longer, or have a higher chance of mortality or readmission than non-transfer patients. To address this issue, I use instrumental variable (IV) techniques. The exogenous variation of transfer due to variation in the number of people eligible for publicly funded health care is used as an instrument. I examine the eligibility for public health care because this research examines publicly funded hospital events, which in general require permanent residency, or citizenship[13]. The change in the eligibility is measured by the first differences in the monthly net migration level. The increase in the number of transfers is exogenous since the health status of the net immigrants is, on average, similar to people already living in New Zealand.

I believe that the change in net migration will not affect the health outcomes. Although permanent residency in New Zealand is granted more frequently to applicants with a higher level of education, which is positively related to health[14], many highly educated citizens and permanent residents also leave the country in the hope of finding higher-paying jobs overseas, mostly in neighbouring Australia. A study of immigrants and expatriates in OECD countries (Dumont & Lemaître, 2005) reports that the proportion of highly skilled immigrants in the country's skilled workforce and that of highly skilled people who are expatriates are both over 20 percent for New Zealand. As a result, the net highly skilled migrants in New Zealand are close to zero, as shown in a chart in their study. In addition, the countries of residence of the new permanent immigrants arriving in New Zealand during the research period show a combination of

[13] Overseas visitors do have access to publicly funded treatment under the Accident Compensation Act if they sustain injuries while in New Zealand. Hospital visits for other causes such as illness are, however, not covered by publicly funded services. People who have a 24 month, or longer, work visa may also access publicly funded health services.
[14] See, for example, Cutler and Lleras-Muney (2006).

developed and developing countries, which may also have an effect on their level of health. The top five countries where these permanent immigrants to New Zealand used to reside are the U.K., Australia, China, India and U.S. (Statistics New Zealand, 2013).

To estimate Equation (1) while addressing the potential issue of endogeneity, I use the two-step estimator for the Poisson model instrumenting the potential endogenous variable transfer, along with a two-stage least squares (2SLS) regression as a base model. The Poisson two-step approach will provide consistent estimates for the count data with over dispersion (Cameron & Trivedi, 2009). I estimate Equations (2) and (3) with IV probit.

## 2.5 Empirical results

The estimation results show that both transfer and CCL lead to unfavourable outcomes in most specifications, supporting the argument that organisations given more difficult tasks are at a disadvantage. In all the models estimated by the IV approach, the instruments are significant at the 1 percent level in the first stage regressions, as shown in Table 2.4. I also present the F-statistics on the excluded instrument, where applicable. The model in column 1 shows that an increase of one permanent immigrant compared with the previous month leads to an increase of 0.03 percentage point in the probability of transfer. Although it is a small increase, considering that the mean of transfer is 6 percent, the increase is not negligible.

**Table 2.4 First stage regressions (Dependent variable: Transfer)**

| | LOS | LOS | Mortality[a] | Readmission[a] |
|---|---|---|---|---|
| Net permanent migration | 0.0003** | 0.0003** | 0.0003** | 0.0002** |
| | (5.59) | (5.59) | (5.21) | (4.76) |
| F-statistics | 31.21 | | | |
| Estimation method | 2SLS | Poisson two-step | IV Probit | IV Probit |

NOTE. –. *z* statistics are in parentheses.
[+] Significant at the 10 percent level.
[*] Significant at the 5 percent level.
[**] Significant at the 1 percent level.
[a] The table presents the coefficients of the probit estimates.

The base model (Model 1) in Table 2.5 shows that transferred patients lead to a longer stay at hospital by over 21 days. As expected, the length of hospital stay increases as the level of complexity becomes higher. The hospital stay for patients assigned to CCL 1 is longer by less than a day, while the most severe cases (CCL 4) increase LOS by over seven days. Models 2 and 3 also confirm that transferred patients and those with more severe conditions have longer hospital stays. The effects of transferred patients in the Poisson and negative binomial models are similar to each other, but the effects of patients with different CCLs vary. The effects of CCL are the largest in the negative binomial model. In the negative binomial model, patients with the two higher levels of complexity stay in hospital longer than transferred patients, whereas in the other two models, transfer has larger effects than any level of complexity.

Transferred patients have negative, but statistically insignificant, effects on the length of hospital stay when I address the issue of potential endogeneity in Models 4 and 5. In both the 2SLS and two-step Poisson models, I test for endogeneity by including the residuals from the first stage regressions in the second stage. The residuals in both models are statistically insignificant, suggesting that endogeneity is not present.

Therefore, I conclude that transfer status increases the length of hospital stay, as indicated in Models 1 to 3.

**Table 2.5 Effects of transfer and CCL on length of stay (*N*=10,728,729[a])**

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Transfer | 21.67** | 8.21** | 6.96** | -13.04 | -2.78 |
| | (114.89) | (193.94) | (172.29) | (-0.40) | (-0.44) |
| CCL 1 | 0.46** | 0.35** | 0.95** | -0.67 | -0.58 |
| | (12.15) | (8.22) | (52.41) | (-0.63) | (-0.29) |
| CCL 2 | 2.36** | 1.70** | 3.81** | 2.13** | 0.33** |
| | (36.62) | (26.60) | (128.41) | (9.48) | (7.70) |
| CCL 3 | 6.02** | 3.34** | 8.08** | 7.90** | 0.85** |
| | (60.06) | (46.99) | (194.89) | (4.47) | (2.51) |
| CCL 4 | 7.55** | 6.29** | 15.09** | 8.79** | 1.11** |
| | (104.85) | (81.07) | (262.91) | (7.52) | (4.95) |
| *p*-value of the endogeneity test | | | | 0.28 | 0.71 |
| Estimation method | OLS | Poisson | Negative binomial | 2SLS | Poisson two-step |

NOTE. – The table reports the effects of case complexity as measured by transfer and complications/comorbidity levels (CCLs) on the length of hospital stay. "Transfer" is a dummy variable, which equals 1 if the patient is transferred from another facility and 0 otherwise. "CCL" indicates the complications/comorbidity levels, which take the value of 0, 1, 2, 3, or 4. CCL 0 is the reference category. Models 1 and 4 present the coefficients of transfer and CCL, while Models 2, 3 and 5 report the average marginal effects. For computational constraints, I report the *z* statistics of the coefficients in Models 2, 3 and 5. In Models 4 and 5, I use the change in the net permanent migration as the instrument for transfer. The test for endogeneity reports the *p*-values of the residuals from the first stage regressions. Table 2.4 presents the first stage regressions for Models 4 and 5. All the models include control variables indicating patient characteristics, facility characteristics, economic indicators and year dummies. *t* or *z* statistics are in parentheses.

[+] Significant at the 10 percent level.
[*] Significant at the 5 percent level.
[**] Significant at the 1 percent level.
[a] Excluding the observations that do not have records on the patients' residence.

Table 2.6 shows that transfer leads to a higher probability of mortality in the base model estimated by Probit. In this model, transfer increases the probability of 30 day mortality by 5 percentage points. In the models where I control for potential endogeneity, the results are mixed. In Model 2, which is estimated by IV probit, shows that transfer still increases the probability of mortality even after I control for endogeneity. Nonetheless, the Wald test of exogeneity suggests that there is no endogeneity in the model. In both models, CCL 1 leads to a lower probability of mortality than the reference category, CCL 0, whereas the higher CCLs increase the probability. This finding may be the result of excluding individual diagnosis codes from the equation. CCL 1 may lead to lower probability than CCL 0, because certain diagnoses with no complications (CCL 0) have higher probability of mortality in general than do some other diagnoses with minor or no complications (CCL 1).

**Table 2.6 Effects of transfer and CCL on mortality (*N*=10,625,264[a])**

| | Model 1 | Model 2 |
|---|---|---|
| Transfer | 0.05** | 0.04** |
| | (195.99) | (8.91) |
| CCL 1 | -0.007** | -0.01** |
| | (-61.20) | (-48.78) |
| CCL 2 | 0.02** | 0.02** |
| | (106.71) | (105.84) |
| CCL 3 | 0.06** | 0.04** |
| | (195.85) | (126.37) |
| CCL 4 | 0.05** | 0.03** |
| | (107.28) | (96.17) |
| Wald test of exogeneity | | 0.21 |
| (*p*-value) | | (0.65) |
| Estimation method | Probit | IV Probit |

NOTE. – The table reports the effects of case complexity, as measured by transfer and complications/comorbidity levels (CCLs), on the probability of 30 day mortality. "Transfer" is a dummy variable, which equals 1 if the patient is transferred from another facility and 0 otherwise. "CCL" indicates the complications/comorbidity levels, which take the value of 0, 1, 2, 3, or 4. CCL 0 is the reference category. All the models present the average marginal effects. For computational constraints, I report the *z* statistics of the coefficients. In Model 2, I use the change in the net permanent migration as an instrument for transfer. Table 2.4 presents the first stage regressions for Model 2. All the models include control variables indicating patient characteristics, facility characteristics, economic indicators and year dummies. *z* statistics are in parentheses.

[+] Significant at the 10 percent level.
[*] Significant at the 5 percent level.
[**] Significant at the 1 percent level.
[a] Excluding the observations that do not have records on the patients' residence.

Table 2.7 reports the estimation results for Equation (3). In both models, transfer and each CCL increase the probability of 30-day readmission. Overall, patients assigned to a higher CCL are more likely to be readmitted to the health care facilities within 30 days. The increase in the probability of readmission due to higher CCLs is substantial, as it ranges from 5 to 20 percentage points. The effects of transferred patients rise when I control for endogeneity, but the effects are statistically insignificant. In the base model, transferred patients only lead to a small increase (0.4 percentage points) in the probability of readmission, whereas in Model 2 they cause increases of 2 percentage points in the probability of readmission. Similar to the regressions on mortality, the IV probit model suggests that endogeneity is not present in the model.

**Table 2.7 Effects of transfer and CCL on readmission (*N*=10,310,999[a])**

| | Model 1 | Model 2 |
|---|---|---|
| Transfer | 0.004** | 0.02 |
| | (4.89) | (0.82) |
| CCL 1 | 0.05** | 0.05** |
| | (48.39) | (40.76) |
| CCL 2 | 0.13** | 0.12** |
| | (103.99) | (103.53) |
| CCL 3 | 0.15** | 0.14** |
| | (122.14) | (77.40) |
| CCL 4 | 0.20** | 0.18** |
| | (125.68) | (104.09) |
| Wald test of exogeneity | | 0.42 |
| (*p*-value) | | (0.52) |
| Estimation method | Probit | IV Probit |

NOTE. – The table reports the effects of case complexity as measured by transfer and complications/comorbidity levels (CCLs) on the probability of 30 day readmission. "Transfer" is a dummy variable, which equals 1 if the patient is transferred from another facility and 0 otherwise. "CCL" indicates the complications/comorbidity levels, which take the value of 0, 1, 2, 3, or 4. CCL 0 is the reference category. All the models present the average marginal effects. For computational constraints, I report the *z* statistics of the coefficients. In Model 2, I use the change in the net permanent migration as an instrument for transfer. Table 2.4 presents the first stage regressions for Model 2. All the models include control variables indicating patient characteristics, facility characteristics, economic indicators and year dummies. *z* statistics are in parentheses.

[+] Significant at the 10 percent level.

[*] Significant at the 5 percent level.

[**] Significant at the 1 percent level.

[a] Excluding the observations that do not have records on the patients' residence.

## 2.6 Robustness checks

### 2.6.1 DRG codes

In the previous section, I include dummy variables for each MDC to control for different diagnoses. I did not directly control for the effects of diagnoses by including

DRG codes in the equation due to the high number of DRG codes. Since DRG codes are arguably the most important factor in the variation of the LOS, mortality and readmission, I re-estimate the equations with DRG code dummies on a random sample of 20 percent of the observations. Due to the computational constraints, I do not use the full dataset. Table 2.8, Table 2.9 and Table 2.10 present the estimation results for Equations (1), (2) and (3), respectively.

**Table 2.8 Effects of complexity on length of stay after controlling for DRG (*N*=2,145,746)**

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| Transfer | 22.46** | 7.28** | 5.68** | 18.32 |
| | (51.09) | (79.30) | (70.68) | (0.37) |
| CCL 1 | -0.38** | -0.03 | 1.35** | 0.38 |
| | (-4.46) | (-0.28) | (37.30) | (0.24) |
| CCL 2 | -0.79** | 0.01 | 2.65** | 2.38** |
| | (-4.17) | (0.11) | (50.28) | (6.61) |
| CCL 3 | 2.76** | 1.26** | 5.45** | 6.21** |
| | (9.03) | (7.63) | (67.89) | (2.27) |
| CCL 4 | 5.58** | 3.81** | 9.89** | 7.65** |
| | (25.16) | (20.69) | (83.85) | (4.43) |
| *p*-value of the endogeneity test | | | | 0.94 |
| Estimation method | OLS | Poisson | Negative binomial | 2SLS |

NOTE. – The table reports the effects of case complexity as measured by transfer and complications/comorbidity levels (CCLs) on the length of hospital stay. “Transfer” is a dummy variable, which equals 1 if the patient is transferred from another facility and 0 otherwise. “CCL” indicates the complications/comorbidity levels, which take the value of 0, 1, 2, 3, or 4. CCL 0 is the reference category. Models 1 and 4 present the coefficients of transfer and CCL, while Models 2 and 3 report the average marginal effects. For computational constraints, I report the *z* statistics of the coefficients in Models 2 and 3. In Models 4, I use the change in the net permanent migration as an instrument for transfer. The test for endogeneity reports the *p*-values of the residuals from the first stage regressions. All the models include control variables indicating DRG codes, patient characteristics, facility characteristics, economic indicators and year dummies. *t* or *z* statistics are in parentheses.

$^{+}$ Significant at the 10 percent level.
$^{*}$ Significant at the 5 percent level.
$^{**}$ Significant at the 1 percent level.

Most DRG code dummies have significant effects on the dependent variables, as is expected. For brevity, I do not report the coefficients of the DRG dummies. Overall, adding DRG codes as additional control variables does not change the results of the main analysis by much, as shown in Table 2.8. On the other hand, the DRG codes seem to absorb some of the effects CCLs have on LOS in Models 1 and 2. In these models, the effects of CCL become smaller. The lower levels of CCL even change the signs, indicating that they decrease the length of hospital stays. Nevertheless, the negative effects of more complex cases, as proxied by CCLs 3 and 4, on the performance measure remain in all the specifications. For the most complex case (CCL 4), the increase in LOS ranges from 4 to 10 days, even after controlling for DRG codes.

**Table 2.9 Effects of complexity on mortality after controlling for DRG**

| | Model 1 | Model 2 |
|---|---|---|
| Transfer | 0.04** | 0.06** |
| | (76.19) | (59.92) |
| CCL 1 | -0.01** | -0.01** |
| | (-19.37) | (-17.54) |
| CCL 2 | 0.01** | 0.01** |
| | (19.25) | (19.76) |
| CCL 3 | 0.04** | 0.03** |
| | (63.74) | (61.85) |
| CCL 4 | 0.10** | 0.06** |
| | (57.20) | (56.23) |
| Estimation method | Probit | IV Probit |
| *N*[a] | 2,123,131 | 2,011,481 |

NOTE. – The table reports the effects of case complexity as measured by transfer and complications/comorbidity levels (CCLs) on the probability of 30-day mortality. “Transfer” is a dummy variable, which equals 1 if the patient is transferred from another facility and 0 otherwise. “CCL” indicates the complications/comorbidity levels, which take the value of 0, 1, 2, 3, or 4. CCL 0 is the reference category. All the models present the average marginal effects. For computational constraints, I report the *z* statistics of the coefficients. In Model 2, I use the change in the net permanent migration as an instrument for transfer. All the models include control variables indicating DRG codes, patient characteristics, facility characteristics, economic indicators and year dummies. *z* statistics are in parentheses.

[+] Significant at the 10 percent level.

[*] Significant at the 5 percent level.

[**] Significant at the 1 percent level.

[a] Some of the DRG dummies and their observations are dropped due to the issue of perfect prediction.

Similar to the main analysis, transferred patients have higher probability of 30-day mortality. In the base model in Table 2.9, transferred patients increase the probability of dying within 30 days by four percentage points. The increase in the probability of mortality slightly increases in Model 2. The effects of CCL dummies do not change much from the main analysis. The largest change is in the effects of the most complex cases, CCL 4, on mortality. When I include the DRG dummies, the effects of CCL 4 become even larger in both models. Patients assigned to CCL 1 are still less likely to die within 30 days of discharge than those in the reference category, CCL 0, while all the other CCLs increase the probability of mortality. Thus, the negative effects of CCL 1 are not due to the omission of DRG codes. It seems that at the lower end of complexity, an increase in CCL does not lead to the increase in mortality, making the CCL indicator an imperfect predictor of mortality.

**Table 2.10 Effects of complexity on readmission after controlling for DRG**

| | Model 1 | Model 2 |
|---|---|---|
| Transfer | 0.03** | 0.03 |
| | (20.11) | (0.52) |
| CCL 1 | 0.04** | 0.04** |
| | (40.36) | (37.78) |
| CCL 2 | 0.07** | 0.07** |
| | (51.33) | (52.79) |
| CCL 3 | 0.11** | 0.11** |
| | (57.65) | (45.40) |
| CCL 4 | 0.18** | 0.16** |
| | (48.11) | (40.44) |
| Estimation method | Probit | IV Probit |
| *N*[a] | 2,062,177 | 2,060,797 |

NOTE. – The table reports the effects of case complexity as measured by transfer and complications/comorbidity levels (CCLs) on the probability of 30-day readmission. “Transfer” is a dummy variable, which equals 1 if the patient is transferred from another facility and 0 otherwise. “CCL” indicates the complications/comorbidity levels, which take the value of 0, 1, 2, 3, or 4. CCL 0 is the reference category. All the models present the average marginal effects. For computational constraints, I report the *z* statistics of the coefficients. In Model 2, I use the change in the net permanent migration as an instrument for transfer. All the models include control variables indicating patient characteristics, facility characteristics, economic indicators and year dummies. *z* statistics are in parentheses.

[+] Significant at the 10 percent level.

[*] Significant at the 5 percent level.

[**] Significant at the 1 percent level.

[a] Some of the DRG dummies and their observations are dropped due to the issue of perfect prediction.

The base model in Table 2.10 shows that transferred patients are more likely to be readmitted to hospital within 30 days of discharge by 3 percentage points. The increase in the probability is much higher than that found in the main analysis. The models that address the issue of endogeneity also show this increased probability of readmission of 3 percentage points. Overall, including the DRG code dummies in the regressions does not change the core findings of the main analysis. Although the size of the effects differs in some cases, transferred patients still have longer hospital stays and higher probabilities of 30-day mortality and readmission.

### 2.6.2 Adult services and pediatrics

Next, I divide the dataset into adult services and pediatrics and estimate OLS and probit models, because pediatric services may have unique characteristics that can lead to different results. As the results from the earlier analyses suggest that endogeneity is not present in the models, I only report the OLS and Probit models. I define pediatric services as treatment given to a patient whose age is 18 or younger. Approximately 23 percent of the total admissions fall into the pediatrics category. Overall, there are large differences in the effects of transfer between the two services. Table 2.11 shows that adult transferred patients stay in hospital much longer than pediatric patients do. Transferred pediatric patients have longer hospital stays by only one day, whereas adult transferred patients stay in hospital almost a month longer. In contrast, the effects of the CCLs are much more comparable, but pediatric patients actually have longer hospital stays than adult patients in the most severe category.

The effects of the complexity measures on the 30-day mortality indicators are also much smaller in pediatric services. Table 2.12 reports that transferred patients in pediatric services increase the probability of mortality by 0.2 percentage point, while those in adult services increase the probability by 7 percentage points. Unlike the above regressions, which measure the effects of transfer and CCL on LOS, the regressions of mortality on complexity measures show that the effects of CCLs also diminish in pediatric services. In all the levels, the effects of CCLs on mortality is smaller in pediatric services than in adult services.

**Table 2.11 Adult services and pediatrics: Length of stay**

| | Adult services | Pediatrics |
|---|---|---|
| Transfer | 28.67** | 0.93** |
| | (113.73) | (35.45) |
| CCL 1 | 1.04** | 0.51** |
| | (21.67) | (50.06) |
| CCL 2 | 2.51** | 2.01** |
| | (33.97) | (58.98) |
| CCL 3 | 5.71** | 4.81** |
| | (51.67) | (62.68) |
| CCL 4 | 7.36** | 10.85** |
| | (91.73) | (43.71) |
| Estimation method | OLS | OLS |
| *N* | 8,257,476 | 2,471,253 |

NOTE. – The table reports the effects of case complexity as measured by transfer and complications/comorbidity levels (CCLs) on the length of hospital stay. "Transfer" is a dummy variable, which equals 1 if the patient is transferred from another facility and 0 otherwise. "CCL" indicates the complications/comorbidity levels, which take the value of 0, 1, 2, 3, or 4. CCL 0 is the reference category. All the models include control variables indicating patient characteristics, facility characteristics, economic indicators and year dummies. *t* statistics are in parentheses.

$^{+}$ Significant at the 10 percent level.

$^{*}$ Significant at the 5 percent level.

$^{**}$ Significant at the 1 percent level.

The effects of transfer and CCL on the probabilities of readmission are larger in pediatric than in adult services. Table 2.13 shows that transferred patients in adult services are more likely to be readmitted to hospital by 3 percentage points than non-transferred patients, whereas those in pediatric services are less likely to be readmitted by 6 percentage points. The effects of different levels of complexity indicators are also slightly larger in pediatric services. Overall, the main finding from the previous section, that transferred patients increase the lengths of stay and probabilities of mortality and readmission still hold for adult services. The size and direction of the effects, however, slightly varies for pediatric services, confirming that they do possess unique characteristics that can alter the results.

**Table 2.12 Adult services and pediatrics: 30-day mortality**

| | Adult services | Pediatrics |
|---|---|---|
| Transfer | 0.07** | 0.002** |
| | (196.40) | (12.44) |
| CCL 1 | -0.01** | -0.0002 |
| | (-61.13) | (-1.57) |
| CCL 2 | 0.03** | 0.006** |
| | (104.76) | (20.29) |
| CCL 3 | 0.07** | 0.02** |
| | (191.98) | (37.08) |
| CCL 4 | 0.06** | 0.02** |
| | (105.64) | (18.85) |
| Estimation method | Probit | Probit |
| *N* | 8,257,476 | 2,471,253 |

NOTE. – The table reports the effects of case complexity as measured by transfer and complications/comorbidity levels (CCLs) on the length of hospital stay. "Transfer" is a dummy variable, which equals 1 if the patient is transferred from another facility and 0 otherwise. "CCL" indicates the complications/comorbidity levels, which take the value of 0, 1, 2, 3, or 4. CCL 0 is the reference category. All the models present the average marginal effects. For computational constraints, I report the *z* statistics of the coefficients. All the models include control variables indicating patient characteristics, facility characteristics, economic indicators and year dummies. *z* statistics are in parentheses.

