Efficiency and Productivity Analysis of New Zealand District Health Boards: An Empirical Enquiry using Bayesian Stochastic Frontier Analysis

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Abstract

The bulk of efficiency studies in healthcare literature that use longitudinal data assume that inefficiency is independent over time. However, if the operating environment imposes significant adjustment costs that prevent healthcare providers from operating at optimum levels, inefficiencies are likely to follow a dynamic process. This implies that inefficiencies may persist from one period to the next, thereby violating the widely held assumption of inefficiency independence. In such a dynamic decision-making environment, a healthcare provider may opt to remain partly inefficient over time and aim for a long-run level of equilibrium efficiency that corresponds to the degree of adjustment costs they face.

While the measurement of healthcare providers' total factor productivity (TFP) and its components has gained considerable traction, existing studies exclusively assume either primal or dual specification, without any comparisons between them. The analysis of the productivity using both specifications can act as a robustness check and, most significantly, assist in highlighting the source of discrepancies in the results.

This thesis aims to address some of these gaps in healthcare literature by applying Bayesian estimation techniques on quarterly data on New Zealand District Health Boards (DHBs) for 2011-2018.

The first empirical chapter investigates the technical efficiency of New Zealand's DHBs in providing hospital services by using a dynamic stochastic frontier specification. The empirical results identify an excessive level of persistence in technical inefficiency in the sector due to high adjustment costs. While high adjustment costs resulted in a low national long-run technical efficiency level, on average, DHBs performed close to the long-run level of technical efficiency.

The second empirical chapter also used a dynamic stochastic frontier specification to estimate cost efficiency while controlling for unobserved and observed DHB specific heterogeneity. The results show that although cost inefficiency persistence is still relatively high in the sector, DHBs that provide hospital services to rural communities tend to have a higher long-run level of cost inefficiency. The chapter also provides evidence that ignoring heterogeneity in stochastic frontier models can lead to biased estimates of model parameters and efficiency estimates.

The final empirical chapter undertakes the TFP change decomposition under both primal and dual specifications. The results from both specifications are consistent and show that the TFP decreased between 2011 and 2018, primarily due to the declining technical change component. However, the scale component remained positive throughout the study period and dampened some of the negative influences of the technical change component on the TFP. Additionally, the results indicated that in 2016, both the scale and efficiency components posted their highest

positive growth in response to the introduction of a performance-based ‘elective initiative’ programme, which briefly raised the TFP in 2016.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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"Who has measured with his palm the waters,

marked off the heavens with a span,

held in his fingers the dust of the earth,

weighed the mountains in scales

and the hills in a balance?" **– Isaiah 40: 12**

Chapter 1 Introduction

1.1 Background

An effective healthcare system is vital to human well-being and a prosperous society. Although investment in healthcare has enhanced population health outcomes, it has also presented a significant challenge to government budgets. A considerable share of healthcare spending is funded through public sources, accounting for nearly 71% of total healthcare expenditure across OECD[1] countries in 2017 (OECD, 2020c). Public health spending in OECD countries currently averages about 6% of gross domestic product (GDP), which over the next two decades is expected to cost an additional two percentage points of GDP (OECD, 2015a).

Without exception, over the past 20 years, New Zealand has also experienced significant public healthcare expenditure growth. Between 1990 and 2019, the government's total real dollar amount spent on healthcare rose by an average of 5% (OECD, 2020b). The New Zealand Treasury expects healthcare expenditure to rise from 6.2% in 2016 to 9.7% by 2060 as a share of GDP (Controller and Auditor-General, 2017). Based on the recent OECD statistics, public healthcare spending in New Zealand averaged around 79.5% of total healthcare expenditure, which is above the OECD average of 73% (OECD, 2020a).

In a 2016 New Zealand Treasury report, the cost pressures from New Zealand superannuation and public healthcare were highlighted as the most pressing fiscal issue for policymakers in New Zealand (The Treasury, 2016a). While the report forecasted the government spending on superannuation to increase by 3.6 percentage points of GDP from 2010 to 2060, public healthcare spending is projected to rise by four percentage points over the same period. High public healthcare spending is likely to pose additional fiscal challenges in the medium and long term, given that the government is New Zealand's primary healthcare provider. Further, New Zealand does not see itself moving away from the tax-supported healthcare system in the foreseeable future (The Treasury, 2014).