$^{+}$ Significant at the 10 percent level.

$^{*}$ Significant at the 5 percent level.

$^{**}$ Significant at the 1 percent level.

**Table 2.13 Adult services and pediatrics: 30-day readmission**

| | Adult services | Pediatrics |
|---|---|---|
| Transfer | 0.03** | -0.06** |
| | (107.61) | (29.83) |
| CCL 1 | 0.04** | 0.06** |
| | (43.87) | (37.21) |
| CCL 2 | 0.12** | 0.17** |
| | (50.01) | (88.68) |
| CCL 3 | 0.14** | 0.24** |
| | (38.09) | (105.87) |
| CCL 4 | 0.20** | 0.22** |
| | (19.27) | (115.15) |
| Estimation method | Probit | Probit |
| *N* | 8,257,476 | 2,471,253 |

NOTE. – The table reports the effects of case complexity as measured by transfer and complications/comorbidity levels (CCLs) on the length of hospital stay. "Transfer" is a dummy variable, which equals 1 if the patient is transferred from another facility and 0 otherwise. "CCL" indicates the complications/comorbidity levels, which take the value of 0, 1, 2, 3, or 4. CCL 0 is the reference category. All the models present the average marginal effects. For computational constraints, I report the *z* statistics of the coefficients. All the models include control variables indicating patient characteristics, facility characteristics, economic indicators and year dummies. *z* statistics are in parentheses.

$^{+}$ Significant at the 10 percent level.

$^{*}$ Significant at the 5 percent level.

$^{**}$ Significant at the 1 percent level.

## 2.7 Conclusion

Using more than 10 million discharges from public hospitals in New Zealand during the period from 1999 to 2011, I show that transferred patients and those assigned to higher comorbidity/complication levels negatively affect hospital performance measures in general. In most specifications, transferred patients have a longer hospital stay. The increase in LOS ranges from 7 to 22 days across different models. Transferred patients are more likely to die within 30 days of discharge by 5 percentage points. They are also more likely to be readmitted to health care facilities within 30 days of discharge by 0.4 percentage points. I do not find that endogeneity is present in the regressions on LOS, mortality and readmission.

Furthermore, I show that higher CCLs have negative effects on performance. The highest CCL, which signifies the most complex cases, increases the length of hospital stay by 6 to 15 days, the probability of 30-day mortality by 4 to 5 percentage points and a probability of 30-day readmission by 17 to 20 percentage points. Therefore, the negative effects of transferred patients on the receiving hospitals suggest that organisations given more difficult tasks due to their high level of expertise may be at a disadvantage if performance reviewers do not take account of individual patients' treatment difficulty levels.

# Chapter 3 Health care provider response to system reform: Effects of capitation on the inter-district movement of patients and health outcomes

## 3.1 Introduction

The capitation scheme pays service providers a fixed amount per enrollee, regardless of actual usage. This is similar to the diagnosis-related group (DRG) based payment method used in hospitals, which reimburses providers based on a pre-determined amount per case. Capitation may be preferred to the DRG based payment system under certain conditions because capitated providers are responsible for all their patients, even those who do not receive treatment (Selden, 1990). The use of capitation payment is increasing in the public sector worldwide, especially in the health care sector[15]. In New Zealand, capitation was introduced to the health sector in 1983, but its use stopped during the period from 2000 to 2003 while the transition for the newly developed district health boards (DHBs) was underway as a part of a system reform. Eventually, capitation was reintroduced in July 2003 to allocate health care funding to the 21 DHBs[16] established to oversee the health care facilities in their regions. Under the new capitation scheme, DHBs receive government funding based on the characteristics of the regional population. Prior to the reintroduction of capitation in 2003, funds were allocated to DHBs based on the services provided by the health care facilities in their districts.

[15] Rice and Smith (1999) provide a survey of capitation systems used in the health care sectors of 19 countries.
[16] There are currently 20 DHBs, as two of the DHBs merged in 2010.

I explore the impact of the policy reform in 2003 on inter-district patient flows by examining every publicly funded hospital discharge in New Zealand over the period of July 1999 to June 2011. My findings show that patient movement between districts decreased after the system reform took place. The decline is more notable among patients with more severe illness. Since 2003, specialist providers are also less likely to receive patients from other districts. The results indicate that sicker patients are less likely to be treated by specialist providers since the reform. Nevertheless, the reform has actually increased the transfer of patients in diagnoses with higher probabilities of mortality; therefore, non-specialist providers are selectively treating patients with more severe, but less fatal, conditions. Overall, the decrease in inter-district movement seems to have had negative effects on health outcomes.

One of the notable changes that the new capitation system has brought to the New Zealand health care sector is the varying amount of funding received by DHBs with different skill levels. Similar to the early prospective payment system discussed in Cutler (1995), capitation has increased the average reimbursement to some providers. The capitation formula assigns higher weights to the populations with greater needs, such as those in high-risk ethnic groups, or with low socioeconomic status. Since DHBs where no specialist hospitals are located (non-tertiary DHBs) tend to have a higher proportion of residents with greater needs, non-tertiary DHBs have experienced higher funding growth under capitation than have specialist providers (tertiary DHBs). In contrast, specialist, or tertiary, providers are typically located in urban areas whose population is deemed to be less at risk, so the level of risk-adjusted capitation funding is relatively low. In theory, the redistribution of funding between the so-called “losers” and “winners” under capitation will balance the initial differences in funding levels when the winning side purchases services from the losing side (Bedard, Dorland, Gregory, & Roberts, 2000). Redistribution, however, may not work well if capitation reduces the movement of patients between districts.

Another change is in the reimbursement method for patients receiving care in a district other than where they normally reside. As the capitation scheme allocates funds to each district for the care of its own residents, the method does not offer a clear rule on reimbursement for the treatment of non-residents. Thus, the government has developed a price list for inter-district flows (IDFs), the term used to refer to patients from other districts. If a patient receives treatment at a DHB other than her own, her DHB pays the other according to the national prices. Whether the IDF prices are set at the adequate level is debatable, however. In a report reviewing the New Zealand health sector reforms, Ashton (2007) argues that payment for IDFs based on the national prices is often insufficient and that the capitation system is unfair to DHBs receiving more patients from other districts. If the national prices set for IDFs are lower than their fair values, the tertiary DHBs, who receive more inter-district patients, will not recover the above-mentioned losses.

Given these two changes, the effects of the new capitation system on patient flow are ambiguous. The providers who receive greater funding under the new system may want to treat the residents within their districts to retain these funds. On the other hand, the allegedly low prices for IDFs may encourage providers to send their patients to another district to receive treatment. Thus, I examine the impact of the policy reform in 2003, which reintroduced capitation on inter-district patient flows. The data includes over ten million discharges and more than three million patients. Publicly funded hospital admissions comprise nearly 80percent of the total admissions in New Zealand. Not having information on privately funded events will not significantly affect the results as the private health sector in New Zealand is small and mainly deals with elective procedures.

If hospitals increase transfers under capitation, the negative effects will not be as large as documented by some past studies, because patient dumping is not an issue in New Zealand due to universal health care. The rise in transfers, combined with low transfer prices, may have negative effects on the receiving hospitals' bottom lines, but the efficiency of the health sector can improve if capitation encourages specialisation. This suggests that if non-tertiary hospitals decrease transfers and attempt to treat more complex cases on their own, the efficiency of the health care sector may decline. If, however, capitation reduces unnecessary transfers, efficiency may improve. Therefore, I further examine whether capitation decreases the probability that more severely ill patients receive treatment in a district outside their residence, and whether this affects health outcomes.

To understand how capitation affects patient flows, I first estimate the effects of capitation on the probability of receiving IDFs. To check the health care providers' responses more directly, I also examine how capitation affects the probability of transferring patients to another district. Although the change to capitation has altered the prices for IDFs, inter-district transfer reflects hospital response more accurately because IDFs include movement unrelated to hospitals' decisions (e.g. admission to a hospital while visiting out of town relatives). In addition, because patients in New Zealand typically do not have a choice of where to receive treatment if their hospital stays are publicly funded, a decision to transfer patients indicates the response of providers.

The new capitation scheme was introduced as part of the health system reform, which aims, among other things, to promote equity. The newly elected government in 1999 initiated the reform to restore a non-commercial system, because an attempt in the 1990s to introduce market-based incentives to the health sector was considered by many to be a failure. By distributing funds according to the relative needs of the regional population, the new capitation scheme helps achieve the goals of the reform. I use a difference in differences estimator to examine the effects of such exogenous change in the payment method on patient movement between districts. As tertiary DHBs receive a much larger proportion of IDFs, any effects of capitation on the probability of receiving IDFs will be more notable in tertiary DHBs. On the other hand, non-tertiary DHBs, which send inter-district transfers more frequently and also receive greater funding under capitation, will show a larger change in the pattern of inter-district transfer. I use the fact that the degrees of patient flows vary across providers depending on their skill levels to identify the effect of the reform.

I find that both IDFs and inter-district transfer decreased since the system reform took place. Capitation reduced the probability that the admitted patient is from another district by 3 percentage points, and the probability of transferring patients to another district by 0.4 percentage points. Given that the mean probabilities of IDFs and inter-district transfer are 14 percent and 2 percent, respectively, the effects are considerable. Tertiary DHBs are less likely to receive patients from another district under capitation than non-tertiary DHBs. Moreover, non-tertiary DHBs, which transfer more patients to another district in general, are less likely to send inter-district transfers under the new scheme.

The findings support the prediction that the capitation scheme will provide health care providers, especially non-tertiary DHBs, with incentives to keep patients within their districts. The results also suggest that the level of payment for inter-district flow may be so high that non-specialist DHBs have reduced their transfer rates. They do not provide conclusive evidence on the level of IDF prices, however. Even if IDF prices are low, the providers may have found it more attractive to keep the funds than pay someone else to do the job due, for instance, to the administration costs involved with transfer. In fact, a non-tertiary DHB urges its staff in an internal newsletter to ensure whether it is necessary to send their patients to another district, because they need to pay another district for the treatment while still paying the medical staff and overheads in their own hospital (Wairarapa District Health Board, 2010). Moreover, because non-tertiary DHBs receive a higher level of funding under capitation and the financial objective of the organisations in the public sector, such as DHBs, is to break even, the reform may have prompted non-specialist providers to treat the patients on their own.

In the analysis of the effects of the complication/comorbidity class level (CCL) on the probability of inter-district movement, I find that patients with more severe conditions are less likely to be treated in a hospital outside their residence under capitation. Compared with the CCL 0, which is the lowest severity of illness, all the higher categories of CCL decrease the probability of IDFs under capitation. The decrease is greatest in the highest level of CCL (2.6 percentage points). Patients assigned to higher CCLs are also less likely to be transferred to another district under capitation. Again, the decrease is greatest in CCL 4 (1.3 percentage points), which is the most complex category. Since the CCL indicates the presence of complications and does not distinguish between different diagnoses, I also use the mean mortality rates of each diagnosis to proxy for the most difficult cases. Interestingly, patients in the diagnoses with higher probabilities of mortality are more likely to be transferred since the reform. Therefore, under capitation, non-tertiary providers still transfer the most difficult cases to another district, but keep the severe, but less fatal, cases.

Taken together with the earlier result that non-tertiary DHBs are less likely to transfer patients to another district, this result suggests that the efficiency of the health care sector may have declined since the reintroduction of capitation, because non-specialist providers have reduced the transfer of more severely ill patients. Thus, I examine the effects of the system reform on 30-day mortality, readmission rates and the length of hospital stay. I find that the probability of mortality within 30 days of discharge declined during the research period, while readmission increased. The length of stay has decreased since the reform took place. Mortality may have decreased because the cases prone to fatality are still likely to be transferred to specialist providers under the capitation system. On the other hand, the decrease in the length of stay and increase in the probabilities of readmission suggest that patients are more likely to be readmitted to hospital because they are discharged earlier under the new system. Moreover, this pattern is more notable among the patients who are not transferred to another district. Thus, the reform seems to have negative effects on the health care sector, by reducing necessary inter-district movement.

The research period prior to the system reform in 2003 can be divided into two sub periods. The early capitation scheme was in place during the first two years, whereas capitation was not used over the period from 2001 to 2003. Although capitation existed in 1999 and 2000, in the main analysis I do not distinguish between the two periods prior to the reform because the early capitation scheme did not have direct impact on health care providers. The early capitation scheme was only used to distribute funds across four regions, while the providers received funds from the purchasing body based on contracts. On the contrary, DHBs have a dual role as purchaser and provider, so they directly receive funds assigned to their districts, and provide health care services using the funds. Therefore, incentives created from the new capitation system will have a greater impact on the provider.

Although a number of studies examine how the DRG-based payment system affects hospitals' transfer patterns, few report the impact of capitation on patient flow between providers. Furthermore, this study investigates how the change in transfer pattern due to the system reform affects health outcomes. Another contribution of this study is that it uses comprehensive data that includes the majority of hospital events in a country to examine the impact of a policy reform. Previous studies on the behaviour of health care providers tend to use relatively small datasets that cover limited geographical areas, or diagnoses. Last, the previous literature reports that a fixed payment system such as PPS increases transfer, but this research shows that the direction of the impact is less clear under capitation, which is a type of fixed payment system. Capitation may increase the inter-district patient flow if the prices for IDFs are set too low. More interestingly, however, hospitals may be discouraged from transferring patients to other districts in order to keep the funds they receive from the government. Although this study uses data from New Zealand hospitals, its findings are applicable to the health sector in other countries where capitation and universal coverage are in place.

## 3.2 Background and related Literature

### 3.2.1 Background

The use of capitation in New Zealand began in 1983 to allocate funds to 14 area health boards (Quin, 2009). Called population based funding, the capitation scheme remained in place during two health system reforms that took place in 1993 and 1999. Its use stopped during the period from 2000 to 2003 while the transition for the newly developed DHBs was underway as part of another system reform. Eventually, capitation was reintroduced in July 2003 to allocate health care funding to the 21 DHBs that had been established in 2001 to oversee the health care facilities in their regions. Although regional health boards existed before DHBs, DHBs have a role different from that of their predecessors. Prior to DHBs, there was a separation between the purchaser and provider of health care, and a single purchaser[17] bought health care services from the regional health boards and other providers. In contrast, DHBs act as both purchaser and provider. DHBs directly receive the funds assigned to their districts and pay their provider arms for the services delivered. Therefore, incentives created from the new capitation system have a greater impact on providers. Under the previous capitation system that existed until 2000, the funds were allocated across four regions via capitation, but the method did not have a direct impact on the providers as they received funds from the purchasing body based on contracts.

The most basic form of capitation pays the same amount for everyone, but some adjustments to reflect the relative needs of different groups of people are often

[17] There was a period when four purchasing agencies were in operation, before they were merged into one. For a concise review of the New Zealand health system reforms, see Quin (2009).

beneficial. For instance, Newhouse, Manning, Keeler and Sloss (1989) show that adding various measures of health and prior utilisation to the existing capitation formula can improve its explanatory power[18]. The New Zealand capitation scheme allocates funds based on the size of the population each DHB serves and other factors that reflect the health care needs of the population, such as age, gender, ethnicity, socio-economic status and geographic characteristics. The funding formula is updated every five years to incorporate the projections from the latest population census. The scheme assigns higher weights to elderly people, those with low socio-economic status and high-risk ethnic groups[19], because their health conditions are generally worse than the rest of the society. Areas that are rural and/or have a higher number of overseas visitors also receive higher levels of funding. Penno et al. (2012) provide a detailed description of how the population based funding formula is calculated. The capitation scheme promotes equity, as it allocates more funding to the regions whose populations have greater needs. As Hauck, Shaw and Smith (2002) suggest, however, allocating more resources to the unhealthy group is contrary to equality of access objective. Smith (2003) also points out that the focus on equity, one of the main objectives of formula funding, may indicate the move away from the pure efficiency solution.

Hospitals in New Zealand are classified into five categories (health centres, sub-acute units, secondary hospitals, lower level tertiary hospitals and higher level tertiary hospitals) depending on the complexity of the cases they normally treat (English, 1998). The DHBs running tertiary hospitals are recognised as tertiary DHBs and receive tertiary adjusters, which compensate for the high costs incurred by complex cases.

[18] A number of studies discuss what factors should be included in the capitation formula. For those interested see, for example, Bedard et al. (2000), Buehler and Holtgrave (2007) and Smith, Rice and Carr-Hill (2001).
[19] In New Zealand these groups are Maori, the indigenous people of New Zealand, and Pacific peoples.

Nevertheless, whether the overall funding to tertiary DHBs is sufficient to compensate for the work they do is still controversial. First, hospitals that possess expertise to treat complex cases are typically in urban areas whose population is deemed to be less at risk, hence the level of risk-adjusted capitation funding is relatively low. Table 3.1 shows that five out of seven tertiary DHBs received less funding than their population shares in the 2003/04 financial year.

Moreover, although the introductory year under capitation saw a sharp rise in the level of funding overall, the growth came, by and large, from the non-tertiary DHBs, as their average growth rate was 45 percent, whereas for the highly skilled DHBs this figure was only 9percent. The excess growth rates shown in Figure 3.1; measured by the annual growth rate of each DHB in excess of the average across DHBs; also confirm that the highly skilled DHBs fared negatively during this period, as only one tertiary DHB's funding grew more than the average, while all but two non-tertiary DHBs surpassed the average. As a result, non-tertiary DHBs in particular experienced the increase in the average price under capitation.

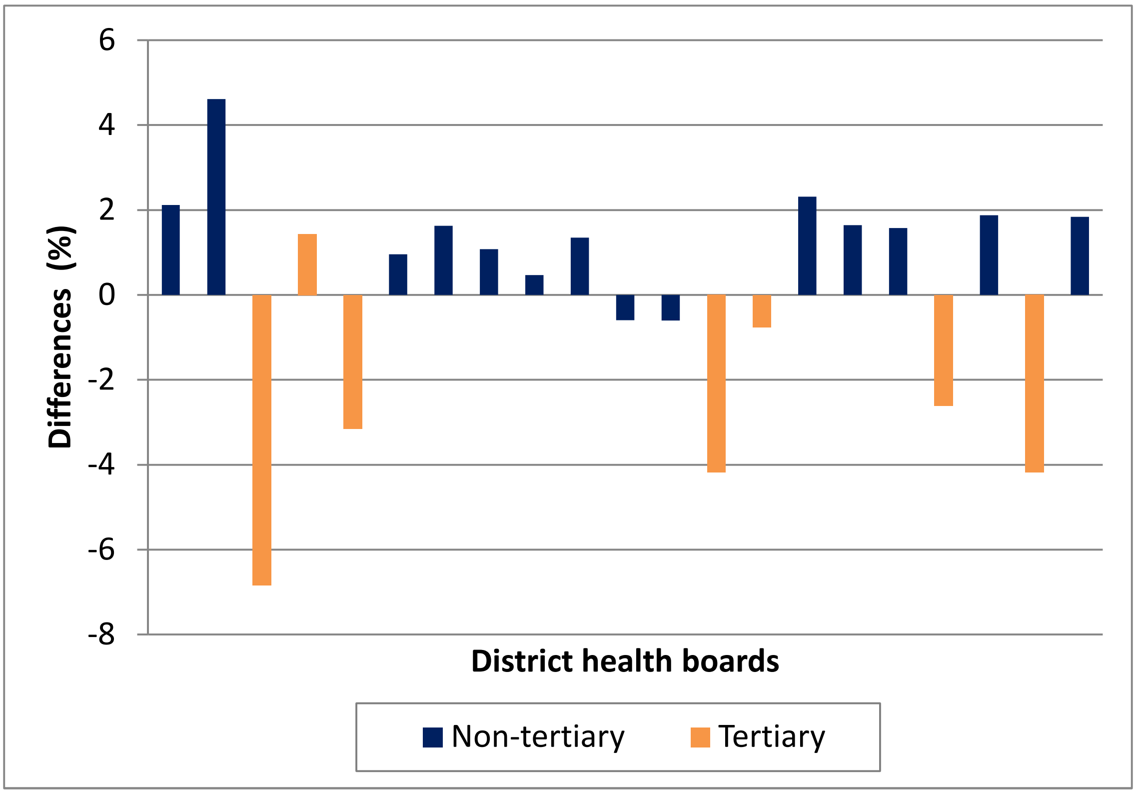
**Table 3.1 DHB funding and population share (%), 2003/2004**

| DHB | Funding share | Population share |
|---|---|---|
| Auckland* | 9.74 | 10.43 |
| Bay of Plenty | 5.45 | 4.82 |
| Canterbury* | 11.15 | 11.33 |
| Capital and Coast* | 5.91 | 6.59 |
| Counties Manukau* | 9.88 | 10.45 |
| Hawke's Bay | 4.06 | 3.70 |
| Hutt* | 3.22 | 3.41 |
| Lakes | 2.65 | 2.52 |
| MidCentral | 4.27 | 4.06 |

| | | |
|---|---|---|
| Nelson Marlborough | 3.47 | 3.27 |
| Northland | 4.20 | 3.64 |
| Otago*[a] | 4.57 | 4.45 |
| South Canterbury | 1.51 | 1.33 |
| Southland[a] | 2.62 | 2.66 |
| Tairawhiti | 1.31 | 1.12 |
| Taranaki | 2.85 | 2.62 |
| Waikato* | 8.53 | 8.32 |
| Wairarapa | 1.11 | 0.97 |
| Waitemata | 10.72 | 11.92 |
| West Coast | 0.92 | 0.76 |
| Whanganui | 1.86 | 1.61 |
| Total | 100.00 | 100.00 |

NOTE.—From Ministry of Health (2004).
* Tertiary DHBs
[a] Since 1 May 2010, Otago and Southland DHBs merged to form Southern DHB.

**Figure 3.1 Differences in the annual funding growth rates between each DHB and the average across DHBs (Mean of differences over 2001-2011 period)**



Second, Wignall and Tringham (2008) argue that tertiary adjusters do not accurately reflect the difficulty of services provided by highly skilled hospitals, due to the complexity involved in categorising and pricing such services. There are mixed views on even the fundamentals, such as what constitutes tertiary services. Moreover, similar to the DRG-based reimbursement, a tertiary adjuster is based on the average costs across tertiary providers, who equally share the adjustment. Thus, if there are large discrepancies in the volume and complexity of tertiary cases across providers, those with higher expertise will be undercompensated, whereas lower level tertiary providers will enjoy a surplus. The inadequacy of the national prices for IDFs is also under criticism. As mentioned in the previous section, Ashton (2007) points out that payment for IDFs based on the national prices is often insufficient and that the capitation system is unfair to DHBs receiving more patients from other districts. This implies that highly skilled providers are at a disadvantage under the capitation funding system, because they treat more out of district patients, as shown in Table 3.2.

**Table 3.2 Descriptive statistics for inter-district flows and transfer by skill level (*N*=10,777,536)**

| | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| | IDF | | | |
| Non-tertiary | 0.05 | 0.23 | 0 | 1 |
| Tertiary | 0.20 | 0.40 | 0 | 1 |
| Total | 0.14 | 0.34 | 0 | 1 |
| | Inter-district transfer | | | |
| Non-tertiary | 0.03 | 0.16 | 0 | 1 |
| Tertiary | 0.02 | 0.13 | 0 | 1 |
| Total | 0.02 | 0.14 | 0 | 1 |

### 3.2.2 Related literature

Few studies examine how capitation affects patient flow between hospitals. Sinkin, Fisher, Dozier and Dye (2005) show that transfer rates for pregnant women enrolled in

Medicaid Managed Care are much lower than those in Medicaid Fee-for-Service, using data on publicly funded cases in upstate New York. Although they do not specify the payment methods used in the Medicaid Managed Care, it is known that capitation is one of the methods Medicaid uses (Buehler & Holtgrave, 2007; Selden, 1990). The lower transfer rates for those in managed care is contrary to the common findings of *patient dumping*, but whether less dumping is good news for patients is unclear. The authors mention that written protocols for maternal and newborn transfer between institutions are in place in the area, because timely transfer and referral to specialist facilities improve outcomes. Thus, lower transfer rates may indicate that patients under Medicaid Managed Care are not receiving the best available care.

Some studies examine the impact of a capitation scheme on referrals, which are the patient flows between primary care providers and specialists. For instance, Allard et al. (2011) compare the incentives provided to general practitioners (GPs) by fee-for-service, capitation and fundholding, which is an extended version of capitation where physicians are also responsible for the costs of specialised and hospital care. Recognising the physicians' heterogeneity in ability and altruism, Allard et al. (2011) show that capitation results in more referrals to costly specialty care than the other two schemes because GPs try to avoid the costs of directly treating the patients. The studies on physician referral under capitation, however, are not directly comparable to my study because there are notable differences between physician referral to specialists and transfer by non-tertiary DHBs to tertiary facilities. For instance, the scope of work performed by non-tertiary and tertiary DHBs are more similar than that performed by GPs and specialists. Most importantly, hospitals transferring patients need to pay the receiving hospital out of their capitation payment, whereas GPs generally do not pay for the specialist care[20].

In contrast to the lack of research on the effects of capitation on transfer, a number of studies investigate how the prospective payment system (PPS) introduced to the U.S. in the 1980s affects transfer pattern. Often called patient dumping, transfer of patients under PPS has received negative attention. Nonetheless, not all of the studies report that transfer is harmful, or find evidence of dumping. Newhouse (1989) tests whether unprofitable patients are more likely to be transferred to hospitals of last resort, which he define as city and county hospitals, under PPS and finds mixed results. Sloan et al. (1988) find no evidence of patient dumping under PPS, after examining 467 hospitals with about 1 million discharges per year over the 1980 to1985 period. Eze and Wolfe (1993) show that the shifting of patients from non-Veterans Affairs to Veterans Affairs hospitals due to PPS may be efficient, if the efficient state is defined as allocations that would occur if hospitals act as the perfect agents of patients.

Besides transferring patients, there are other ways that providers can respond to reimbursement methods. Ellis and McGuire (1996) use a panel dataset of Medicaid psychiatric discharges in New Hampshire during the period from 1987 to 1992 to study the effects of the change to a fixed payment scheme, which provided more generous reimbursement to private hospitals with specialised psychiatric facilities. They decompose the effects of a reimbursement scheme into moral hazard, selection and practice-style effects. Moral hazard effects cause a change in treatment intensity, while the selection effect changes the average severity of patients. The practice-style effect

[20] The fundholding scheme is an exception.

refers to changes in the share of patients treated at different hospitals. The empirical tests show that the moral hazard effects decreased LOS in the private hospitals by 1.8 days, while the practice style effects reduced it by 3 days. In contrast, selection effects increased LOS by 0.3 day. In a health system where public financing is a dominant source of funding, as in New Zealand, selection and practice-style effects are usually less prevalent because hospitals and patients have limited choices. Nevertheless, my study shows that those effects are still relevant in a market with universal health coverage. The direction of the effects, however, may be different.

Several studies investigate how health care providers respond to capitation[21]. Ellis and Miller (2009) point out that capitation may lead providers to select profitable patients, reduce the level of services and increase the use of lower-cost alternatives to physicians, such as nurses and physician assistants. A number of studies confirm that capitation reduces the level of services (Hennig-Schmidt, Selten, & Wiesen, 2011; Lurie, Christianson, Finch, & Moscovice, 1994; Melichar, 2009; Yip, Supakankunti, Sriratanaban, Janjaroen, & Pongpanich, 2001); however, Hennig-Schmidt et al. (2011) and Lurie et al. (1994) find that patients in capitated plans are no worse off, despite receiving less care. Machnes (1996) finds that a capitation system removes excessive maintenance services found under per diem systems at psychiatric hospitals in Israel.

The change to a pre-payment system (PPS) in 1983 for U.S. Medicare reimbursement created a large body literature documenting how providers responded to the change from cost reimbursement to the new pre-payment system. See, for instance,

[21] The impact of capitation is widely researched in primary care settings: See, for example, Iversen and Luras (2006) for a review of the research.

Acemoglu and Finkelstein (2008), Cutler (1995), Frank and Lave (1989), Hodgkin and McGuire (1994), Lave and Frank (1990) and Soderstrom (1993). Although most studies find that the PPS reduced resource use intensity, or care quality, some present the opposite effects. This strand of research suggests that the direction of the effects depends on the specific design of the reimbursement system. Feess, Mueller and Wohlschlegel (2008) show that a PPS lowered complication and readmission rates in German hospitals. The decline in complication and readmission rates is due to the lower reimbursements hospitals receive under a PPS for complications and readmissions, inducing hospitals to exert greater efforts in the area of care quality. Norton, van Houtven, Lindrooth, Normand and Dickey (2002) suggest that prospective payments can increase care quality, if an increase in the average price offsets a decline in the marginal price.

Dranove (1987) points out that a DRG-based reimbursement scheme can save costs if hospitals specialise in DRGs for which they have lower production costs. On the contrary, if hospitals specialise in treating more profitable patients, cost saving may not occur. He suggests that creating additional DRGs, or tying DRG rates to casemix variation, will improve the rate-setting performance. A study by Dafny (2005) reports how hospitals respond to the refinements to DRG codes by examining the DRG price changes in 1988 in the U.S., which increased the DRG weights for the top codes within DRG pairs. The results show that hospitals upcoded patients to diagnosis codes with the largest price increases, but neither increased the volume of admissions to take advantage of the price increase, nor raised the quality of care. Hospitals also spread the extra funds received across all DRGs, implying that specialisation, which Dranove (1987) suggests is a potential benefit of a PPS, did not occur.

Finkelstein (2007) investigates the effects of another major change in the U.S. health system; the introduction of Medicare in 1965. Although Medicare was introduced to all the states in the U.S., the rates of private health coverage prior to Medicare differ across regions. She uses the variation in private insurance coverage to identify the effects of Medicare on health care spending. Her findings suggest that the introduction of Medicare may be one of the reasons for the rising health care expenditure in the U.S. from 1950 to 1990.

Outside the U.S. health care sector, Wagstaff and Moreno-Serra (2009) study whether the transition to social health insurance systems in former communist countries in Europe and Central Asia improves health outcomes. Their findings reveal that the reform increased health expenditure, but failed to improve mortality and morbidity indicators. Ernst and Szczesny (2008) report risk selection by providers after the reform, which introduced high-powered incentives, using data from a small German hospital over the 1989 to 2002 period. They find that the number of high-risk patients significantly decreased after the introduction of capped budgets, which pay hospitals per diem payments for each day a patient stays up to the limit of the planned stay. None, or only a part of, the costs are reimbursed for the period exceeding the planned stay. Ernst and Szczesny (2008) also note that increased financial incentives may be beneficial if they lead hospitals to specialise in what they do best. The environment in which the hospital in their study operates is similar to the New Zealand health care sector. In both countries, it is relatively easy for secondary hospitals to transfer patients to higher-level hospitals due to the hospital structure and universal health care. The difference in the incentives faced by capped budgets, or PPS from capitation, in my study, however, is that the capitation system may provide incentives not to transfer patients.

### 3.3 Data

The data used in this study; the National Minimum Dataset[22]; are compiled by the New Zealand Ministry of Health. The dataset provides patient discharge data for all publicly funded hospital events in New Zealand for the period from 1 July 1999 to 30 June 2011. The current National Minimum Dataset was started in 1999. Although the original National Minimum Dataset was compiled in 1993 and back-loaded with information from 1988 onwards, it does not include all the required information for this research. Also, because the early data on some of the information, such as patient residence, are not directly comparable to the later data, I use the current National Minimum Dataset for consistency. The dataset includes 10,777,536 observations, 3,243,791 patients and 555 facilities. Each record in the dataset contains information such as the age, gender and ethnicity of a patient, facility in which the patient was treated, district the patient resides in, a diagnosis type and severity, length of stay, transfer status, admission type (e.g. elective, or acute) and event end type (e.g. death, self-discharge, or routine discharge). Each patient in the dataset has a unique identification number, so I can check the patient's admission and discharge history during the research period. Some patients in the dataset had multiple hospital admissions.

As mentioned earlier, New Zealand ranks hospitals into five categories (health centres, sub-acute units, secondary hospitals, lower level tertiary hospitals and higher level tertiary hospitals) depending on the complexity of cases that they treat (English, 1998). In total, 11 hospitals are classified as tertiary. Approximately 30percent of the admissions in our dataset are treated in tertiary hospitals. The 21 district health boards

[22] For a more detailed description of this dataset, see New Zealand Health Information Service (2008).

(DHBs)[23] oversee the facilities in their districts, providing funding and care for all of the admissions in the dataset. The DHBs running tertiary hospitals are recognised as tertiary DHBs. Although 8 DHBs receive the tertiary adjuster, I exclude 1 DHB (MidCentral DHB) and consider only 7 DHBs as tertiary, because MidCentral DHB operates not a tertiary, but a secondary hospital, which provides some lower level tertiary services (English, 1998)[24]. Moreover, the excluded DHB received only NZ$0.6 million out of the pool of NZ$116 million in the 2004-05 funding round. In contrast, the mean of the tertiary adjuster received by the other 7 tertiary DHBs is NZ$16 million (Wignall & Tringham, 2008). The 7 tertiary DHBs treat about 58percent of the total admissions in the dataset.

DRGs, which classify diagnosis types into several hundred groups[25], code the patients' diagnosis types. The Major Diagnostic Category (MDC) provides another method of classifying diagnoses. The MDC divides all the diagnoses into 25 groups, based mainly on an organ system. As there are too many groups of DRGs, I use MDC code dummies to control for the effects of varying diagnoses in the regression analysis. Table 2.1 in the previous chapter of this dissertation provides the description of the MDC codes and the number of observations in the dataset that belong to each code. I include only 23 MDCs in the regression, because MDCs 0 and 99 have too few observations. CCL, which ranges from 0 to 4, indicates the severity of illness. CCL 0 signifies the least severe illness, while CCL 4 is the most severe. Each patient is also

[23] Since 1 May 2010 only 20 DHBs have been in operation, as Otago and Southland DHBs merged to form Southern DHB.
[24] I also run the analysis with eight tertiary DHBs, but the results remain almost the same.
[25] More than 1 version of DRG code is available, as the code is constantly updated. The DRG code version 3.1, used for the observations in the earlier years of our dataset, classifies the diagnoses into 667 groups, while the current code divides them into 742.

assigned a cost-weight, which is used for calculating payments to the hospital treating the patient.

In order to check the effects of policy reform on patient movement, I create two dummy variables. The first indicates whether the admitted patient is transferred to another facility at the end of stay. The dummy equals one if the patient's discharge type is 'DA (discharge to an acute facility)', 'DP (psychiatric patient transferred for further psychiatric care)', 'DT (discharge of non-psychiatric patient to another healthcare facility)', 'EA (discharge from emergency department acute facility to specialist facility for neonates and burns only)', or 'ET (discharge from emergency department acute facility to another healthcare facility)'. I also create an additional dummy to identify whether the patient is transferred to another DHB. Inter-district transfers comprise approximately 2percent of total admissions. I record an admission as an IDF if the facility providing care is in a district outside the patient's residence. Not all the IDFs are transfers, as some patients are admitted as routine admissions (as opposed to transfers) to a hospital outside their districts. IDFs account for 14percent of the total admissions. On average, patients transferred between districts have higher severity of illness, while IDFs show slightly lower severity, as presented in Table 3.3.

**Table 3.3 Descriptive statistics for CCL (*N*=10,776,648)**

| | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| Non-inter-district transfer | 0.937 | 0.892 | 0 | 4 |
| Inter-district transfer | 1.317 | 1.018 | 0 | 4 |
| Non-IDF | 0.945 | 0.890 | 0 | 4 |
| IDF | 0.944 | 0.937 | 0 | 4 |

Figure 3.2 and Figure 3.3 illustrate how the proportion of IDFs and inter-district transfer, respectively, has changed over the research period. Overall, there is a downward trend in the proportion of IDFs in both tertiary and non-tertiary DHBs, but the movement is more notable in tertiary DHBs. The change in the proportion of inter-district transfers shown in Figure 3.3 is less straightforward. Non-tertiary DHBs transferred more patients to another district until 2003, when the new capitation scheme was introduced, after which they decreased inter-district transfers; however, the proportion of inter-district transfers has started increasing again since 2009. On the other hand, the proportion of inter-district transfers in tertiary DHBs started declining in 2005, two years after the introduction of the new scheme, only to increase again in 2009.

The increase in inter-district transfer in the last three years may be due to another set of reforms undertaken by the newly elected government. As Gauld (2012) explains in his study, the new centre-right government has retained DHBs and the capitation system, because of its election promise that it would not overhaul the structure of the health system, but has made other changes to improve coordination among the DHBs. The attempt to enhance centralisation and coordination across regions may have resulted in the increase in inter-district transfer. In addition, the global financial crisis, which started in 2007, led the government to put pressure on providers to use their funds more efficiently. Such pressure could have also increased inter-district transfer.

**Figure 3.2 Proportion of IDFs received by skill level**

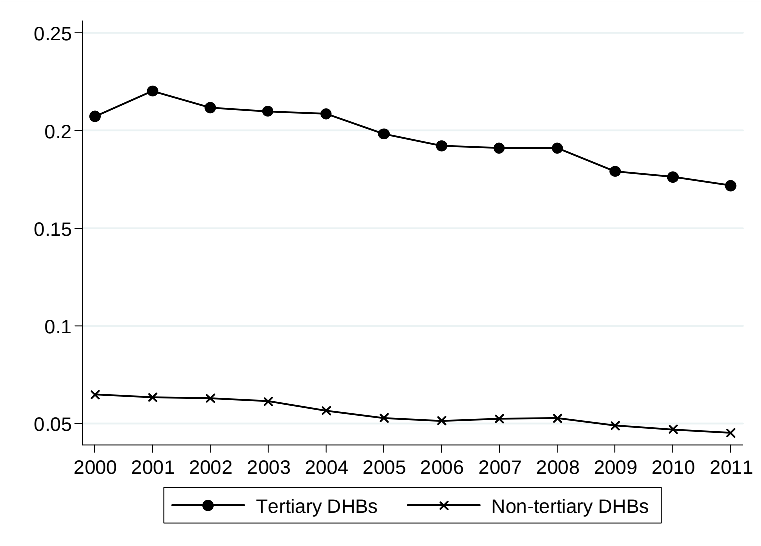
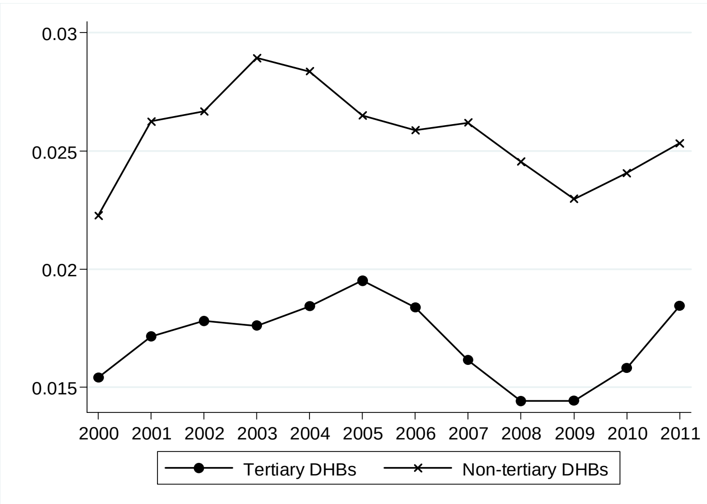



**Figure 3.3 Proportion of inter-district transfer sent by skill level**




The new capitation system takes effect in the latter eight years of the research period. I include eleven dummy variables (the 1999-2000 period is the reference category) to measure the effects of years before and after capitation. The year dummies indicate the financial years, so the 2000 dummy, for instance, refers to the period that starts from

July 1, 2000 and ends in June 30, 2001. Since the new capitation system was introduced in July 2003, the 2003 dummy indicates the year of reform.

To indicate the skill levels of providers, I use a dummy variable indicating whether the provider is in a tertiary, or non-tertiary, DHB. The key variable of interest is the interaction terms between the year dummies and tertiary dummy. These interaction terms will capture the differences in the effects of capitation between highly and less skilled providers. I also create a second set of interaction terms to check whether there are differences in the effects of capitation across cases with varying complexities. These interaction terms are between four groups of CCLs and the year dummies. In addition, I create a dummy variable indicating post-capitation years. The interaction terms between this post-reform dummy and the tertiary and CCL dummies, respectively, will help examine the average effects of the post-reform period on patient movement.

In addition to the analysis of the effects of the new capitation system on patient movement, I also study health outcomes, such as 30-day mortality and readmission, before and after the reform. To compute the mortality variable, I exclude the observations from the last month of the research period, because the mortality variable measures death within 30 days of discharge. To compute 30-day readmission, I exclude patients who died in hospital, or within 30 days of the last discharge date. Table 3.4 presents the descriptive statistics of the entire dataset, as well as the subsets used for robustness checks. Since I exclude the observations in MDCs 0 and 99, the number of observations used in the analysis is 10,776,648.

**Table 3.4 Descriptive statistics**[26]

| | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| | A. Entire dataset: 1999-2011 (*N*=10,776,648) | | | |
| IDF | 0.137 | 0.343 | 0 | 1 |
| Inter-district transfer | 0.018 | 0.133 | 0 | 1 |
| Post-reform years | 0.702 | 0.457 | 0 | 1 |
| Tertiary | 0.584 | 0.493 | 0 | 1 |
| CCL 0 | 0.342 | 0.474 | 0 | 1 |
| CCL 1 | 0.450 | 0.497 | 0 | 1 |
| CCL 2 | 0.140 | 0.347 | 0 | 1 |
| CCL 3 | 0.058 | 0.233 | 0 | 1 |
| CCL 4 | 0.010 | 0.101 | 0 | 1 |
| Gender (Female dummy) | 0.558 | 0.497 | 0 | 1 |
| Age | 42.722 | 27.937 | 0 | 112 |
| European | 0.674 | 0.469 | 0 | 1 |
| Maori | 0.163 | 0.369 | 0 | 1 |
| Pacific Islander | 0.069 | 0.254 | 0 | 1 |
| Asian | 0.047 | 0.212 | 0 | 1 |
| Others | 0.047 | 0.211 | 0 | 1 |
| Average costweight by DHB | 1.123 | 0.191 | 0 | 1.688 |
| 30-day mortality[a] | 0.030 | 0.169 | 0 | 1 |
| 30-day readmission[b] | 0.243 | 0.429 | 0 | 1 |
| Unemployment rates | 5.070 | 1.656 | 2 | 9.1 |
| Median weekly household income (NZ$, 2011 price) | 1,257.08 | 151.52 | 808.59 | 1,544.07 |
| | B. DHB period: 2001-2011 (*N*=9,223,433) | | | |
| IDF | 0.134 | 0.341 | 0 | 1 |
| Inter-district transfer | 0.021 | 0.142 | 0 | 1 |
| Post-reform years | 0.820 | 0.384 | 0 | 1 |
| Tertiary | 0.583 | 0.493 | 0 | 1 |
| CCL 0 | 0.344 | 0.475 | 0 | 1 |
| CCL 1 | 0.450 | 0.498 | 0 | 1 |
| CCL 2 | 0.138 | 0.344 | 0 | 1 |
| CCL 3 | 0.058 | 0.234 | 0 | 1 |
| CCL 4 | 0.010 | 0.101 | 0 | 1 |
| Gender (Female dummy) | 0.557 | 0.497 | 0 | 1 |
| Age | 42.985 | 27.932 | 0 | 112 |
| European | 0.672 | 0.469 | 0 | 1 |
| Maori | 0.165 | 0.371 | 0 | 1 |
| Pacific Islander | 0.071 | 0.256 | 0 | 1 |
| Asian | 0.050 | 0.217 | 0 | 1 |

[26] MDCs 0 and 99 are excluded.