In general, the rise in healthcare expenditure can be attributed to a variety of demand and supply factors, including the epidemiological transition[2], demographic shifts and investment in advanced medical technology. For example, chronic health problems such as obesity, cardiovascular disease, hypertension, and dementia are more persistent and widespread, placing pressure on public healthcare services to meet the rising demand for medications and treatments (Deloitte, 2016). In New Zealand, the escalation in chronic long-term conditions such as Type 2

[1] Organisation for Economic Cooperation and Development.
[2] Internationally, deaths from infectious diseases such as measles, smallpox, and tuberculosis have decreased, while deaths from age-related or lifestyle-related conditions such as heart disease and lung cancer have increased. The term 'epidemiological transition' refers to this shift in the types of diseases that cause death (Te Ara, 2016).

diabetes and other diseases linked to unhealthy lifestyles such as obesity have been a significant driver of healthcare demand (The Treasury, 2013b). For example, diabetes is one of the fastest-growing health problems in New Zealand and is associated with multiple cardiovascular diseases (Ministry of Health, 2020b). Moreover, between 2011 and 2013, the number of hospital bed-days occupied by diabetes patients rose from 9% to 14% (Health Quality & Safety Commission, 2015).

The rising life expectancy is also a significant driver of healthcare demand. Data shows that one in four people will be aged over 65 by 2050 in about two-thirds of OECD countries, and the share of those aged over 80 years is expected to double, from 4% in 2010 to 10% in 2050 (OECD, 2015b). In 2005 a New Zealand report found that while people aged 65 and over accounted for 27% of all medical procedures in the New Zealand public hospitals, this proportion increased to 33% in 2014 (Ministry of Health, 2016). Ministry of Health (2020a) suggests that older people will use 50% of all health services by 2025.

The last four decades have also seen significant advances in medical technology, which is considered a key driver of increasing healthcare expenditure (Smith et al., 2009; Sorenson et al., 2013). While it is widely accepted that healthcare technology contributes to higher survival rates, it has also led to rising costs by extending the scope and range of potential treatments (Mays et al., 2013).

Another contributing factor towards higher healthcare expenditures is the rise in labour costs. As the national income rises, labour costs also rise, which is a significant input in healthcare. The productivity gains in New Zealand tend to be relatively low in the labour-intensive service sector, such as healthcare, which drives up the unit costs of delivering overtime healthcare (The Treasury, 2013b). The phenomenon of rising labour costs with no or very little increase in labour productivity is also known as ‘Baumol's cost disease’ (Atanda et al., 2018).

According to an OECD report by Joumard et al. (2010), the New Zealand health system is the least efficient in the OECD, particularly in the acute care sector. The study argued that an increase in the New Zealand healthcare system's general technical efficiency level could add up to 2.7 years to the life expectancy of New Zealanders. The study also highlighted high administration costs and high outpatient expenditure relative to the low number of doctor consultations as a significant source of healthcare inefficiency in New Zealand.

Another OECD study found that New Zealand could save up to 2.5% of GDP per year if it increases its healthcare technical efficiency to the average efficiency level of other highly efficient OECD countries (OECD, 2010). Similarly, Gauld (2012) argued that New Zealand has an excessive number of District Health Boards (DHBs) and Primary Health Organizations

(PHOs) in comparison to its size, resulting in high transaction costs and duplication in planning purchasing, and administrative activities.

There is no denying that New Zealand's investment in the public healthcare system is critical to the improvement of its population's well-being and quality of life. Effective healthcare improves the level of health of its citizens and enhances productivity by promoting human capital development (Bleakley, 2010; Bloom & Canning, 2003). Healthcare plays a vital role in decreasing poverty by reducing mortality and morbidity in the population (McKee & Healy, 2000); however, public healthcare consumes a significant amount of the annual budget. In the 2019/20 financial year, the New Zealand government allocated close to $19.8 billion towards public healthcare, the second-highest area of spending after social security and welfare (The Treasury, 2019). Increasing investment in public healthcare urges policymakers to ensure that the existing healthcare system works efficiently to meet the increasing demand for healthcare while staying under fiscal constraints.