| | | | | |
|---|---|---|---|---|
| Others | 0.043 | 0.202 | 0 | 1 |
| 30-day mortality[a] | 0.0295 | 0.169 | 0 | 1 |
| 30-day readmission[b] | 0.246 | 0.431 | 0 | 1 |
| Average costweight by DHB | 1.135 | 0.195 | 0.71 | 1.688 |
| Unemployment rates | 4.919 | 1.658 | 2 | 9.1 |
| Median weekly household income (NZ$) | 1,282.69 | 134.76 | 891.15 | 1544.07 |
| | C. Pre-DHB and pre-reform period under the early capitation system: 1999-2001 (*N*=1,553,912) | | | |
| IDF | 0.152 | 0.359 | 0 | 1 |
| Inter-district transfer | 0.020 | 0.139 | 0 | 1 |
| Post-reform years | 0.000 | 0.000 | 0 | 0 |
| Tertiary | 0.585 | 0.493 | 0 | 1 |
| CCL 0 | 0.332 | 0.471 | 0 | 1 |
| CCL 1 | 0.447 | 0.497 | 0 | 1 |
| CCL 2 | 0.153 | 0.360 | 0 | 1 |
| CCL 3 | 0.057 | 0.231 | 0 | 1 |
| CCL 4 | 0.010 | 0.102 | 0 | 1 |
| Gender (Female dummy) | 0.562 | 0.496 | 0 | 1 |
| Age | 41.159 | 27.908 | 0 | 111 |
| European | 0.686 | 0.464 | 0 | 1 |
| Maori | 0.152 | 0.359 | 0 | 1 |
| Pacific Islander | 0.061 | 0.238 | 0 | 1 |
| Asian | 0.032 | 0.176 | 0 | 1 |
| Others | 0.069 | 0.254 | 0 | 1 |
| 30-day mortality[a] | 0.296 | 0.169 | 0 | 1 |
| 30-day readmission[b] | 0.226 | 0.418 | 0 | 1 |
| Average costweight by DHB | 1.049 | 0.150 | 0.779 | 1.342 |
| Unemployment rates | 5.974 | 1.319 | 2.5 | 9 |
| Median weekly household income (NZ$) | 823.07 | 118.32 | 594 | 1,027 |
| | D. DHB and pre-reform period: 2001-2003 (*N*=1,656,622) | | | |
| IDF | 0.150 | 0.357 | 0 | 1 |
| Inter-district transfer | 0.022 | 0.146 | 0 | 1 |
| Post-reform years | 0.000 | 0.000 | 0 | 0 |
| Tertiary | 0.588 | 0.492 | 0 | 1 |
| CCL 0 | 0.337 | 0.473 | 0 | 1 |
| CCL 1 | 0.448 | 0.497 | 0 | 1 |
| CCL 2 | 0.148 | 0.355 | 0 | 1 |
| CCL 3 | 0.057 | 0.232 | 0 | 1 |
| CCL 4 | 0.010 | 0.102 | 0 | 1 |
| Gender (Female dummy) | 0.557 | 0.497 | 0 | 1 |
| Age | 41.922 | 27.885 | 0 | 112 |
| European | 0.680 | 0.466 | 0 | 1 |
| Maori | 0.157 | 0.364 | 0 | 1 |
| Pacific Islander | 0.065 | 0.246 | 0 | 1 |
| Asian | 0.039 | 0.193 | 0 | 1 |
| Others | 0.059 | 0.236 | 0 | 1 |

| | | | | |
|---|---|---|---|---|
| 30-day mortality[a] | 0.031 | 0.174 | 0 | 1 |
| 30-day readmission[b] | 0.241 | 0.427 | 0 | 1 |
| Average costweight by DHB | 1.094 | 0.166 | 0.737 | 1.416 |
| Unemployment rates | 5.114 | 1.264 | 2.8 | 9.1 |
| Median weekly household income (NZ$) | 934.57 | 114.24 | 690 | 1,063 |
| | E. DHB and post-reform period: 2003-2011 (*N*=7,566,115) | | | |
| IDF | 0.130 | 0.337 | 0 | 1 |
| Inter-district transfer | 0.020 | 0.142 | 0 | 1 |
| Post-reform years | 1.000 | 0.000 | 1 | 1 |
| Tertiary | 0.582 | 0.493 | 0 | 1 |
| CCL 0 | 0.345 | 0.475 | 0 | 1 |
| CCL 1 | 0.451 | 0.498 | 0 | 1 |
| CCL 2 | 0.135 | 0.342 | 0 | 1 |
| CCL 3 | 0.058 | 0.234 | 0 | 1 |
| CCL 4 | 0.010 | 0.101 | 0 | 1 |
| Gender (Female dummy) | 0.557 | 0.497 | 0 | 1 |
| Age | 43.219 | 27.938 | 0 | 110 |
| European | 0.670 | 0.470 | 0 | 1 |
| Maori | 0.167 | 0.373 | 0 | 1 |
| Pacific Islander | 0.072 | 0.258 | 0 | 1 |
| Asian | 0.052 | 0.222 | 0 | 1 |
| Others | 0.039 | 0.194 | 0 | 1 |
| 30-day mortality[a] | 0.029 | 0.168 | 0 | 1 |
| 30-day readmission[b] | 0.247 | 0.431 | 0 | 1 |
| Average costweight by DHB | 1.145 | 0.199 | 0.711 | 1.688 |
| Unemployment rates | 4.875 | 1.729 | 2 | 9.1 |
| Median weekly household income (NZ$) | 1,174.38 | 147.16 | 802 | 1,423 |

[a] The observations from the last month of the research period are excluded.
[b] Only the surviving patients at 30 days of discharge are included.

### 3.4 Methodology

The unit of my analysis is the DHB, not individual hospitals. Although not all the facilities in tertiary DHBs are tertiary hospitals, it is more helpful to examine the behaviour of DHBs, as the capitation scheme distributes funds to DHBs, which then operate individual hospitals with the funds. In addition, DHBs organise some of the publicly funded operations to be performed in private hospitals in order to maximise the efficiency of resource use; therefore, what I observe in the data may not be the behaviour of the hospital where the event took place, but the response of the DHB. I estimate the equations with logistic regression with clustered standard errors to account for the correlations in the errors at patient level.

A potential problem with the identification strategy is that any changes I observe after the reform may reflect other factors that might have changed over time across providers. Thus, I include time-varying regional factors, such as the unemployment rate, median weekly income and mean cost-weights in the equations to control for their effects on the outcome variables. After estimating the equations, I examine the pattern of the coefficients of the interaction terms between tertiary providers and year fixed effects to check the trend before and after the reform.

The first equation measures the impact of the new capitation system on the probability that the admitted patient is the resident of another district. The equation takes the following form:

$$IDF_{it} = \beta_0 + \beta_1 YEAR_t + \beta_2 H_i + \beta_3 H_i \times YEAR_t$$

$$+ \sum_{j=1}^{4} \beta_{j+3} \, CCL_{ij} \times YEAR_t + \beta_8 \boldsymbol{X}_{it} + \varepsilon_{it} \quad (1)$$

where $IDF_{it}$ is a dummy variable, which equals 1 if admission *i* takes place in a district other than where the admitted patient resides and 0 otherwise. $YEAR_t$ is a set of year fixed effects. $H_i$ is a dummy variable, which takes the value of 1 if the DHB receiving admission *i* is tertiary. $CCL_{ij}$ is a dummy variable indicating the level of CCL (*j*=1, 2, 3 and 4). The reference category, CCL 0, indicates the lowest level of severity. I hypothesise that capitation has different effects on DHBs depending on their skill levels. The change in the reimbursement of IDFs has a larger impact on tertiary DHBs, because tertiary DHBs are more likely to receive patients from other districts. I measure the varying effects of capitation on different DHBs by the interaction term, $H_i \times YEAR_t$. $\beta_3$ <0 indicates that tertiary DHBs are less likely to receive patients from another DHB in year $t$. $CCL_{ij} \times YEAR_t$ measures the effects of capitation on varying levels of illness severity. Negative signs for $\beta_4$ to $\beta_7$ signify that a higher CCL reduces the probability that the patient is from another district in year $t$.

$\boldsymbol{X_{it}}$ is a list of control variables, including the average cost-weight of the DHB receiving admission $i$ in year $t$, age, gender, ethnicity, diagnostic information such as CCL and MDC[27], and economic indicators such as unemployment rates and median weekly income of the region the patient resides in. The mean cost-weight of the DHB measures the average difficulty of cases that the DHB treats. The quality of life may affect health, which in turn can influence case complexity and the transfer decision. The regional unemployment rates and household income data are only available at the level of regional councils, which cover wider areas than DHBs. In total, there are 12 regional councils.

The second equation, shown below, is a more direct test of how DHBs respond to the policy reform for two reasons. First, I examine the probability of sending patients, rather than receiving. The sending pattern is a more direct indicator of the behaviour of health care providers, especially in a market where the providers cannot reject transferred patients. Second, I limit the analysis to transfers, which reflects provider behaviour with less noise, since IDFs include patient movement that is not initiated by providers. The equation takes the following form:

[27] I have also included hospital characteristics such as hospital size and teaching status, but the results exhibited no qualitative change.

$$IT_{SENT_{it}} = \gamma_0 + \gamma_1 YEAR_t + \gamma_2 H_i + \gamma_3 H_i \times YEAR_t$$

$$+ \sum_{j=1}^{4} \gamma_{j+3} \, CCL_{ij} \times YEAR_t + \gamma_8 \boldsymbol{X}_{it} + \varepsilon_{it} \quad (2)$$

where $IT\_SENT_{it}$ is a dummy variable, which equals 1 if admission *i* is transferred to another DHB at the end of the stay and 0 otherwise. The other variables are as described above. Capitation provides larger incentives to non-tertiary DHBs regarding transfer. Non-tertiary DHBs not only transfer patients more frequently, but also receive greater funding under capitation. To retain the increased funds, they may treat patients in their districts rather than transfer them out. $\gamma_3$ measures whether tertiary DHBs are more likely to transfer patients to another DHB in year *t*. Positive signs would indicate that non-tertiary DHBs are less likely to transfer patients to another district under capitation. $\gamma_4$ to $\gamma_7$ measure whether patients assigned to CCLs 1 to 4, respectively, are more likely to be transferred to another DHB than those assigned to CCL 0 in year *t*.

Finally, the last set of equations measures how the introduction of the new capitation system affects health outcomes. The first measure of health outcome is 30-day mortality and the equation takes the following form:

$$MORT_{it} = \delta_0 + \delta_1 YEAR_t + \delta_2 IT\_SENT_i + \delta_3 IT\_SENT_i \times YEAR_t + \delta_4 \boldsymbol{Z}_{it} + \varepsilon_{it} \quad (3)$$

where $MORT_{it}$ is a dummy variable, which equals 1 if patient *i* died within 30 days of discharge and 0 otherwise. The coefficient of the interaction term between $IT\_SENT_i$ and year fixed effects measures the effects of the reform on mortality for the patients transferred to another district. $\mathbf{Z}_{it}$ is a list of control variables such as a tertiary dummy, the mean average costweight of a DHB receiving patient *i* in year *t*, CCL, MDC codes, age, gender and ethnicity. As the quality of life can affect mortality, I also include the economic indicators, unemployment rates and median weekly household income of the region in which the patient resides.

The second measure of outcome is 30-day readmission, and the equation takes the following form:

$$READ_{it} = \delta_0 + \delta_1 YEAR_t + \delta_2 IT\_SENT_i + \delta_3 IT\_SENT_i \times YEAR_t + \delta_4 \boldsymbol{Z}_{it} + \varepsilon_{it} \quad (4)$$

where $READ_{it}$ is a dummy variable, which equals 1 if patient *i* was admitted to any facility in the dataset within 30 days of discharge and 0 otherwise. Again, the other variables are as described above. The third and last measure of health outcome is the length of stay in hospital, which is estimated by the following equation:

$$LOS_{it} = \delta_0 + \delta_1 YEAR_t + \delta_2 Transfer_i + \delta_3 Transfer_i \times YEAR_t + \delta_4 \boldsymbol{Z}_{it} + \varepsilon_{it} \quad (5)$$

where $LOS_{it}$ measures the length of stay in hospital for patient *i* in year *t*. $Transfer_i$ in this equation is a dummy variable, which equals 1 if the patient admitted is a transfer from another district and 0 otherwise. I examine the effects of the patients admitted as a transfer, instead of those transferred to another district, because the dependent variable is the length of stay in the health care facility that received the patients.

### 3.5 Results

As the interpretation of interaction terms in nonlinear models is not straightforward, I use the following approach by Karaca-Mandic, Norton and Dowd (2012). To compute the marginal effects of the interaction term between the year dummies and *H* (the tertiary dummy), I calculate the marginal effects of year *t* on the probability of inter-district movement when *H* equals one and zero, respectively, and take the difference. To obtain the marginal effects of the interaction term between the year dummies and *CCL*, I compute the marginal effects of year *t* for each level of *CCL* and take the difference between the marginal effects for CCL 1-4, respectively, and CCL 0, which is the reference category. Similarly, to obtain the marginal effects of the interaction term between *POST* and *CCL*, I compute the marginal effects of *POST* for each level of CCL and take the difference between the marginal effects for CCL 1-4, respectively, and CCL 0. An example of this calculation process is described in the Appendix.

### 3.5.1 Effects of the system reform on providers of different skills

Table 3.5 reports the average marginal effects of the key variables. I also estimate the regressions without the interaction terms to check the average effects of the system reform (Columns 1 and 2). Columns 3 and 4 present the results from estimating Equations 1 and 2. Panel A reports the average effects of the post-reform period on patient flows, using a dummy variable indicating the years under the new capitation. Panel B shows the models including the individual year effects. Column 3 in panel A shows that tertiary DHBs are less likely to receive patients from another DHB under capitation. The decrease of 2 percentage points is considerable, given that there is a mean probability of 19 percent that the admitted patient is from another district for tertiary DHBs. As a result, any negative effects on tertiary DHBs from the change in IDF prices will be somewhat mitigated, because they receive less IDFs since the introduction of the new system. The decrease in IDFs under the new capitation system supports the argument that capitation motivates DHBs to keep the patients in their districts. The reduction is greater in tertiary DHBs, which is the usual destination for IDFs.

**Table 3.5 Effects of capitation on patient flow (*N*=10,776,648)**

| | (1)<br>IDF received | (2)<br>Inter-district transfer sent | (3)<br>IDF received | (4)<br>Inter-district transfer sent |
|---|---|---|---|---|
| | | A. Post-reform dummy | | |
| Post×Tertiary | | | -0.0195** | 0.0049** |
| Post×CCL1 | | | -0.0054** | -0.0060** |
| Post×CCL2 | | | -0.0021 | -0.0012** |
| Post×CCL3 | | | -0.0163** | -0.0092** |
| Post×CCL4 | | | -0.0264** | -0.0135** |
| Post | -0.033** | -0.0044** | -0.0183** | -0.0061** |
| Tertiary | 0.1214** | -0.0118** | 0.1214** | -0.0118** |
| CCL1 | 0.0003** | 0.0119** | 0.0004** | 0.0120** |
| CCL2 | 0.0008** | 0.0207** | 0.0085** | 0.0208** |
| CCL3 | 0.0243** | 0.0320** | 0.0244** | 0.0320** |
| CCL4 | 0.0940** | 0.0548** | 0.0941** | 0.0549** |
| | | B. Year dummies | | |
| 2000 ×Tertiary | | | -0.0021** | -0.0040** |
| 2001 ×Tertiary | | | 0.0022* | -0.0018** |
| 2002 ×Tertiary | | | 0.0167** | -0.0029** |
| 2003 ×Tertiary | | | 0.0253** | -0.0022 |
| 2004 ×Tertiary | | | 0.0280** | 0.0022** |
| 2005 ×Tertiary | | | 0.0028** | 0.0038** |
| 2006 ×Tertiary | | | -0.0020** | 0.0035 |
| 2007 ×Tertiary | | | -0.0271** | 0.0034** |
| 2008 ×Tertiary | | | -0.0507** | 0.0055 |
| 2009 ×Tertiary | | | -0.0556** | 0.0059+ |
| 2010 ×Tertiary | | | -0.0580** | 0.0045* |
| 2000 | 0.0077** | 0.0023** | 0.0055** | 0.0019 |
| 2001 | 0.0000 | 0.0003 | -0.006 | -0.0019** |
| 2002 | 0.0144** | 0.0015** | 0.0054** | -0.0015** |
| 2003 | 0.0316** | 0.0024** | 0.019** | -0.002** |
| 2004 | 0.0283** | 0.0020** | 0.0085** | -0.004** |
| 2005 | -0.0007 | -0.0023** | -0.0267** | -0.0108** |
| 2006 | -0.0084** | -0.0054** | -0.0389** | -0.0152** |
| 2007 | -0.0287** | -0.0081** | -0.0661** | -0.0193** |
| 2008 | -0.0652** | -0.0085** | -0.1028** | -0.0202** |
| 2009 | -0.0797** | -0.0074** | -0.1185** | -0.0199** |
| 2010 | -0.0718** | -0.0050** | -0.118** | -0.0199** |
| 2000 × CCL 1 | | | -0.0048** | 0.0054** |
| 2001 × CCL 1 | | | -0.0075** | 0.0022** |
| 2002 × CCL 1 | | | -0.0131** | 0.0046** |
| 2003 × CCL 1 | | | -0.0127** | 0.0043** |
| 2004 × CCL 1 | | | -0.0139** | 0.0026* |
| 2005 × CCL 1 | | | -0.0128** | -0.0013** |
| 2006 × CCL 1 | | | -0.0104** | -0.0050** |
| 2007 × CCL 1 | | | -0.0109** | -0.0086** |
| 2008 × CCL 1 | | | -0.0065** | -0.0109** |
| 2009 × CCL 1 | | | -0.0111** | -0.0102** |
| 2010 × CCL 1 | | | -0.0140** | -0.0082** |
| 2000 × CCL 2 | | | -0.0053** | 0.0007 |
| 2001 × CCL 2 | | | -0.0047** | 0.0007** |
| 2002 × CCL 2 | | | -0.0106** | 0.0008+ |
| 2003 × CCL 2 | | | -0.0084** | 0.0034 |
| 2004 × CCL 2 | | | -0.0109** | 0.0030* |

| | | |
|---|---|---|
| 2005 × CCL 2 | -0.0064** | -0.0018** |
| 2006 × CCL 2 | -0.0097** | -0.0062** |
| 2007 × CCL 2 | -0.0118** | -0.0085** |
| 2008 × CCL 2 | -0.0037 | -0.0075** |
| 2009 × CCL 2 | -0.0085** | -0.0067 |
| 2010 × CCL 2 | -0.0097** | -0.0018** |
| 2000 × CCL 3 | -0.0024+ | 0.0012 |
| 2001 × CCL 3 | -0.0141** | -0.0011* |
| 2002 × CCL 3 | -0.0165** | -0.0039 |
| 2003 × CCL 3 | -0.0211** | -0.0024** |
| 2004 × CCL 3 | -0.0261** | -0.0053** |
| 2005 × CCL 3 | -0.0249** | -0.0107+ |
| 2006 × CCL 3 | -0.0280** | -0.0164 |
| 2007 × CCL 3 | -0.0273** | -0.0196 |
| 2008 × CCL 3 | -0.0188** | -0.0214** |
| 2009 × CCL 3 | -0.0260** | -0.0193** |
| 2010 × CCL 3 | -0.0276** | -0.0118** |
| 2000 × CCL 4 | 0.0003 | 0.0011 |
| 2001 × CCL 4 | -0.0001 | -0.0015 |
| 2002 × CCL 4 | -0.0151** | -0.0094 |
| 2003 × CCL 4 | -0.0057** | -0.0057+ |
| 2004 × CCL 4 | -0.0160** | -0.0142** |
| 2005 × CCL 4 | -0.0209** | -0.0194+ |
| 2006 × CCL 4 | -0.0277** | -0.0240 |
| 2007 × CCL 4 | -0.0395** | -0.0386* |
| 2008 × CCL 4 | -0.0318** | -0.0299 |
| 2009 × CCL 4 | -0.0486** | -0.0223 |
| 2010 × CCL 4 | -0.0380** | -0.0100 |

NOTE. – All the models are estimated with logistic regression. The table reports the average marginal effects of the new capitation system introduced in 2003 on patient flow. Models 1 and 2 are estimated without the interaction terms. Due to computational constraints, I did not calculate the standard errors of the marginal effects. Instead, I report the statistical significance of the coefficients from the logistic regression. The patient flow is measured by the probability that the admitted patient is from another district (inter-district flows, or IDFs) and the probability of transferring patients to another district. "Post" is a dummy variable, which equals 1 if the admission took place in the years under the new capitation system. "Post×Tertiary" is an interaction term between "Post" and "Tertiary"; a dummy variable, which equals 1 if the DHB receiving the patient is classified as tertiary. "Post×CCL" denotes an interaction term between "Post" and "CCL", which measures the severity of illness and ranges from 0 (least severe) to 4 (most severe). All the models include variables indicating the patient characteristics and economic indicators.

$^{+}$ Significant at the 10 percent level.

$^{*}$ Significant at the 5 percent level.

$^{**}$Significant at the 1 percent level.

The results, however, do not provide conclusive evidence on whether the IDF prices are too low. The decrease in inter-district movement may suggest that the prices are in fact too high. At the same time, the prices may be low, but DHBs may have found it more attractive to keep the funds than paying someone else to do the job, because they still have to pay staff and overhead costs in their own hospitals. As non-tertiary DHBs receive a higher level of funding under capitation and the financial objective of the organisations in the public sector, such as DHBs, is to break even, the reform may have prompted non-specialist providers to treat more complex cases, which they would have sent to another provider prior to the reform. The overall effects of capitation on IDFs are also negative, as presented in column 1. The decrease of 3 percentage points is substantial, given that the mean value of IDFs during the research period is 14percent.

Column 4 in panel A reports that capitation decreases the probability that non-tertiary DHBs transfer patients to another district by 0.5 percentage points. Overall, capitation decreases the probability of inter-district transfer by a small degree; 0.04 percentage points. The decrease in inter-district transfer provides further evidence that the scale of funding redistribution is small between the areas whose funding increased and those that received less than their population share. It also shows that, even when I restrict the inter-district patient movement to a narrower category, the earlier results still hold.

In panel B, I estimate the models with individual year dummies, instead of the single post-reform dummy presented in panel A. Column 1 shows that, after a slight decrease in 2001 from the previous year, the probability of receiving patients from another district increases until 2003, the year when the new capitation is introduced, and then begins to decrease. In the last year of our research period, the probability of IDFs increases again, but the level is still much lower than the reference category, 1999. Similarly, in column 2 the probability of transferring patients to another district decreases temporarily in 2001, and then starts increasing again until the year when the capitation is introduced. The size of the year fixed effects declines from 2003, the year of the system reform. The probability of inter-district transfer starts increasing again in the last two years of the research period, but the overall effects of the post-reform period are negative, as shown in panel A.

The interaction terms between the year and tertiary dummies in column 3 show that tertiary DHBs are more likely to receive IDFs than non-tertiary DHBs until 2005, but less likely since 2006. The decline begins in 2004, however, when the probability of receiving IDFs sharply decreases from 2.8 percentage points to 0.28. Column 4 shows that non-tertiary DHBs are less likely to transfer patients to another district since 2004, a year after the introduction of new capitation. The table shows that there is a lagged response to the system reform in both models. McHugh (2008) notes that DHBs whose capitation shares are less than their historical funding share received funds from a transitional funding pool in the financial year 2004/05. This transitional period may be the reason for finding lagged responses to the system reform.

### 3.5.2 Effects of the system reform on complex cases

Columns 3 and 4 in Table 3.5 also show whether capitation affects the movement of complex cases between districts. Compared with the patients assigned to the reference category of CCL 0, the lowest level of severity, those in higher categories of CCL are less likely to be treated in a district outside their residence since the reform. The decrease is greatest in the most severe cases (2.6 percentage points), followed by CCL 3 (1.6 percentage points) and CCL 1 (0.5 percentage points). The coefficient for Post×CCL2 is statistically insignificant. Capitation also decreases the probability that patients assigned to higher CCLs are transferred to another district. Again, the decrease is greatest in CCL 4 (1.4 percentage points), the most severe category, followed by CCL

3 (0.9 percentage points), CCL 1 (0.6 percentage points) and CCL 2 (0.1 percentage points).

I can also compute the changes in marginal effects when CCL increases by 1 unit by taking the difference between the interaction terms. In column 3, the increase from CCL 1 to CCL 2 under capitation raises the probability that the admitted patient is from another district by 0.3 percentage points. The increases, however, from CCL 2 to 3 and from CCL 3 to 4 decrease the probability of IDF by 1.4 percentage points and 1 percentage point, respectively. Similarly, the probability of transferring patients to another district decreases under capitation when the illness severity level is increased from 0 to 1 (0.6 percentage points), 2 to 3 (0.8 percentage points) and 3 to 4 (0.4 percentage points), whereas the change from level 1 to 2 increases the probability of transfer by 0.5 percentage points. Overall, the largest decline in the inter-district patient movement under capitation is observed when CCL increases from 2 to 3, the second most severe cases.

Columns 3 and 4 in panel B report the interaction terms between the CCL and individual year dummies. Patients assigned to CCLs 1 and 2 are less likely to transfer to another district from 2005, two years after the reform. For those in the most severe category, the statistically significant decline starts from the year of reform, although the declines in the last three years of the research period are statistically insignificant. The pattern is not as clear for patients in the CCL 3 category. While I observe a statistically significant decrease in the probability of inter-district transfer in the year of reform, the decline is also present in 2001, before the new capitation is introduced. Nevertheless, the estimation results for the overall effects in column A confirm the decrease in the probability of sending inter-district transfer under capitation. In contrast, it is harder to check the pattern of the probability of receiving IDFs, because in most years, patients assigned to higher CCLs are less likely to be received as IDFs. As explained above, however, the rate of inter-district transfer should reflect the responses of providers more accurately than IDFs.

Next, since CCL indicates the presence of complications and does not distinguish between different diagnoses, I use the mean mortality rate of each diagnosis as another measure of case difficulty. Table 3.6 shows the estimation results for the new regressions measuring whether complex cases are more, or less, likely to be transferred to another district since the reform. The results show that the patients in diagnoses with higher probabilities of mortality are more likely to be transferred to another district under the new payment system by 0.7 percentage points. The probability of transfer sharply increases from 2004, a year after the new capitation system is introduced. Thus, non-tertiary DHBs are still transferring the most difficult cases, while selectively treating the severe, but less fatal, cases. This finding suggests that the new payment system makes it attractive to keep the more severe cases, as long as they are not suffering from the most serious conditions.

**Table 3.6 Effects of mortality on transfer (*N*=10,624,264)**

| | (1) Inter-district transfer |
|---|---|
| | A. Post-reform dummy |
| Post×Mortality | 0.007** |
| Post | -0.00005 |
| Mortality | 0.0251** |
| | B. Year dummies |
| 2000×Mortality | 0.003 |
| 2001×Mortality | 0.006** |
| 2002×Mortality | 0.007** |
| 2003×Mortality | 0.006** |
| 2004×Mortality | 0.012** |
| 2005×Mortality | 0.008** |
| 2006×Mortality | 0.012** |
| 2007×Mortality | 0.012** |
| 2008×Mortality | 0.007** |
| 2009×Mortality | 0.006** |
| 2010×Mortality | 0.028** |
| 2000 | 0.0003* |
| 2001 | -0.0005** |
| 2002 | -0.0001 |
| 2003 | 0.0006** |
| 2004 | 0.0006** |
| 2005 | -0.0008** |
| 2006 | -0.0019** |
| 2007 | -0.0021** |
| 2008 | -0.0023** |
| 2009 | -0.0016** |
| 2010 | -0.0008** |
| Mortality | 0.0208** |

NOTE. – All the models are estimated with logistic regression. The table reports the average marginal effects of the mortality rates of a diagnosis on inter-district transfer. Due to computational constraints, I did not calculate the standard errors of the marginal effects. Instead, I report the statistical significance of the coefficients from the logistic regression. The dependent variable is the probability of transferring patients to another district. "Post" is a dummy variable, which equals 1 if the admission took place in the years under the new capitation system. "Post×Mortality" is an interaction term between "Post" and "Mortality", which signifies the mean mortality rate of the patient's diagnosis. All the models include variables indicating the patient characteristics and economic indicators.

[+] Significant at the 10 percent level.
[*] Significant at the 5 percent level.
[**] Significant at the 1 percent level.

### 3.5.3 Effects of the system reform on health outcomes

The finding that the reform decreases the inter-district movement of patients with severe conditions, taken together with the result that tertiary DHBs receive fewer IDFs, may indicate a loss of efficiency in the health care sector. To study the implications for efficiency, I check the effects of the reform on the probabilities of 30-day mortality and readmission and the lengths of hospital stay. Table 3.7 presents the effects of the post-reform period on the health outcome measures. Columns 2, 4 and 6 show the estimation results for Equations (3), (4) and (5), while columns 1, 3 and 5 present models without the interaction terms. The probability that the admitted patient dies within 30 days of discharge decreases by 0.2 percentage points in the post-reform years, as shown in column 1. In the model including individual year dummies, the probability of mortality decreases in most years, but the size of the decreases in the post-reform years is larger than those in the pre-reform period. Mortality may have decreased because of advancements in technology, or improved standards of living over the research period. Another possible reason for the decrease in mortality may be that the most difficult diagnoses, which have higher probabilities of mortality, are still transferred to another district after the reform, as shown in Table 3.6.

Column 2 presents the model that includes the interaction terms between the transfer and time dummies. Panel A shows that the probability of 30-day mortality for transferred patients is positive but statistically insignificant. The model with individual year dummies in panel B also reveals that in most years there are no statistically significant differences in the probability of mortality between transferred and non-transferred patients. Mortality is significantly lower for transferred patients in the last 2 years of the research period, but in 2006 it is significantly higher by 2 percentage points. The weak effects of the reform on mortality may be due to the fact that mortality is a rare event, which affects only a few diagnoses. In addition, death within 30 days of discharge may have occurred due to reasons not related to the treatment received in hospital. Therefore, the other outcome measures, readmission and length of stay, may provide a better indication of the effects of the reform on health outcomes.

**Table 3.7 Effects of capitation on health outcomes**

| | (1) Mortality (*N*=10,672,988) | (2) Mortality (*N*=10,672,988) | (3) Readmission (*N*=10,357,929) | (4) Readmission (*N*=10,357,929) | (5) Length of stay (*N*=10,728,729) | (6) Length of stay (*N*=10,728,729) |
|---|---|---|---|---|---|---|
| | | | A. | Post reform dummy | | |
| Post × Transfer | | 0.0001 | | -0.0478** | | 11.57** |
| Post | -0.0021** | -0.0017** | 0.0287** | 0.0287* | -0.17** | 0.05** |
| Transfer | 0.036** | 0.036** | -0.0552** | -0.0545** | 17.28** | 18.50** |
| | | | B. | Individual year dummies | | |
| 2000 ×Transfer | | -0.0133 | | -0.0302** | | 13.86** |
| 2001 ×Transfer | | -0.0097 | | -0.0083 | | 24.33** |
| 2002 ×Transfer | | -0.0004 | | -0.0310** | | 37.23** |
| 2003 ×Transfer | | -0.0154+ | | -0.0345** | | 51.30** |
| 2004 ×Transfer | | -0.0037 | | -0.0428** | | 52.99** |
| 2005 ×Transfer | | 0.0009 | | -0.0376** | | 40.69** |
| 2006 ×Transfer | | 0.0203* | | -0.0657** | | 52.27** |
| 2007 ×Transfer | | -0.0077 | | -0.0663** | | 46.51** |
| 2008 ×Transfer | | -0.0004 | | -0.0248* | | 57.12** |
| 2009 ×Transfer | | -0.0199** | | -0.0788** | | 39.24** |
| 2010 ×Transfer | | -0.0441** | | -0.1560** | | 25.31** |
| 2000 | -0.0007* | -0.0009* | 0.0137** | 0.0143** | -0.11** | -0.003 |
| 2001 | 0.0011** | 0.001** | 0.0275** | 0.0287** | 0.05 | 0.16** |
| 2002 | -0.0006 | -0.0007 | 0.0323** | 0.0352** | 0.05 | 0.16** |
| 2003 | -0.0015** | -0.0018** | 0.0347** | 0.0404** | 0.01 | 0.20** |
| 2004 | -0.0015** | -0.0018** | 0.0362** | 0.0457** | -0.09* | 0.20** |
| 2005 | -0.0031** | -0.0034** | 0.0483** | 0.0619** | -0.55** | -0.29** |
| 2006 | -0.0027** | -0.003** | 0.0564** | 0.0735** | -0.43** | -0.20** |
| 2007 | -0.0016** | -0.0018** | 0.0563** | 0.0797** | -0.44** | -0.19** |
| 2008 | 0.0001 | 0.0002 | 0.0569** | 0.0829** | -0.29** | 0.11** |
| 2009 | -0.0001 | -0.0001 | 0.0507** | 0.0801** | -0.44** | -0.02** |
| 2010 | -0.0004 | -0.0003 | 0.0411** | 0.0795** | -0.57** | -0.18** |
| Transfer | 0.036** | 0.037** | -0.0544** | -0.0509** | 17.34** | 18.84** |

NOTE. – Models (1) to (4) are estimated by logistic regression, while (5) and (6) are estimated with negative binomial regression. Columns (1) to (4) report the average marginal effects of the new capitation system. Due to computational constraints, I did not calculate the standard errors of the marginal effects. Instead, I report the statistical significance of the coefficients from the logistic regression. “Mortality” is a dummy variable, which equals 1 if the patient died within 30 days of discharge. “Readmission” is a dummy variable, which equals 1 if the patient was readmitted to any facility in the dataset within 30 days of discharge. “Post” is a dummy variable, which equals 1 if the admission took place in the years under the new capitation system. “Transfer” indicates a dummy variable, which equals 1 if the patient is transferred to another district in columns (1) to (4), while indicating a dummy variable that equals 1 if the admitted patient is from another district in columns (5) and (6).

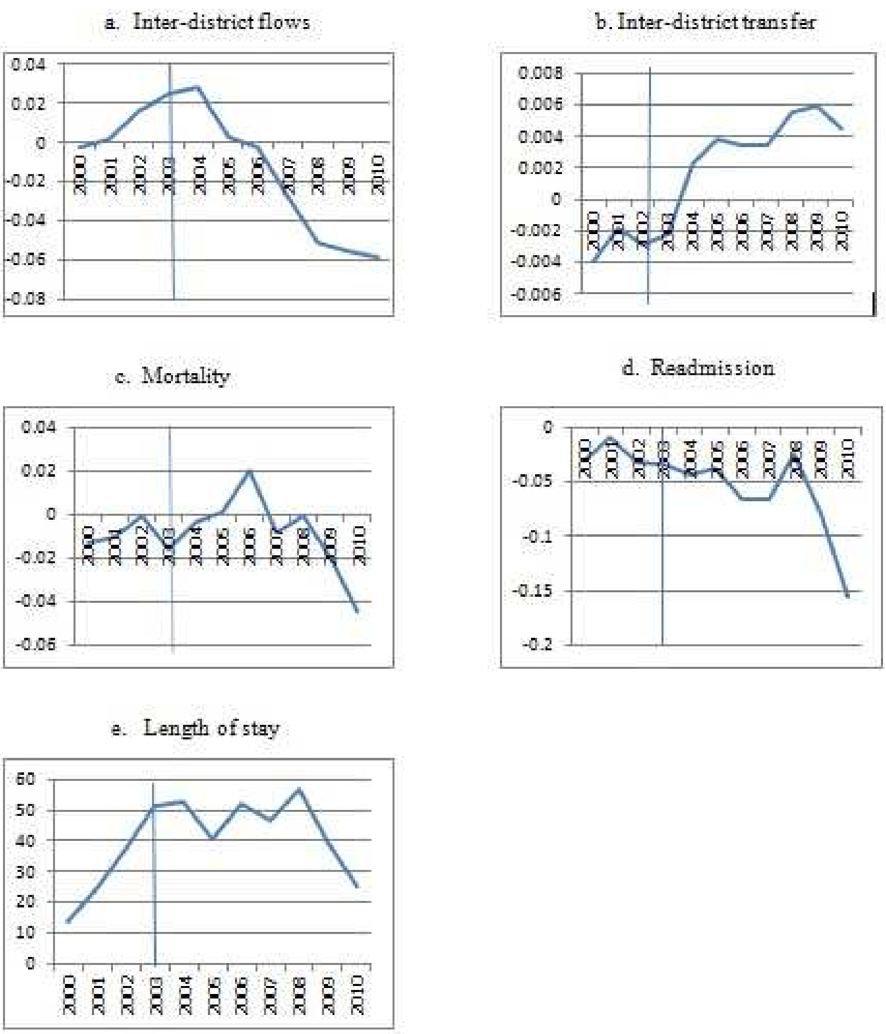
Columns 3 and 4 in Table 3.7 report the effects of the reform on 30-day readmission among the patients who did not die during the 30-day period. Unlike mortality, the probability of readmission increased since the reform. The model with individual year effects shows that the probability of 30-day readmission is higher in all the years than in 1999, the reference category. Although the probability of readmission has increased overall since the reform, patients transferred to another district are less likely to be readmitted than non-transfer patients. Transferred patients are less likely to be readmitted to hospital in all years, but the lower probabilities are amplified from 2004, a year after the reform took place. With the exception of 2008, the probabilities of readmission for transferred patients are much larger than for the pre-reform years.

Columns 5 and 6 present the results from the regressions measuring the effects of the reform on the length of hospital stay. Overall, the length of stay decreases after the reform by a small degree, however, transferred patients stay in hospital over 11 days longer than non-transfer patients since the reform took place. Taken together with the above results, it seems that the reform has negative effects on health outcomes, as patients stay in hospital for a shorter period of time, but are more likely to be readmitted since the reform. These effects are more notable among the patients receiving treatment in their own districts. Those transferred to another district stay longer in hospital and have lower probabilities of readmission under the new capitation system. Since low-skilled providers are less likely to transfer patients to another district under the new system, the results suggest that the decrease in inter-district transfer may be a cause of the worsening health outcomes.

As the system reform has affected all the providers, there is a concern that the effects of the policy reform found above may include those of other factors changing over time.

The pattern of the coefficients of the interaction terms between tertiary, or transfer dummies, and year dummies presented in Figure 3.4 shows, however, that there is a clear change in the trend in all but one of the outcome variables immediately after the reform. Readmission is the only variable that shows a slight response lag. There is a reversal in the trend in mortality from 2006. As explained above, however, the effects of the reform on mortality may not be as clear as those on other outcomes, because mortality is a rare event which may occur due to reasons unrelated to the treatment received in hospital.

**Figure 3.4 Pattern of coefficients for the interaction terms**[i]




[i] Graphs a and b plot the interaction terms between tertiary and year dummies, while graphs c to e plot the interaction terms between transfer and year dummies

To summarise, I find that tertiary DHBs are less likely to receive IDFs since the implementation of the policy reform that reintroduced capitation. A cause for the reduction seems to be the reduced inter-district transfer sent from non-tertiary DHBs. Under capitation, non-tertiary DHBs are less likely to transfer patients to another district. The findings suggest that the policy reform encourages non-tertiary DHBs, which receive greater funding under capitation, to treat patients in their districts. Although more severely ill patients are less likely to be treated in tertiary DHBs under the new capitation system, the probability of mortality has decreased since the reform. Readmission, on the other hand, increased under the new capitation system, while the length of hospital stay decreased. If patients are more likely to be readmitted due to shorter hospital stays, the reform will have negative effects on the health care sector. I do not find evidence that IDF prices are low, although it is difficult to reach a conclusion on this issue. Nevertheless, the results still imply that the level of funding to highly skilled DHBs decreased under capitation, because the redistribution of initial funding did not seem to have occurred to a full extent during the research period.

## 3.6 Robustness checks

### 3.6.1 Analysis of the subset

For the two years at the start of the dataset, the predecessor of DHBs, Hospital and Health Services (HHS), was in operation. Although there are similarities between the two structures, the areas and roles of HHS were somewhat different from those of DHBs. Since I determine inter-district movement and the skill levels of the regional health boards based on DHBs, the observations from these two years do not accurately reflect the behaviour of DHBs. Thus, I limit the analysis to the years excluding 1999 and 2000 as a robustness check. The total number of observations for this subset is 9,223,433. Table 3.8 presents the average marginal effects of the key variables on patient flow.

Overall, declines in patient movement under capitation are still present in the subset. Capitation decreases the probability of receiving IDFs for tertiary DHBs by 1.8 percentage points. The probability of transferring patients to another district for non-tertiary DHBs is lower by 0.5 percentage points. Patients assigned to higher CCLs are still less likely to be treated in another district under capitation, however, the size of the decrease is slightly smaller in every category of CCL and ranges from 0.05 to 1.9 percentage points, compared with the decrease of 0.2 to 2.6 percentage points in the main analysis.

**Table 3.8 Effects of capitation on patient flow since 2001 (*N*=9,223,433)**

| | (1) IDF received | (2) Inter-district transfer sent | (3) IDF received | (4) Inter-district transfer sent |
|---|---|---|---|---|
| | | A. Post-reform dummy | | |
| Post×Tertiary | | | -0.0183** | 0.005** |
| Post×CCL1 | | | -0.0018** | -0.0065** |
| Post×CCL2 | | | 0.0005* | -0.0015 |
| Post×CCL3 | | | -0.0082** | -0.0078** |
| Post×CCL4 | | | -0.0190* | -0.0105** |
| Post | -0.0264** | -0.0040** | -0.01** | -0.0051** |
| | | B. Year dummies | | |
| 2002 ×Tertiary | | | 0.0129* | -0.0013 |
| 2003 ×Tertiary | | | 0.0227 | -0.0006+ |
| 2004 ×Tertiary | | | 0.0256** | 0.0039** |
| 2005 ×Tertiary | | | 0.0030 | 0.0053** |
| 2006 ×Tertiary | | | -0.0008 | 0.0048+ |
| 2007 ×Tertiary | | | -0.0252** | 0.0047** |
| 2008 ×Tertiary | | | -0.0532** | 0.0069** |
| 2009 ×Tertiary | | | -0.0596** | 0.0073** |
| 2010 ×Tertiary | | | -0.0607** | 0.0060** |
| 2002 | 0.0141** | 0.0012** | 0.0126** | 0.0005* |
| 2003 | 0.0323** | 0.0021** | 0.0291** | 0.0003* |
| 2004 | 0.0295** | 0.0018** | 0.0218** | -0.0019** |
| 2005 | 0.0051** | -0.0024** | -0.0065 | -0.0082** |
| 2006 | 0.0001 | -0.0055** | -0.0142** | -0.0125** |

| | | | | |
|---|---|---|---|---|
| 2007 | -0.0190** | -0.0082** | -0.0382** | -0.0168** |
| 2008 | -0.0591** | -0.0087** | -0.08** | -0.0178** |
| 2009 | -0.0750** | -0.0076** | -0.0973** | -0.0175** |
| 2010 | -0.0666** | -0.0051** | -0.0938** | -0.0172** |
| 2002 × CCL 1 | | | 0.0122** | 0.0016** |
| 2003 × CCL 1 | | | 0.0307** | 0.0001** |
| 2004 × CCL 1 | | | 0.0278** | -0.0033** |
| 2005 × CCL 1 | | | 0.0036** | -0.0028** |
| 2006 × CCL 1 | | | 0.0005* | -0.0046* |
| 2007 × CCL 1 | | | -0.0184** | -0.0067* |
| 2008 × CCL 1 | | | -0.0581** | -0.0102** |
| 2009 × CCL 1 | | | -0.0756** | -0.0109** |
| 2010 × CCL 1 | | | -0.0687** | -0.0101** |
| 2002 × CCL 2 | | | 0.0120** | -0.0008* |
| 2003 × CCL 2 | | | 0.0322** | 0.0007** |
| 2004 × CCL 2 | | | 0.0284** | -0.0013** |
| 2005 × CCL 2 | | | 0.0076 | -0.0016 |
| 2006 × CCL 2 | | | -0.0011** | -0.0040 |
| 2007 × CCL 2 | | | -0.0218** | -0.0048** |
| 2008 × CCL 2 | | | -0.0576** | -0.0049 |
| 2009 × CCL 2 | | | -0.0754** | -0.0056** |
| 2010 × CCL 2 | | | -0.0665** | -0.0017 |
| 2002 × CCL 3 | | | 0.0158** | -0.0037** |
| 2003 × CCL 3 | | | 0.0297** | -0.0033** |
| 2004 × CCL 3 | | | 0.0231** | -0.0078** |
| 2005 × CCL 3 | | | -0.0008** | -0.0087** |
| 2006 × CCL 3 | | | -0.0091** | -0.0123** |
| 2007 × CCL 3 | | | -0.0269** | -0.0140** |
| 2008 × CCL 3 | | | -0.0625** | -0.0171** |
| 2009 × CCL 3 | | | -0.0828** | -0.0165** |
| 2010 × CCL 3 | | | -0.0745** | -0.0099** |
| 2002 × CCL 4 | | | 0.0037** | -0.0089** |
| 2003 × CCL 4 | | | 0.0314** | -0.0062** |
| 2004 × CCL 4 | | | 0.0202** | -0.0164** |
| 2005 × CCL 4 | | | -0.0091** | -0.0167** |
| 2006 × CCL 4 | | | -0.0198** | -0.0192+ |
| 2007 × CCL 4 | | | -0.0499** | -0.0326** |
| 2008 × CCL 4 | | | -0.0866** | -0.0248** |
| 2009 × CCL 4 | | | -0.1172** | -0.0185** |
| 2010 × CCL 4 | | | -0.0965** | -0.0070 |

NOTE. – All the models are estimated with logistic regression. The table reports the average marginal effects of the new capitation system introduced in 2003 on patient flow. The data exclude the first two years. Due to computational constraints, I did not calculate the standard errors of the marginal effects. Instead, I report the statistical significance of the coefficients from the logistic regression. The patient flow is measured by the probability that the admitted patient is from another district (inter-district flows, or IDFs) and the probability of transferring patients to another district. "Post" is a dummy variable, which equals 1 if the admission took place in the years under the new capitation system. "Post×Tertiary" is an interaction term between "Post" and "Tertiary", a dummy variable that equals 1 if the DHB receiving the patient is classified as tertiary. "Post×CCL" denotes an interaction term between "Post" and "CCL", which measures the severity of illness and ranges from 0 (least severe) to 4 (most severe). All the models include variables indicating the patient characteristics and economic indicators.

In panel B, which presents the models with individual year dummies, the changes in the probability of IDFs for patients in different CCLs are more notable. Unlike the main analysis where we observe lower probabilities in most years and CCLs, here we see that patients assigned to relatively more severe levels (CCLs 3 and 4) are less likely to be admitted to facilities in another district since 2005, which is two years after the reform took place; instead the decline starts from 2004. The lower CCLs also show similar patterns. Patients in CCLs 1 and 2 are less likely to be transferred to another DHB since 2004, which is a year after the reform. The probabilities of inter-district transfer for those in CCLs 3 and 4 are always lower than the reference category; however, in both CCLs the probabilities of transfer increase until 2003, and then start decreasing. Therefore, the earlier results that patient movement between districts declines since the system reform are not sensitive to the change in research period.

### 3.6.2 Effects of readmission on mortality

In the main analysis, I conclude that the system reform seems to have negative effects on health outcomes, as the probability of readmission increased, while the length of hospital stay decreased, since the reform took place. Although mortality also decreased after the reform, the decrease may be due to other reasons, such as the improved standard of living, or selective transfer by non-tertiary DHBs, as explained in the main analysis. Nevertheless, the decrease in mortality and increase in readmissions may also be interpreted as positive effects of the reform on the health sector. This will be true if patients are less likely to die due to increased readmission. To explore this possibility, I check whether the probability of readmission has any effects on mortality since the year the reform was introduced. Table 3.9 presents the estimation results.

The results indicate that readmission is not the cause of the change in mortality. The change in the probability of 30-day mortality after the reform for patients readmitted to any health care facilities in the dataset is statistically not different from that for those who are not readmitted. Panel A shows that the interaction term between the readmission and post-reform dummies is statistically insignificant. Panel B shows that, in all years except for 2011, the probability of mortality is lower for readmitted patients. There is no clear pattern in the changes in the interaction terms across time. This finding supports the earlier conclusion that the system reform seems to have negative effects on health outcomes.

**Table 3.9 Effects of mortality on transfer (*N*=10,625,264)**

| | 30-day mortality |
|---|---|
| | A. Post-reform dummy |
| Post×Readmission | -0.0002 |
| Post | -0.0016** |
| Readmission | -0.0033** |
| | B. Year dummies |
| 2000×Readmission | -0.0013* |
| 2001×Readmission | -0.0016* |
| 2002×Readmission | -0.0022** |
| 2003×Readmission | -0.0019** |
| 2004×Readmission | -0.0023** |
| 2005×Readmission | -0.002** |
| 2006×Readmission | -0.0024** |
| 2007×Readmission | -0.0016** |
| 2008×Readmission | -0.0013* |
| 2009×Readmission | -0.0013* |
| 2010×Readmission | 0.0009 |
| 2000 | -0.0006** |
| 2001 | 0.0013 |
| 2002 | -0.0003* |
| 2003 | -0.0016** |
| 2004 | -0.0016** |
| 2005 | -0.0026** |
| 2006 | -0.0020** |
| 2007 | -0.0006** |
| 2008 | 0.0014** |
| 2009 | 0.0013** |
| 2010 | 0.0007** |
| Readmission | -0.0033** |

NOTE. – All the models are estimated with logistic regression. The table reports the average marginal effects of the probability of 30-day readmission on mortality across time. Due to computational constraints, I did not calculate the standard errors of the marginal effects. Instead, I report the statistical significance of the coefficients from the logistic regression. The dependent variable is the probability of dying within 30 days of discharge. "Post" is a dummy variable, which equals 1 if the admission took place under the new capitation system. "Post×Readmission" is an interaction term between "Post" and "Readmission", which signifies the probability of readmission within 30 days of discharge. All the models include variables indicating the patient characteristics and economic indicators.

[+] Significant at the 10 percent level.
[*] Significant at the 5 percent level.
[**] Significant at the 1 percent level.

### 3.7 Conclusion

The reintroduction of capitation due to a system reform in New Zealand decreased the movement of patients between districts. Non-tertiary DHBs, in particular, are less likely to transfer patients to another district under capitation. This finding suggests that capitation provides incentives to health care providers to keep patients within their districts in order to keep the allocated funds. The probability of IDFs, a more general measure of inter-district patient movement, also decreased considerably under capitation. Tertiary DHBs, who receive more out of district patients, experienced a larger decline in the probability of receiving IDFs. Considering that the growth of funding was much higher for non-tertiary DHBs under capitation, the results imply that the redistribution of funds between districts did not occur as much as some believe. I also find that more severely ill patients were less likely to be moved between districts since the policy reform. Those patients with diagnoses with higher probabilities of fatality are, however, still transferred, suggesting that non-tertiary providers selectively treat more severe, but less fatal, cases. Health outcomes have deteriorated since the reform, as the length of stay in hospital has declined, but the probability of readmission has increased. Therefore, the reform seems to have reduced necessary patient movement between districts.

The findings that the probability of readmission increased and the length of hospital stay decreased after the reform imply that health outcomes have worsened. It will be helpful, however, to examine other indicators of health outcomes in future studies to clarify the efficiency issue. In addition, it is not possible to make a conclusion about whether the prices for IDFs are lower than their fair value. The decrease in IDFs may suggest that the prices are high, however, the opposite can still be true if the providers simply find it more attractive to retain the funding given to the region due to, for example, administration costs. The net effects of the system reform on highly skilled providers are also unclear. On the one hand, the redistribution of funds did not take place on a large scale under the new capitation system, so the reduced level of funds tertiary providers receive have not been compensated for. On the other hand, however, they receive fewer patients, so their workload has been reduced. I leave it to future studies to explore these questions in more detail.

## Appendix

**Table A1 Marginal effects of interaction terms**

| | |
|---|---|
| I. Dependent variable: IDF (Equation 1) | |
| Marginal effects of POST for Tertiary (A) | -0.0217 |
| Marginal effects of POST for Non-tertiary (B) | -0.0412 |
| Marginal effects of POST×Tertiary (A-B) | -0.0195 |
| Marginal effects of POST for CCL 1 (E) | -0.0350 |
| Marginal effects of POST for CCL 2 (F) | -0.0317 |
| Marginal effects of POST for CCL 3 (G) | -0.0459 |
| Marginal effects of POST for CCL 4 (H) | -0.0560 |
| Marginal effects of POST for CCL 0 (I) | -0.0296 |
| Marginal effects of POST×CCL1 (E-I) | -0.0054 |
| Marginal effects of POST×CCL2 (F-I) | -0.0021 |
| Marginal effects of POST×CCL3 (G-I) | -0.0163 |
| Marginal effects of POST×CCL4 (H-I) | -0.0264 |
| II. Dependent variable: Inter-district transfer (Equation 2) | |
| Marginal effects of POST for Tertiary (C) | -0.0075 |
| Marginal effects of POST for Non-tertiary (D) | -0.0026 |
| Marginal effects of POST×Tertiary (C-D) | 0.0049 |
| Marginal effects of POST for CCL 1 (J) | -0.0013 |
| Marginal effects of POST for CCL 2 (K) | -0.0073 |
| Marginal effects of POST for CCL 3 (L) | -0.0025 |
| Marginal effects of POST for CCL 4 (M) | -0.0105 |
| Marginal effects of POST for CCL 0 (N) | -0.0148 |
| Marginal effects of POST×CCL1 (J-N) | -0.0060 |
| Marginal effects of POST×CCL2 (K-N) | -0.0012 |
| Marginal effects of POST×CCL3 (L-N) | -0.0092 |
| Marginal effects of POST×CCL4 (M-N) | -0.0135 |

# Chapter 4 Public health care provider reimbursement in New Zealand

## 4.1 Introduction

To provide incentives for cost containment and efficiency, many countries have changed the hospital payment system from cost reimbursement to prospective payment, which pays the health care providers fixed prices regardless of the actual costs incurred (Ellis & Miller, 2009). As the prices are often determined based on the average costs across providers under the prospective payment system, a problem arises if the distribution of patients across providers is uneven. For instance, under a diagnosis related group (DRG) based payment method, if the proportion of patients with more severe conditions is higher in one hospital than in others, the payment received by the hospital treating sicker patients will be insufficient to cover the treatment costs. Another form of the prospective payment system pays providers based on the characteristics of the potential patients enrolled to use their services. The same issue remains under this method if the distribution of the severity of illness varies within a population group across providers, or if the characteristics of the patients who actually use the health care services differ from those of the enrolled people.

The New Zealand public health sector has adopted such a payment system, which allocates funds across regions based on the regional population, rather than the actual treatment provided. As the first step in studying the adequacy of this payment system, this research examines how the actual usage of health care services by patients is associated with the current level of payment, computed based on the characteristics of the population. To examine the relation, I regress the current government funding on the characteristics of those actually treated. The explanatory variables include the measures of case complexity, as well as a number of hospital, patient and regional characteristics. Besides examining which population groups use more, or less, of the health care services than their population share, I am also interested in the relation between the level of funding and the measures of case complexity, such as the transfer status and complications/comorbidity levels (CCLs). As the current funding is based on the characteristics of population, it does not directly compensate the higher costs incurred by complexity measures such as CCLs.

Most explanatory variables in my model are computed based on the actual usage, rather than the number of people in the population, as in the current funding formula. For example, in the current formula the number of people in the population in certain ethnic groups affects the level of funding to the district health boards (DHBs). On the other hand, the explanatory variables in this study measure the percentage of patients in DHBs who belong to these ethnic groups and who actually receive treatment. These variables will help me observe how the usage of hospital services by various population groups differs from the number of people in these population groups, which forms a basis of the funding formula. If the proportion of a population group residing in a district differs from the proportion of the group that actually uses the health care services, the district with a higher proportion of those groups whose actual usage exceeds their population share may end up receiving lower levels of funding per case.

Overall, I find that increases in the proportion of Maori and Pacific Island patients, and in the average age of patients, are associated with lower levels of per case funding, despite these population characteristics receiving higher weights under the current funding method. An increase in the proportion of Maori and Pacific Island patients in a

DHB is associated with a 0.14 percent lower level of funding in the base model. A 1 percent increase in the average age of the treated patients is also associated with a 0.14 percent lower level of funding per case. These findings suggest that the actual usage of health care services by these population groups is higher than their population share. I also find that the average complexity level for the patients who receive treatment in their own DHBs has statistically insignificant relation to the level of per case funding. Thus, the case complexity of the treated patients may not be reflected in the population characteristics used to compute the level of funding.

The per case funding received from the government is also lower for providers treating a higher proportion of transferred patients; however, I am not able to conclude that the lower level of funding indicates insufficient reimbursement for highly skilled providers. Providers treating patients from another district receive additional payment from the district where the patients reside in. As the government takes this additional payment into consideration when it allocates funding, providers who treat a greater number of patients from another district receive less funding initially. The regression results show that a 1 percent increase in the percentage of transferred patients is associated with a 0.01 percent lower level of funding per case in the base model. I also estimate instrumental variable (IV) models in addition to the base model estimated by ordinary least squares (OLS), which may be biased due to potential endogeneity. If providers who receive a higher level of funding attract more transfers, simultaneity bias may affect the OLS estimator. The negative effects of transfer become slightly larger in the IV model with the most complete specification.

The level of funding for tertiary DHBs is lower than that for non-tertiary providers by about 8 percent, whereas that for teaching DHBs is higher by 8 percent. Tertiary

DHBs receive tertiary adjusters to cover the high costs incurred from treating complex cases. The tertiary adjuster, however, is paid as a part of the reimbursement for inter-district flows (IDFs), which providers receive from the other DHBs for treating their residents. Therefore, similar to the coefficients for transferred patients, the negative sign for the tertiary dummy reflects the lower levels of government funding received by tertiary DHBs due to the additional payment they get from the other DHBs, rather than a shortfall in reimbursement for tertiary DHBs.

My data are from the New Zealand Ministry of Health and cover all the publicly funded events in New Zealand from July 2003 to June 2011. The total number of observations is approximately 7.5 million. I aggregate the data by DHB and year to compute the actual usage by different population groups, as well as the percentages of transferred patients and average CCLs. Although the unit of the aggregate analysis, DHBs, was established in 2001, I restrict the analysis to the period after 2003, because a different funding system was in place prior to 2003.

To my knowledge, this study is the first to examine the relation between the patients' actual usage of hospital services and the level of funding computed based on the regional population under the New Zealand capitation system. The new capitation system has received much attention in the New Zealand health sector since its introduction in 2003, but no studies have yet to analyse the relation between the two, or the adequacy of payment. Moreover, many past studies on health care funding use observations from U.S. Medicare patients, who only account for less than 15 percent of that nation's population and have different demographics than the general public. As the effects of case complexity vary across DRGs, and also because the heterogeneity of the patients is what causes the inadequacy of the prospective payment system, I believe it is crucial to include as diverse diagnoses, patients and providers to conduct an accurate analysis.

This study is the first step in understanding the adequacy of payment. In order to compute the adequate level of funding, the actual costs of treating patients would have been ideal; however, no centralised data that record costs incurred at individual event level across providers are available at the time of this research. Although the limitation of this study is that I do not observe the actual costs of treating patients, I can still show how the differences between the treated and actual population affect the funding received by hospitals.

## 4.2 Background and related literature

### 4.2.1 Health care payment system in New Zealand

The capitation funding system in New Zealand, called Population-based Funding, categorises the population into groups based on age (five year groupings, such as 0-4 and 5-10), gender, ethnicity (Maori, Pacific peoples and others) and socio-economic deprivation level (Quintiles 1 to 5)[28]. The New Zealand Deprivation Index (Salmond & Crampton, 2002; Salmond, Crampton, & Atkinson, 2007) is used to determine the deprivation level of the area in which a patient resides. Quintile 1 indicates the least deprived 20 percent of areas in New Zealand, while quintile 5 signifies the most deprived 20 percent. For each group, such as a Maori male in the age band of 20 to 24 living in the area that belongs to the deprivation quintile 3, the expected cost per person

[28] For detailed discussion on the methods of allocating funds by using the Population-based Funding Formula, see Penno et al. (2012).

is calculated by using the historical average expenditure. The expected cost for each age, gender, ethnicity and deprivation cell group is multiplied by the number of people residing in the DHB's area who belong to each group. The information on the population of each district is obtained from the census that takes place every five year.

In addition, there are three further adjusters to compensate DHBs for unavoidable differences in costs. First, high-risk groups such as Maori, or Pacific Islanders, and populations in deprivation quintiles 4 and 5 receive an extra NZ$50 per person to improve health equality. There is also a rural adjuster, which is designed to compensate providers for the higher costs associated with providing services to rural communities. The rural adjuster is computed by using a variety of formulas to recognise higher costs for inter-hospital transfer, the provision of community services due to low population density, small facilities, providing services to residents of offshore islands, rural GPs, and travel and accommodation for patients. Lastly, the overseas adjuster is added to reimburse DHBs for the services provided to eligible non-residents, such as New Zealand citizens residing overseas and temporarily visiting the country, citizens of countries that have reciprocal agreements with New Zealand and refugees. The overseas adjuster is calculated based on the average costs incurred by eligible overseas visitors.

Below is the final population-based funding formula, as reported in Penno et al. (2012). I provide an example of the computation process in the Appendix.

*Funding Share= % Population* x *Age/Sex/Deprivation/Ethnicity Costweights + Unmet Needs Adjuster + Rural Adjuster + Overseas Adjuster*

As the Population-based Funding Formula pays each DHB for the characteristics of its population, it does not provide a payment rule for the services provided to residents of the other DHBs. Under the current system the treatment of non-residents, referred to as inter-district flows (IDFs), is reimbursed separately based on a list of national prices and the actual volume of the flows. The national prices are based on the average cost of treating the corresponding diagnosis across all DHBs. Under the current system, funding from the government includes the net payment each DHB makes for IDFs, so the level of funding is higher for DHBs who send residents to another DHB more than they receive out-of-district patients.

Tertiary DHBs also receive the tertiary adjuster, which compensates for the high costs associated with treating complex cases. Once the Ministry of Health defines tertiary services at the specialty level through consultation with DHBs, the average cost by DRG across all tertiary services is calculated and compared with the average cost across all secondary services. The DRG in tertiary services whose cost is not different from the average cost of the secondary services is discarded from the calculation of the tertiary adjuster. Furthermore, the tertiary DRGs whose costs are inconsistent across tertiary providers are also discarded. For instance, if only some tertiary providers incur high costs for a DRG in tertiary services, those DRGs are excluded from the tertiary adjuster calculation. After these filters are performed, the adjuster to each tertiary provider is calculated as the difference between the average cost for a DRG in tertiary services and the average secondary cost, multiplied by the case-weighted volume of the DRG each tertiary provider treats.

Wignall and Tringham (2008) describe the process of calculating the tertiary adjuster in detail and also discuss some issues related to the method. They argue that using the average cost across all tertiary providers does not recognise the apparent differences among tertiary providers in terms of the level of expertise. They further claim that defining tertiary services at the specialty level across all tertiary providers overpays some lower-level tertiary DHBs, who only provide tertiary-level services to a few DRGs in that specialty. The tertiary adjuster is not a new addition to the current system, as it was in place even before the introduction of the capitation system. Under the current system, the adjuster is paid as part of the IDF payment. All DHBs pay each tertiary provider their share of the tertiary adjuster as the IDF payment.

### 4.2.2 Related literature

The capitation system used by the New Zealand government to distribute funds to DHBs is a type of prospective payment system, where the price of a diagnosis is determined based on the average cost of treatment across all providers. Shleifer (1985) shows that setting the price equal to the costs of similar firms can induce a socially efficient level of cost reduction. Using the costs of comparable firms as a benchmark is superior to using the firm's own costs in the past, as there is no incentive for cost reduction in the latter case. He describes Medicare's prospective payment system as one of the examples of this yardstick competition. He also acknowledges, however, that such a system may insufficiently compensate hospitals treating sicker patients.

#### 4.2.2.1 Adequacy of compensation under the prospective payment system

A number of studies argue that health care providers treating more complex cases are underpaid under the prospective payment system. Lynk (2001) measures the price variation within, as well as across, DRGs and finds that among the hospital-specific variables the average casemix index has the most significant impact on price divergence, indicating that those hospitals able to treat more complex DRGs also attract sicker and more costly patients within the same DRG. He concludes that, because patients are not equally distributed across hospitals in terms of the severity of illness, the payment based on the average costs of treatment in a DRG shortchanges hospitals receiving more expensive patients. Sikand, Williams, White and Moran (2005) show that the payment a tertiary care centre in the U.K. receives for the treatment of polytrauma patients covers a mere 10 3percent of the full costs. Dormont and Milcent (2004) examine 7,314 stays in 36 French public hospitals and provide an example of a DRG that does not receive additional payment for an innovative procedure despite the high costs incurred by such a procedure. Based on this, they argue that the payment system penalises innovative hospitals.

Like this essay, some of the previous research examines the reimbursement for transferred cases under the prospective payment system. Buczko (1997) notes the differences in the methods of reimbursing transfers sent and received under the prospective payment system at the time of his research, but states that neither the reimbursement to the sending hospital, nor that to the receiving hospital, compensates transfer adequately. Bernard et al. (1996) also state that accepting a transfer is not financially viable under the prospective payment system. Using Medicare data for the financial years 1990 and 1991, Carter and Rumpel (1993) show that transfer cases at the sending hospital cost more than both the amount received from the existing payment method and the average costs incurred by the corresponding DRGs.

Newhouse (1996) shows that modifying assumptions of Shleifer’s yardstick competition model changes the conclusion that fully prospective pricing is the optimal reimbursement scheme. One of the assumptions relaxed is that of a homogenous product, as unobserved heterogeneity across patients affects hospital cost functions. Paying the average cost of all the hospitals, as Shleifer suggests, will underpay hospitals with a higher amount of unobserved patient heterogeneity. In addition, Pope (1990) points out that one of the unobservable differences in costs stems from variation in the severity of illness within a DRG. Chalkley and Malcomson (2002) state that large variations in the cost of treatment within the same DRG mean that low cost patients are overpaid under this system. They show the cost savings to the purchaser from introducing cost sharing to fixed price payment systems can range from 7 percent to over 60 percent depending on the degree of cost variation in DRGs.

Some of the measures that reflect the variation of severity in a DRG include admission sources and different types of care setting. Munoz, Soldano, Lauchlin, Margolis and Wise (1988) argue that hospitals with a high proportion of emergency room admissions may be disadvantaged under the DRG payment, as the costs per ER patient are higher than those per non-ER patient for the same DRG. Melnick, Serrato and Mann (1989) find that emergency, or urgent admission, incurs systematically higher costs than elective admission by examining all inpatient discharges from 96 short-term, acute care hospitals in New Jersey in 1982. Using discharge data for University Hospitals of Cleveland between January and November, 1983, Coulton et al. (1985) find that in 10 out of 13 DRGs they examine, the costs of the cases treated in an intensive care unit are much higher than those treated in routine care wards. The authors argue that since payments under the prospective payment system are based on the average costs, hospitals delivering a greater amount of intensive care will receive unfairly low payments.

#### 4.2.2.2 Adjustment to the prospective payment system

As a result of the above debate, some countries adjusted their prospective payment systems to take account of the factors reflecting justifiable differences across providers. A study by Chalkley and Malcomson (2002) points out that the Medicare payment system in the U.S. is not a pure fixed price model. McClellan (1997) also notes various features that are retrospective in the U.S. prospective payment system; such as procedure-based payments, outlier payments, and hospital and geographic adjustments; and measures the extent to which these features can explain the variation in costs. Moreover, a large proportion of DRGs is related not to diagnoses, but to procedures.

Theoretical studies on the optimal health care payment system often find that such adjustments can improve the prospective payment system. Malcomson (2005) and Siciliani (2006) derive the optimal pricing and provision of medical care when there are different types of treatment available for the same diagnosis and the purchaser cannot observe the recipient, or the actual costs. Malcomson shows that it is optimal for the purchaser to pay different prices for different types of treatment, even when the underlying diagnosis is the same. An interesting finding by Siciliani is that the optimal contract pays hospitals that provide identical treatment at different prices. Hospitals with high average severity receive a higher price for surgical treatments and a lower price for medical treatments. Furthermore, Miraldo, Siciliani and Street (2011) show that the optimal price for the high-cost provider is higher than that of the low-cost provider.

Similarly, De Fraja (2000) finds that paying different prices to hospitals is optimal when hospitals' costs are private information and the payment depends on the number of cases treated. In his model, more efficient hospitals treat more cases and receive a higher price per case. This is because the purchaser should provide an incentive to the more efficient provider to induce them to treat expensive cases. This finding may have implications for this essay. Although I do not examine the efficiency of the hospitals, that the purchaser pays a higher price to hospitals treating a large volume of cases may suggest that the highly skilled hospitals in my data should receive a higher price per case, as they treat more cases in general.

The empirical evidence also dictates that including additional adjusters, such as the severity of illness indicator, improves the prospective payment system. Averill et al. (1992), using data on 76,798 patients in 25 New Jersey hospitals, show that adjusting for severity of illness within DRGs can improve the fairness of the prospective payment system. They also confirm the claim that a DRG-based prospective payment system is unfair to certain hospitals, as the severity of illness is not distributed evenly across hospitals. Adding the severity measures increases the payment to teaching hospitals with the moderate level of Medicaid patients and large non-teaching community hospitals, while decreasing the payment to small nonteaching hospitals. Nevertheless, they acknowledge that their study may have underestimated the actual impact of severity on hospital payments, as hospitals in New Jersey are relatively homogeneous. Horn, Horn, Sharkey and Chambers (1986) use a data set including DRGs in 15 hospitals of different teaching types from all sections of the U.S. and confirm the results of their earlier study that the severity of illness index explains a large proportion of the variability in patient resource use.

#### 4.2.2.3 Debate on adjustment factors and methods

Although the relevant studies find that alteration to the prospective payment system is preferable, finding the exact method of adjustments is not easy. Ament, Dreachslin, Kobrinski and Wood (1982) use a nested analysis of variance for 50 hospitals for the 1976 fiscal year to show that both a DRG based classification and the two other classifications he tests fail to account for enough variance in total patient charges. Siciliani (2006) argues that the adjustments to teaching hospitals, or hospitals treating a higher share of low income patients, only partially corrects for the disadvantages encountered by hospitals with high average severity, because the observable variables, such as teaching status, are imperfectly correlated with the average severity.

Melnick, Serrato and Mann (1989) state that disadvantages encountered by hospitals treating more emergency, or urgent, admissions under the prospective payment system are confirmed. The solutions, however, are not easy to come by because the single adjuster does not improve the system, as well as because hospitals can easily respond to the change in incentives by coding the patients as emergency, or urgent, admissions. Nyman and Dowd (1991) examine the claims that Medicare should raise the limits for the reimbursement of costs for rural providers for home health agencies in Wisconsin in the period from 1987 to 1988. They find that there are no grounds for the claim, as the costs are higher in the urban area, contrary to the assumptions. Any financial disadvantages rural providers encounter seem to stem from the fact that rural agencies provide the types of visits that are more costly. Therefore, Nyman and Dowd (1991) conclude that changing the reimbursement limits for different types of visits, instead of for rural providers, would be more appropriate.

The adequacy of the adjustment for teaching hospitals in the U.S. prospective payment system (PPS) has generated great interest in the health literature[29]. For example, in a study that examines potential access problems to severely ill patients under the prospective payment system, Newhouse (1983) points out that the adjustment for indirect costs of teaching included in the Medicare reimbursement may end up increasing the salaries of residents at teaching hospitals, decreasing hospital profits and

[29] The interested reader can refer to Rogowski and Newhouse (1992), Dalton and Norton (2000), Anderson and Lave (1986), Thorpe (1988), Sloan, Feldman and Steinwald (1983) and Welch (1987), among others.

reducing the number of patients treated. This is because the additional payment to teaching hospitals to mitigate the negative effects of treating severely ill patients depends on the house officer/bed ratio, which increases the demand for house officers, whose supply is inelastic.

The studies reviewed above suggest that some form of adjustment to the prospective payment system for differences across hospitals, or patients, is beneficial, but they do not have consensus on which factor should be included in the adjustment. Transfer status is a good candidate for the adjustment factor in the prospective payment formula, because the studies reviewed above show a correlation of transfer with the severity of illness. In addition, transfer status is relatively harder to manipulate since the sending hospital makes the decision to transfer, and not the hospital treating the transferred patients. I also examine the relation between payment and CCL. As CCL is a measure for the severity of illness within a DRG, it is a natural candidate for the adjustment factor. This measure may be more prone to manipulation by hospitals than transfer status, however, because the hospitals may inflate CCL in order to receive a larger payment.

## 4.3 Data and methodology

### 4.3.1 Data

I use the National Minimum Dataset compiled by the New Zealand Ministry of Health over the period of July 2003 to June 2011. The National Minimum Dataset records all the publicly funded hospital events in the country. The sample starts from 1 July 2003, because a different funding system was in place prior to that date. I use information from the New Zealand Ministry of Health annual reports on the level of funding given to each DHB[30]. The amount of funding given to each DHB is recorded under the statement of non-departmental expenses in the annual reports. In addition, the DHBs reimburse one another for the treatment their own residents receive from other DHBs. I lack information on the amount each DHB receives for the treatment of non-residents and pays for the treatment of its own residents in another district, because not all DHBs state these figures in their annual reports. Thus, I include the net flows of patients between districts as a control variable in the model. The net flows in a DHB measure the differences between the percentages of non-residents the DHB treats and its own residents receiving treatment elsewhere.

As mentioned above, the method of funding DHBs changed in July 2003 from financing the health care providers based on the services they deliver, to distributing funds according to the characteristics of each DHB's population and districts. The characteristics included in the payment formula are the size, age, gender, ethnicity and socio-economic status of population, overseas visitors to the district and the level of ruralness. In addition to the funding based on the formula, DHBs receive tertiary adjusters to cover the higher costs of complex cases. As tertiary adjusters are based on the average costs of those services defined as tertiary, an argument has arisen similar to those over the adequacy of DRG payments, which is that the adjustment is insufficient for those providers who treat a disproportionately high share of tertiary services.

[30] The annual reports can be viewed on the Ministry of Health website: http://www.health.govt.nz/about-ministry/corporate-publications/annual-reports.

### 4.3.2 Methodology

The model presented in this study includes information on the actual usage of health services. The existing payment formula focuses on the characteristics of the residents of the districts, as the name *Population Based Funding Formula* suggests; however, it lacks a medium to account for the differences of the cases actually treated by the providers. In particular, the complexity of cases, widely known to affect costs, is not perfectly incorporated into the formula. Although the tertiary adjusters reimburse providers for more complex cases, the method of developing the adjusters has also come under criticism, as the adjusters are based on the average costs across providers (Wignall & Tringham, 2008).

Therefore, in addition to the variables in the existing formula, the model in this study contains measures of complexity such as the proportion of transferred patients at a DHB, the average CCL, teaching and tertiary status, and mean cost-weights, which measure the costliness of cases. Each hospital event is given a cost-weight based on the DRG code, length of stay, total hours on mechanical ventilation, and other relevant procedure and diagnosis codes used to measure the costliness of the case (New Zealand Health Information Service, 2008). The cost-weight is calculated using the Weighted Inlier Equivalent Separation (WIES) method, which is updated each financial year[31]. As cost-weights vary by DRGs, they also proxy for the differences in the types of DRGs the providers treat. Although the complexity measures do not directly enter into the current payment formula, they are known to affect the costs of health care services. The

[31] Information on the details of the WIES methodology for each year is available on the New Zealand Health Information Service website http://www.nzhis.govt.nz/moh.nsf/pagesns/300.

complexity measures may affect the payment indirectly through the historical costs, since a large part of the payment formula utilises information on the historical average costs.

As Table 4.1 shows, transfers between tertiary providers occur most frequently. Transfers between non-tertiary providers, and those from non-tertiary to tertiary providers, have very similar shares[32]. A small proportion of transfers are from tertiary to non-tertiary providers. Transfer from tertiary and non-tertiary providers typically occurs when tertiary providers send the transferred patients back to their original facilities. Since I use transfer as the measure of complexity, I do not count the tertiary to non-tertiary transfer as part of the transfer variable. I also include the annual volume of services to measure the size of the providers. To a certain extent, the volume of services will measure efficiency as well. In order to encourage providers to enhance the quality of care, I also include in the model a measure of quality, the 30-day mortality rates of the DHB.

**Table 4.1 Direction of transfer**

| Direction | Mean |
|---|---|
| Non-tertiary to tertiary | 0.21 |
| Tertiary to tertiary | 0.53 |
| Non-tertiary to non-tertiary | 0.22 |
| Tertiary to non-tertiary | 0.04 |

[32] Approximately 10 percent of the transferred cases do not have any records regarding the sending facility. In this case, I consider the cases to be transferred from private hospitals, whose records do not show in my data. Since private hospitals in New Zealand mostly perform elective procedures with relatively lower levels of complexity, I treat them as non-tertiary.

I examine how the actual usage by different population groups and relevant factors are associated with the government funds distributed to each DHB, using the following equation:

$$\ln(F_{ht}) = \beta_0 + \beta_1 \ln(Transfer_{ht}) + \beta_2 \ln(LowCCL\_residents_{ht}) + \beta_3 \ln(HighCCL\_residents_{ht}) + \beta_4 \ln(LowCCL\_nonresidents_{ht}) + \beta_5 \ln(HighCCL\_nonresidents_{ht}) + \beta_6 \ln(Age_{ht}) + \beta_7 \ln(Ethnic_{ht}) + \beta_8 \ln(Gender_{ht}) + \beta_9 \ln(Dep_{ht}) + \beta_{10} ln(Rural_{ht}) + \beta_{11} \ln(Overseas_{ht}) + \beta_{12} ln(CW_{ht}) + \beta_{13} Tertiary_h + \beta_{14} Teach_h + \beta_{15} \ln(Volume_{ht}) + \beta_{16} ln(Netflow_{ht}) + \beta_{17} \ln(Mort_{ht}) + \beta_{18} Year_t + \varepsilon \quad (1)$$

where *h* indexes DHBs and *t* specifies years. $F_{ht}$ specifies the government funding for the region where DHB *h* is located. I use the level of funding per case treated at hospital *h* in year *t* as the measure of government funding.

$Transfer_{ht}$ indicates the proportion of transferred patients at DHB *h*. I divide the patients into the DHBs' residents and non-residents when measuring the effects of CCLs on funding, because the treatment of non-residents receives additional reimbursement through IDF payment. $LowCCL\_residents_{ht}$ is the average CCL value of the patients who are assigned to CCL 0, 1, or 2 and reside in DHB *h*'s territory, while $HighCCL\_residents_{ht}$ measures the average CCL value of the DHBs' residents assigned to CCL 3, or 4. I do not use the average value of CCLs for each particular case, because the number of patients assigned to CCLs 3, or 4, is much smaller than that of the lower CCLs. $LowCCL\_nonresidents_{ht}$ and $HighCCL\_nonresidents_{ht}$ signify the average CCL value of the patients assigned to the corresponding CCLs and who do not reside in DHB *h*'s territory.

$Age_{ht}$ is the average age of patients treated at DHB *h*, $Ethnic_{ht}$ is the proportion of Maori and Pacific Peoples, and $Gender_{ht}$ is the proportion of female patients. $Dep_{ht}$ is the deprivation index, which measures the socioeconomic status, $Rural_{ht}$ is the ruralness indicator, and $Overseas_{ht}$ is the overseas adjuster measuring the share of overseas visitors in the region. $Tertiary_h$ is a dummy variable, which equals 1 if DHB *h* is classified as tertiary and 0 otherwise. $Teach_h$ is a dummy variable, which equals 1 if DHB *h* operates a teaching hospital. $Volume_{ht}$ signifies the discharge volume per capita, and $Netflow_{ht}$ indicates the differences between the proportion of patients from another district who receive treatment in DHB *h* and DHB *h*'s own patients who receive treatment in another district. $Mort_{ht}$ is the 30-day mortality rate, and $CW_{ht}$ is the mean cost-weight. The model also includes year fixed effects. All the continuous variables are in natural log form. I estimate this model by OLS with White (1980) heteroskedastic errors. The payment function above is closely related to the behavioural cost functions discussed in Lave and Lave (1970), because costs form the basis for payment in public hospitals. Lave and Lave (1970) use utilisation, hospital size and the product mix measures in their cost function. I do not include the utilisation measures, such as occupancy rates used in their study, because utilisation indicators are not a suitable entry in my payment function. The health sector in New Zealand has been working towards reducing hospital bed utilisation in order to control costs and promote early prevention at the primary care level (Davis, Lay-Yee, Scott, & Gauld, 2007; Malcolm, 2007). To be consistent with this objective, the payment function should reward the DHBs that reduce utilisation, but doing so may provide perverse incentives to hospitals, such as the premature discharge of patients. Table 4.2 reports the descriptive statistics of the variables.

**Table 4.2 Descriptive statistics (*N*=168)**

| | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|
| | | A. Entire dataset | | |
| Percentage of transferred patients | 0.04 | 0.03 | 0.00 | 0.14 |
| Average CCL 0-2 of DHBs' residents | 0.78 | 0.06 | 0.60 | 0.95 |
| Average CCL 3-4 of DHBs' residents | 3.13 | 0.02 | 3.05 | 3.17 |
| Average CCL 0-2 of non-residents | 0.75 | 0.09 | 0.57 | 1.08 |
| Average CCL 3-4 of non-residents | 3.17 | 0.09 | 3 | 3.35 |
| Tertiary | 0.33 | 0.47 | 0 | 1 |
| Teaching | 0.43 | 0.50 | 0 | 1 |
| Funding per case (NZ$, 2011 price) | 10,552.06 | 1,914.52 | 6,769.28 | 18,038.13 |
| Volume | 45,033 | 35,546 | 5,886 | 138,460 |
| Percentage of net flow | -0.01 | 0.03 | -0.06 | 0.10 |
| Percentage of Maori/Pacifica patients | 0.22 | 0.13 | 0.04 | 0.51 |
| Percentage of female patients | 0.56 | 0.02 | 0.49 | 0.59 |
| Average age | 44.75 | 3.64 | 35.53 | 51.82 |
| Deprivation | 21.21 | 10.42 | 5.85 | 49.40 |
| Rural | 4.75 | 3.04 | 0.02 | 11.21 |
| Overseas | 4.76 | 6.83 | 0.22 | 28.13 |
| Average cost-weights | 1.62 | 5.08 | 0.09 | 47.71 |
| Mortality rates | 0.03 | 0.01 | 0.02 | 0.05 |
| Population | 201,679 | 153,294 | 30,530 | 540,007 |
| | | B. Tertiary DHBs | | |
| Percentage of transferred patients | 0.07 | 0.03 | 0.02 | 0.14 |
| Average CCL 0-2 of DHBs' residents | 0.78 | 0.05 | 0.66 | 0.90 |
| Average CCL 3-4 of DHBs' residents | 3.13 | 0.02 | 3.09 | 3.16 |
| Average CCL 0-2 of non-residents | 0.73 | 0.07 | 0.57 | 0.90 |
| Average CCL 3-4 of non-residents | 3.18 | 0.06 | 3.07 | 3.35 |
| Teaching | 0.86 | 0.35 | 0.00 | 1.00 |
| Funding per case (NZ$, 2011 price) | 9,374.59 | 1,375.90 | 6,769.28 | 11,494.74 |
| Volume | 78,651.14 | 36,094.75 | 27,605.00 | 138,460.00 |
| Percentage of net flow | 0.07 | 0.13 | -0.10 | 0.34 |
| Percentage of Maori/Pacifica patients | 0.22 | 0.12 | 0.06 | 0.47 |
| Percentage of female patients | 0.56 | 0.01 | 0.54 | 0.59 |
| Average age | 42.09 | 3.74 | 35.53 | 49.93 |
| Deprivation | 19.76 | 7.30 | 10.40 | 36.60 |
| Rural | 3.27 | 3.32 | 0.02 | 11.21 |
| Overseas | 10.59 | 8.97 | 1.26 | 28.13 |
| Average cost-weights | 2.54 | 7.89 | 0.15 | 47.71 |
| Mortality rates | 0.03 | 0.01 | 0.02 | 0.04 |
| Population | 335,094 | 129,937 | 138,200 | 508,200 |
| | | C. Non-tertiary DHBs | | |
| Percentage of transferred patients | 0.03 | 0.02 | 0.00 | 0.09 |

| | | | | |
|---|---|---|---|---|
| Average CCL 0-2 of DHBs' residents | 0.79 | 0.06 | 0.60 | 0.95 |
| Average CCL 3-4 of DHBs' residents | 3.13 | 0.03 | 3.05 | 3.17 |
| Average CCL 0-2 of non-residents | 0.76 | 0.10 | 0.59 | 1.08 |
| Average CCL 3-4 of non-residents | 3.16 | 0.10 | 3 | 3.35 |
| Teaching | 0.21 | 0.41 | 0.00 | 1.00 |
| Funding per case (NZ$, 2011 price) | 11,140.80 | 1,878.13 | 7,661.65 | 18,038.13 |
| Volume | 28,223.29 | 20,002.92 | 5,886.00 | 98,481.00 |
| Percentage of net flow | -0.11 | 0.09 | -0.48 | -0.01 |
| Percentage of Maori/Pacifica patients | 0.22 | 0.13 | 0.04 | 0.51 |
| Percentage of female patients | 0.55 | 0.02 | 0.49 | 0.59 |
| Average age | 46.08 | 2.76 | 39.63 | 51.82 |
| Deprivation | 21.93 | 11.64 | 5.85 | 49.40 |
| Rural | 5.49 | 2.60 | 0.49 | 10.19 |
| Overseas | 1.85 | 2.14 | 0.22 | 9.16 |
| Average cost-weights | 1.17 | 2.71 | 0.09 | 25.52 |
| Mortality rates | 0.03 | 0.01 | 0.02 | 0.05 |
| Population | 134,971 | 117,274 | 30,530 | 540,007 |

As the National Minimum Dataset does not provide information on the deprivation index, ruralness indicator and share of overseas visitors, I derive these variables from the *Population-based Funding Formula 2003* (Ministry of Health, 2004). The deprivation, rural and overseas adjusters have been updated once in 2007 since the introduction of the funding formula. Using the *New Zealand Deprivation Index 2006* (2007), I update the level of deprivation for each admission. The updated rural and overseas adjusters are obtained from Penno et al. (2012). From 2001 to April 2010, 21 DHBs operated. In May 2010, Otago and Southland DHBs merged to form Southern DHB. I do not reflect this change in my analysis and run the regression with 21 DHBs throughout the research period, because the last financial year in my dataset is the only year when only 20 DHBs were in operation[33].

[33] Moreover, I do not have information on the rural and overseas indicators for the new DHB. The financial year ending on June 30, 2010 was the transition period, so the funding was not only allocated to

The payment function described above is closely related to the behavioural cost functions discussed in Lave and Lave (1970), because costs form the basis for payment in public hospitals. Lave and Lave (1970) use utilisation, hospital size and the product mix measures in their cost function. I do not include utilisation measures, such as occupancy rates, as used by Lave and Lave (1970), because utilisation indicators are not a suitable factor for inclusion in my payment function. The health sector in New Zealand has been working towards reducing hospital bed utilisation in order to control costs and promote early prevention at the primary care level (Davis, Lay-Yee, Scott, & Gauld, 2007; Malcolm, 2007). To be consistent with this objective, the payment function should reward DHBs that reduce utilisation, but doing so may provide perverse incentives to hospitals, such as the premature discharge of patients.

A similar argument can be made about directly including other types of efficiency measures. In addition, because efficient hospitals can provide services at cheaper costs, extra payment as a reward for efficiency will result in a financial surplus, which is neither desirable, nor consistent with the objective of cutting costs in the public health sector. On the other hand, if payment is reduced to reflect the lower costs, efficient providers will be unfairly penalised. In my model, discharge volume, which measures the size of the providers, will also provide some incentives for efficiency. I include the volume measures with the quality indicator mortality rates to minimise the adverse

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Otago and Southland DHBs, but was also set aside for Southern DHB. To maintain 21 DHBs, I divide the funding given to the newly formed DHB into two amounts based on the funding given to its predecessors in the previous year.

effects on patients that may arise if the providers reduce care quality in an attempt to increase the volume of services.

I examine the coefficients of the models to check the relation between the actual usage by patients and the levels of funding. The base model estimates Equation (1) with OLS. As there may be endogeneity between funding and transfer, I also use an instrumental variable approach. Endogeneity may arise if providers who receive higher funding per case attract more transferred patients. I control for potential endogeneity by using the lag of the percentage of transferred patients as an instrument. The proportion of transferred patients at a DHB in the previous year will not affect the funding level in the current year, especially since transfer is not a factor considered in the funding formula. Moreover, as I include various control variables that may be correlated with transfer status, such as patient and facility characteristics, economic conditions and diagnoses[34], I believe that the error term is not likely to include factors that may be correlated with the lag of transfer.

### 4.4 Regression results

In this section, I examine the coefficients of Equation (1) to check the relationship between the level of funding and the characteristics of the population that actually used the hospital services. The explanatory variables in Equation (1) include factors that are directly reimbursed under the current system, as well as those that are not part of the

[34] I control for the diagnoses of patients by including the average cost-weights by provider. As cost-weights vary by DRGs, they proxy for the differences in the types of diagnoses the providers treat.

current funding formula. Although some of the factors are included in both my model and the current formula, they will not have an identical relation with the level of funding. This is because the model in this study includes those factors based on the actual usage, whereas the current formula includes them based on the population. For instance, under the current formula the level of funding depends on the population of Maori and Pacific peoples, while in my model I include the proportion of Maori and Pacific peoples in health care facilities who actually receive treatment.

Table 4.3 presents the estimation results. Column 1 shows the estimation results from the most complete specification. Columns 2 to 5 report the models excluding some of the variables that indicate the providers' skill levels, in order to check whether multicollinearity among them alters the results. Columns 6 to 9 present the results from the IV estimation. All the models include year dummies, which show that the level of funding per case increases over the research period.

The results show that treating a higher proportion of Maori and Pacific Island patients is associated with a lower level of funding, a somewhat surprising result considering that these patients belong to the high-risk ethnic groups receiving additional funding. The finding suggests that in those districts that treat a higher proportion of Maori and Pacific Islanders, the proportion of the Maori and Pacific Islanders among patients is higher than the proportion of these ethnic groups in the population of the district. Another reason for this funding anomaly may be that the unmet needs adjuster, which pays an additional NZ$50 per Maori/Pacific Islander residing in a district, does not capture the non-linearity in treatment costs for these groups. Treating a higher number of patients in the high-risk ethnic groups, for example, may cost much more than treating a lower number. Similarly, I observe the negative coefficients of overseas visitors, although the overseas adjustor compensates providers for the treatment of the visitors. This suggests that the areas with a high percentage of visitors also provide a large volume of services. If this is the case, the overseas adjuster will increase the level of funding, but may not increase the per case funding.

There are also negative correlations between the average age of patients and the level of funding. The negative coefficients of age suggest that older people use health care services more frequently, which seems intuitive. Thus, the level of funding per case for those districts with an older population will be lower, as the actual usage by this group exceeds the population in the group residing in the districts. Interestingly, the mean mortality rate shows positive and significant coefficients, implying that the mortality rate may be a significant factor predicting the average costs of hospital services, because the current funding is computed based on the average costs.

**Table 4.3 Effects of case complexity on funding per case**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Transfer | -0.0133 | -0.0210 | -0.00490 | -0.0197 | | -0.0207 | -0.0280+ | -0.0116 | -0.0283+ |
| | (-0.99) | (-1.58) | (-0.36) | (-1.33) | | (-1.40) | (-1.94) | (-0.76) | (-1.74) |
| CCL 0-2 (residents) | -0.110 | -0.0632 | -0.0221 | | -0.130 | -0.0995 | -0.0538 | -0.00903 | |
| | (-1.05) | (-0.58) | (-0.21) | | (-1.27) | (-0.99) | (-0.52) | (-0.09) | |
| CCL 3-4 (residents) | 0.528 | 0.226 | 0.462 | | 0.441 | 0.576 | 0.282 | 0.505 | |
| | (0.44) | (0.19) | (0.38) | | (0.37) | (0.51) | (0.25) | (0.44) | |
| CCL 0-2 (non-residents) | -0.00417 | 0.0146 | -0.0380 | | -0.00739 | -0.00239 | 0.0158 | -0.0374 | |
| | (-0.08) | (0.26) | (-0.72) | | (-0.15) | (-0.05) | (0.31) | (-0.76) | |
| CCL 3-4 (non-residents) | 1.135** | 1.114** | 1.019** | | 1.148** | 1.128** | 1.107** | 1.009** | |
| | (3.49) | (3.38) | (3.07) | | (3.57) | (3.75) | (3.61) | (3.27) | |
| Tertiary | -0.0832** | | -0.0526* | -0.0607* | -0.0877** | -0.0807** | | -0.0493* | -0.0585* |
| | (-3.05) | | (-2.07) | (-2.31) | (-3.33) | (-3.13) | | (-2.02) | (-2.35) |
| Teaching | 0.0801** | 0.0495* | | 0.0415* | 0.0751** | 0.0829** | 0.0532** | | 0.0456* |
| | (4.18) | (2.52) | | (2.18) | (3.81) | (4.75) | (2.90) | | (2.53) |
| Volume | -0.493** | -0.455** | -0.432** | -0.479** | -0.485** | -0.497** | -0.460** | -0.434** | -0.485** |
| | (-5.36) | (-5.40) | (-5.15) | (-5.28) | (-5.10) | (-5.95) | (-5.99) | (-5.66) | (-5.80) |
| Net flow | -0.0540 | -0.0699+ | -0.0604 | -0.0589 | -0.0551 | -0.0535 | -0.0689+ | -0.0601+ | -0.0583 |
| | (-1.42) | (-1.68) | (-1.56) | (-1.51) | (-1.44) | (-1.54) | (-1.80) | (-1.68) | (-1.62) |
| Age | -0.143 | -0.0779 | 0.0474 | -0.198 | -0.0849 | -0.175 | -0.112 | 0.0233 | -0.238 |
| | (-0.78) | (-0.37) | (0.25) | (-1.06) | (-0.47) | (-1.02) | (-0.57) | (0.13) | (-1.32) |
| Gender | 0.164 | -0.0209 | 0.204 | -0.0492 | 0.225 | 0.131 | -0.0487 | 0.173 | -0.0908 |
| | (0.66) | (-0.08) | (0.82) | (-0.16) | (0.90) | (0.56) | (-0.21) | (0.74) | (-0.32) |
| Ethnicity | -0.135** | -0.0934** | -0.107** | -0.133** | -0.131** | -0.137** | -0.0969** | -0.108** | -0.135** |
| | (-3.90) | (-3.16) | (-3.13) | (-3.43) | (-3.75) | (-4.33) | (-3.58) | (-3.42) | (-3.73) |
| Deprivation | 0.123** | 0.0866* | 0.106** | 0.118** | 0.126** | 0.121** | 0.0859** | 0.104** | 0.116** |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (3.12) | (2.60) | (2.80) | (2.73) | (3.29) | (3.29) | (2.77) | (2.90) | (2.83) |
| Rural | -0.00829 | -0.00440 | -0.00591 | -0.00205 | -0.00862+ | -0.00811+ | -0.00434 | -0.00566 | -0.00176 |
| | (-1.65) | (-0.98) | (-1.16) | (-0.40) | (-1.72) | (-1.74) | (-1.06) | (-1.20) | (-0.37) |
| Overseas | -0.0380** | -0.0391** | -0.0182* | -0.0243** | -0.0407** | -0.0365** | -0.0375** | -0.0162* | -0.0227** |
| | (-3.85) | (-3.98) | (-2.22) | (-2.89) | (-4.35) | (-3.98) | (-4.06) | (-2.11) | (-2.83) |
| Cost-weights | 0.00535 | 0.00901 | 0.00667 | 0.00586 | 0.00503 | 0.00553 | 0.00908 | 0.00688 | 0.00613 |
| | (0.78) | (1.29) | (0.94) | (0.87) | (0.73) | (0.88) | (1.41) | (1.05) | (0.97) |
| Mortality | 0.191* | 0.265** | 0.210* | 0.187* | 0.174* | 0.200** | 0.272** | 0.219** | 0.197** |
| | (2.51) | (3.99) | (2.60) | (2.45) | (2.44) | (2.75) | (4.32) | (2.83) | (2.64) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Constant | 7.132** | 7.598** | 6.943** | 9.147** | 7.027** | 7.190** | 7.642** | 6.992** | 9.273** |
| | (4.56) | (4.96) | (4.31) | (9.40) | (4.62) | (4.92) | (5.33) | (4.65) | (9.95) |
| Adj. $R^2$ | 0.786 | 0.774 | 0.774 | 0.755 | 0.786 | | | | |
| Estimation method | OLS | OLS | OLS | OLS | OLS | IV | IV | IV | IV |
| *N* | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 | 168 |

NOTE. – The table reports the relation between the actual usage of health care services and the level of funding per case. “Transfer” signifies the percentage of transferred patients at a DHB. “CCL 0-2 (residents)” indicates the average CCL value of the DHB’s own patients assigned to CCLs 0, 1, or 2, while “CCL 3-4 (residents)” indicates the average CCL value of the DHB’s residents assigned to CCLs 3, or 4. “CCL 0-2 (non-residents)” and “CCL 3-4 (non-residents)” are the average CCL values of the patients from another district assigned to the corresponding CCLs. In the IV models, I use the lagged values of “transfer” as instruments. Table 4.5 presents the first stage regressions. The description of the other explanatory variables is provided in the main text. *t* statistics are in parentheses. Robust standard errors are used.

+ Significant at the 10 percent level.

* Significant at the 5 percent level.

** Significant at the 1 percent level.

Table 4.3 shows that treating a higher proportion of transferred patients is associated with a lower level of funding. In the base model presented in column 1, a 1 percent increase in the percentage of transferred patients is associated with a 0.013 percent lower level of funding per case. The effects of transfer, however, are statistically insignificant in most specifications. At the lower level of complexity (CCLs 0 to 2), there are negative correlations between funding per case and the average value of CCL for both residents and non-residents. In the base model, a 1 percent increase in the average CCL value for the resident patients with milder conditions is associated with a 0.1 percent lower level of funding, while the average CCL for the non-resident patients in the same categories has even smaller coefficients. The negative signs for the CCL assigned to the resident patients with milder conditions indicate that there are negative correlations between the average CCL of the patients and the factors included in the funding formula. The coefficients are, however, statistically insignificant. The finding still suggests that the characteristics of population may not reflect the complexity of the cases treated in health care facilities.

On the other hand, at the higher levels of complexity (CCLs 3 and 4) there are positive correlations between the level of funding and the average value of CCLs. The coefficients are only statistically significant for the patients from another district. A 1 percent increase in the average CCL for non-resident patients is associated with an approximately 1 percent higher level of funding per case for the high complexity cases, whereas the coefficients for the average CCL assigned to resident patients are much smaller and statistically insignificant. Taken together with the finding above that the coefficients for the average CCL assigned to resident patients in low complexity levels are negative but insignificant, the results may suggest that the case complexity of the resident patients treated in health care facilities is not reflected in the level of government funding.

The net flow variable shows a negative sign, as expected. Providers treating a higher proportion of non-residents receive less funding from the government than their share of the population, because other DHBs where the patients actually reside reimburse the care providers for the treatment. Table 3.1 in the previous chapter shows that tertiary DHBs, who tend to receive more patients from other districts, receive relatively lower levels of funding for their population size under the current funding system. In addition, tertiary DHBs also receive lower levels of funding per case. The negative sign of the tertiary dummy is also as expected, because the tertiary adjuster is paid as a part of the IDF pricing, which is reflected in the net flow variable. As providers receive additional payment for tertiary services from the other DHBs, the level of government funding is lower for tertiary DHBs. Funding per case for tertiary DHBs is 8 percent lower than that for non-tertiary DHBs. In contrast, the level of funding for teaching DHBs is 8.3 percent higher than that for non-teaching DHBs.

Columns 2 to 5 in Table 4.3 present models excluding tertiary, teaching, CCL indicators, and transfer, respectively, to check whether the effects of the variables indicating case complexity and skill levels change due to multicollinearity. Most of the above variables show high correlations with one another, as shown in Table 4.4. The coefficients of transfer change a little bit when I exclude the other indicators of complexity, especially in Models 2 and 3. None of the changes are, however, large enough to alter the significance and direction of the coefficients. Similarly, the coefficients of CCLs do not change much when I exclude the other complexity indicators. The largest change is in the average CCL value for the non-resident patients assigned to lower CCLs. Its coefficients change the sign, but they are still statistically insignificant. The sizes of the coefficients of tertiary and teaching dummies are sensitive to the exclusion of each other, reflecting the high correlation between them (0.61).

Columns 6 to 9 in Table 4.3 present the results from the IV models. The instrument; the lagged values of the transfer variable; is significant at the 1 percent level in all the first stage regressions, as shown in Table 4.5. Using the IV approach slightly increases the negative signs of transfer. In Models 7 and 9, where I exclude the tertiary dummy and CCL variables, respectively, a 1 percent increase in the proportion of transferred patients is associated with lower funding per case by about 0.03 percent. The coefficients in these models become marginally significant.

To summarise, the results show that the characteristics of population may not accurately predict the actual usage by some population groups. Increases in the proportion of Maori and Pacific Island patients, and in the average age of patients, are associated with lower levels of per case funding, although these population characteristics receive higher weights in the funding computation method. Therefore, the actual usage of health services by these population groups may exceed their population share. I also find that the case complexity of the resident patients does not have a statistically significant relation with the level of funding. This finding suggests that the characteristics of population used to compute the government funding may not reflect the complexity levels assigned to the patients who actually receive treatment.

**Table 4.4 Correlations among key variables**

| | Funding per case | Transfer | Tertiary | Teaching | Net flow | CCL 0-2 (residents) | CCL 3-4 (residents) | CCL 0-2 (non-residents) | CCL 3-4 (non-residents) |
|---|---|---|---|---|---|---|---|---|---|
| Funding per case | 1 | | | | | | | | |
| Transfer | -0.31 | 1 | | | | | | | |
| Tertiary | -0.44 | 0.64 | 1 | | | | | | |
| Teaching | -0.42 | 0.56 | 0.61 | 1 | | | | | |
| Net flow | -0.69 | 0.63 | 0.64 | 0.44 | 1 | | | | |
| CCL 0-2 (residents) | -0.16 | 0.11 | -0.11 | 0.17 | -0.19 | 1 | | | |
| CCL 3-4 (residents) | -0.11 | -0.08 | 0.09 | 0.08 | 0.14 | 0.08 | 1 | | |
| CCL 0-2 (non-residents) | -0.06 | -0.12 | -0.17 | -0.11 | -0.13 | 0.40 | 0.08 | 1 | |
| CCL 3-4 (non-residents) | 0.06 | 0.02 | 0.08 | -0.09 | 0.07 | -0.19 | 0.51 | 0.12 | 1 |

NOTE. – Transfer indicates the percentage of transferred patients in a DHB. Tertiary and teaching are dummy variables. Net flow is the difference between the proportion of patients from another district who receive treatment in a DHB, and the DHB's own patients who receive treatment in another district. "CCL 0-2 (residents)" indicates the average CCL value of the DHB's own patients assigned to CCLs 0, 1, or 2, while "CCL 3-4 (residents)" indicates the average CCL value of the DHB's residents assigned to CCLs 3, or 4. "CCL 0-2 (non-residents)" and "CCL 3-4 (non-residents)" are the average CCL values of the patients from another district assigned to the corresponding CCLs.

**Table 4.5 First stage regressions**

| | (1)<br>Percentage of transfer | (2)<br>Percentage of transfer | (3)<br>Percentage of transfer | (4)<br>Percentage of transfer |
|---|---|---|---|---|
| Lagged transfer | 0.839** | 0.844** | 0.845** | 0.844** |
| | (18.19) | (18.82) | (19.25) | (18.70) |
| CCL 0-2 (residents) | 0.254 | 0.214 | 0.325 | |
| | (0.87) | (0.75) | (1.08) | |
| CCL 3-4 (residents) | 2.912 | 3.202 | 2.877 | |
| | (0.91) | (1.00) | (0.90) | |
| CCL 0-2 (non-residents) | -0.0508 | -0.0679 | -0.0778 | |
| | (-0.31) | (-0.42) | (-0.47) | |
| CCL 3-4 (non-residents) | -0.188 | -0.171 | -0.280 | |
| | (-0.24) | (-0.22) | (-0.37) | |
| Tertiary | 0.0738 | | 0.0982 | 0.0727 |
| | (1.07) | | (1.33) | (1.11) |
| Teaching | 0.0626 | 0.0904 | | 0.0717 |
| | (1.00) | (1.31) | | (1.21) |
| Volume | -0.0303 | -0.0646 | 0.0178 | -0.0218 |
| | (-0.22) | (-0.47) | (0.15) | (-0.17) |
| Netflow | 0.00999 | 0.0243 | 0.00503 | 0.00818 |
| | (0.38) | (1.22) | (0.18) | (0.32) |
| Age | -1.069* | -1.135* | -0.925* | -1.043* |
| | (-2.10) | (-2.14) | (-2.05) | (-2.09) |
| Gender | -0.773 | -0.613 | -0.746 | -0.783 |
| | (-1.05) | (-0.93) | (-1.02) | (-1.04) |
| Ethnicity | 0.0656 | 0.0293 | 0.0881 | 0.0956 |
| | (0.89) | (0.49) | (1.21) | (1.31) |
| Deprivation | -0.116 | -0.0845 | -0.130 | -0.119 |
| | (-1.44) | (-1.32) | (-1.62) | (-1.46) |
| Rural | 0.00580 | 0.00237 | 0.00770 | 0.00888 |
| | (0.39) | (0.16) | (0.53) | (0.57) |
| Overseas | 0.0522 | 0.0536 | 0.0680* | 0.0535 |
| | (1.43) | (1.49) | (2.09) | (1.46) |
| Cost-weights | -0.00720 | -0.0105 | -0.00622 | -0.00433 |
| | (-0.41) | (-0.64) | (-0.36) | (-0.25) |
| Mortality | 0.474** | 0.411* | 0.492** | 0.498** |
| | (2.66) | (2.56) | (2.72) | (2.91) |
| Constant | 1.878 | 1.475 | 1.740 | 4.999* |
| | (0.57) | (0.46) | (0.53) | (2.60) |
| Year fixed effects | Yes | Yes | Yes | Yes |
| *F*-statistics on excluded instrument | 324.15 | 346.97 | 363.78 | 322.08 |

NOTE. – The table presents the first stage regressions for Models 6 to 9 in Table 4.3. "Lagged transfer" is the instrument and signifies the lagged values of the transfer variable. The description of the other variables is provided in the main text. *t* statistics are in parentheses.

$^{+}$ Significant at the 10 percent level.

$^{*}$ Significant at the 5 percent level.

$^{**}$ Significant at the 1 percent level.

In addition, the level of funding per case is lower for providers treating a higher proportion of transferred patients. The size of the decrease in funding associated with transferred patients is not statistically significant. The negative sign of the transfer variable reflects the lower level of funding per population received by providers treating a higher number of non-residents. These providers receive lower levels of funding from the government because the other DHB, where the patient's residence is located, reimburses the care providers for the services delivered.

### 4.5 Conclusion

This study examines the capitation funding system in New Zealand, which allocates funds across districts based on the characteristics of population, rather than the actual treatment provided. I test the relation between the current funding level and the actual usage by population to study how differences between the actual usage and the characteristics of population affect the payment. In addition to examining the use of health care services by different population groups, I am also interested in the levels of funding for providers treating a higher proportion of complex cases, because the current funding system does not fully incorporate the level of complexity in its method of computation.

I find that the characteristics of the population may not accurately predict the actual usage by some population groups. Increases in the proportion of Maori and Pacific Island patients, and in the average age of patients, are associated with lower levels of per case funding, despite these population characteristics receiving higher weights under the current payment system. This finding suggests that the usage of health care services by these population groups may exceed their population share. I also find that an increase in the average CCL for patients who receive treatment in their own DHBs does not have a statistically significant relation to the level of funding. This result may suggest that the population characteristics do not accurately reflect the complexity of the treated cases.

Overall, this essay shows that the differences between the actual usage and the population size may be a source of inaccurate funding allocation under the capitation funding system. Despite this, I cannot make a conclusion on the adequacy of funding allocation. To study the adequacy of payment, we need to understand how the complexity of cases and other relevant factors affect the actual costs. I plan to obtain cost data across providers to examine this issue in a future study.

## Appendix

### A1. An example of the funding share calculation[35]

Step 1: Multiply the expected cost for each demographic group by the population of the particular group in each DHB.

e.g. If the average cost of treatment for a Maori female whose age is between 40 and 44 and who is living in an area that belongs to the NZ Dep Index quintile 5 is NZ$2,000, and the number of people in this population group is 30, the estimated cost for this group will be NZ$60,000.

Step 2: Add all the demographic group costs together.

Step 3: Add the unmet need adjuster. Maori and Pacific Islanders receive NZ$50 per head as an unmet need adjuster. In addition, populations in NZ Dep Index quintile 4, or 5, receive NZ$50 per head. Thus, for a Maori living in an area in the deprivation quintile 4 the DHB will receive NZ$100.

Step 4: Add each DHB's share of overseas and rural adjusters.

Step 5: Calculate each DHB's costs as a percentage of the total DHB costs. Multiply the percentage by the available budget to obtain the level of funding.

[35] Modified from McHugh (2008) and Penno et al.(2012).

# Chapter 5 Conclusions

In the first essay of this dissertation, I show that complex cases, as measured by the transfer status, and comorbidity and complication indicators, negatively affect performance measures in New Zealand hospitals, using more than 10 million discharges from public hospitals during the period from 1999 to 2011. This study is the first to address the issue of potential endogeneity between the transfer status and performance measures. The positive relation between the two that was observed in the past studies may have been due to the simultaneity bias, because the health care facilities may be more prone to transfer those patients who are likely to have longer hospital stays and/or higher probabilities of mortality and readmission.

In most specifications, transferred patients have a longer hospital stay. The increase in LOS ranges from 7 to 22 days across different models. Transferred patients are more likely to die within 30 days of discharge in all the specifications than non-transferred patients. Overall, there is an increase of about 5 percentage points in the likelihood of mortality for transferred patients. Transferred patients also have a higher probability of 30-day readmission in most specifications. The increase in the probability of readmission for transferred patients ranges from 0.4 to 3 percentage points. I do not find that endogeneity is present in the models.

Furthermore, I show that higher CCLs have negative effects on performance measures. The highest CCL, which signifies the most complex cases, increases the length of hospital stay by 6 to 15 days, a probability of 30-day mortality by 4 to 5 percentage points, and a probability of 30-day readmission by 17 to 20 percentage points. Therefore, the negative effects of transferred patients on the receiving hospitals suggest that organisations given more difficult tasks due to their high level of expertise may be at a disadvantage if performance reviewers do not take account of the task difficulty.

In the second essay, I study the effects of a health system reform in New Zealand, which took place in 2003. The reintroduction of capitation due to the system reform decreased the movement of patients between districts. Low-skilled health care providers, in particular, are less likely to transfer patients to another district since the reform. The finding suggests that capitation provides health care providers with incentives to keep patients within their districts. The probability of IDFs, a more general measure of inter-district patient movement, also decreased considerably since the reform took place. Tertiary DHBs, who receive more out of district patients, experienced a larger decline in the probability of receiving IDFs. As the funding growth was much higher for non-tertiary DHBs under capitation, the results imply that the higher funding these DHBs received is not redistributed across the districts as much as some believe.

I also find that more severely ill patients are less likely to be moved between districts since the policy reform; however, diagnoses with higher probabilities of fatality are still more likely to be transferred, suggesting that non-tertiary providers selectively treat more severe, but less fatal, cases. Health outcomes seem to have deteriorated since the reform, as patients stay in hospital for a shorter period of time, but are more likely to be readmitted to hospital. Therefore, the reform seems to have reduced necessary patient movement between districts.

In future studies, it will be helpful to examine other indicators of health outcomes to check whether my conclusion that the health outcomes have deteriorated since the reform holds. In addition, my study does not provide a clear indication of whether the prices for IDFs are lower than their fair value. The decrease in IDFs may suggest that the prices are high; however, the opposite can still be true if providers simply found it more attractive to retain the funding given to their region. Another issue that warrants further study is the net effects of the system reform on highly skilled providers. On the one hand, the redistribution of funds did not take place in a large scale under the new capitation system, so the reduced level of funds that highly skilled providers receive has not been compensated for. On the other hand, however, they receive fewer patients, so their workload has been reduced. I leave this issue for future research.

The third essay examines the relation between the current funding level and the actual usage by population to study how differences between the actual usage and the characteristics of population affect the level of funding. In addition to examining the usage of health care services by different population groups, I check the levels of funding for providers treating a higher proportion of complex cases, because the current funding system does not fully incorporate the level of complexity in its computation method.

The finding of this essay suggests that the usage of health care services by certain population groups may exceed their population share. Increases in the proportion of Maori and Pacific Island patients, and in the average age of patients, are associated with lower levels of per case funding, despite these population characteristics receiving higher weights under the current payment system. I also find that an increase in the average CCL for patients who receive treatment in their own DHBs does not have a statistically significant relation to the level of funding. This result may suggest that the population characteristics do not accurately reflect the complexity of the treated cases.

This essay shows that the differences between the actual usage and the population size may be a source of imperfect funding allocation under the current funding system, which computes the level of funding based on the characteristics of population. I cannot make a conclusion on the adequacy of funding allocation, however. To study the adequacy of the payments, we need to understand how the complexity of cases and other relevant factors affect the actual costs. I plan to obtain cost data across providers to examine this issue in a future study.

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