1.2 Principal health reforms in New Zealand

New Zealand has witnessed regular and wide-ranging reform in its healthcare system. The 1938 Social Security Act is the origin of the modern New Zealand healthcare system, aiming to provide free healthcare services for all New Zealanders. However, the Act was not fully implemented due to widespread resistance from medical professionals (Easton, 2002; Mays et al., 2013). Instead, a dual system developed where mental health, maternity, and hospital services were provided to the public free of charge, while General Practitioners (GPs) could charge a fee over and above any subsidy (Ashton, 2005). As a result, primary services were delivered by the private sector. In contrast, hospital services were provided free of charge by public hospitals. The healthcare system's governance was organised into 18 District Health Offices and 29 Hospital Boards, which provided hospital and community services (Quin, 2009).

The next four decades saw a series of minor health care reviews. In 1972, a major study initiated by the Department of Health addressed the need for a comprehensive approach to healthcare services, emphasising health promotion policies and the equal provision of health services (Department of health, 1974). However, the early 1980s saw the New Zealand public healthcare system under intense pressure, with long waiting lists where many regions struggled to meet local communities' healthcare needs (Mays et al., 2013).

In 1988, a task force appointed by the government prepared a report on the state of public hospitals titled "Unshackling the Hospitals". The findings of this report argued that with better management of resources, savings of up to 30% could be made (Fraser et al., 1988). The report recommended a significant restructuring of the public health system. However, the government of the time did not act on the report's recommendations. Nevertheless, the report's findings drew considerable attention to the management of healthcare resources and placed healthcare efficiency in the spotlight (Ashton, 2009).

In the early 1990s, the incoming government appointed a ministerial task force to advise the government on making healthcare services more accessible to the general public (Upton, 1991). Based on the task force's recommendations, a complete reform of the health system began in 1993, leading to four regional health authorities (RHAs). The RHAs were entrusted with the responsibility for purchasing all personal health and disability services for their regions from both public and private providers. The hospital facilities were transferred to 23 Crown Health Enterprises (CHEs) that were now required to adopt a commercial approach to healthcare delivery. For the first time, this reform saw the emergence of the 'purchaser-provider split', which aimed to achieve savings by introducing competition into the healthcare system. At this time, the existing Department of Health has renamed the MoH and given the task of monitoring the performance of the RHAs. It also took up a regulatory role for all the purchasers and providers of healthcare.

However, the 1993 reform failed to achieve the expected results. Waiting times for healthcare services such as elective surgeries continued to climb (Mays et al., 2013). This failure ultimately led to the disestablishment of the RHAs in 1997. Soon after, in 1998, a new single Health Funding Authority (HFA) was formed, which continued to operate under the 'purchaser-provider split' scenario. The 23 CHEs were renamed Hospital and Health Services (HHSs) and were contracted by the HFA to deliver hospital, community and public health services. Legally, HHSs were considered to have an autonomous status and to operate within a commercial framework. However, they were not bound to achieve surplus but were expected to cover expenses and not run deficits (Cumming et al., 2014).

The reforms of the 1990s proved highly contentious due to the high cost of implementation and the general opposition of healthcare professionals towards the commercial nature of the reform(Cumming et al., 2014). Meanwhile, timely access to hospital services continued to be a significant issue. Public access to primary healthcare was often limited due to the continuous increase in co-payments (Ashton, 2005).

At the end of 1999, the newly elected government quickly enacted the New Zealand Public Health and Disability Act 2000, which lead to a significant restructuring of the health sector. The government considered the previous HHSs to be overly competitive, lacking in efficiency, accountability, and community inclusion (Quin, 2009). The reforms reintroduced the local governance system, resulting in the establishment of the 21 DHBs[3] that replaced the existing 23

[3] Currently, there are 20 DHBs, as in 2010, Otago and Southland DHBs merged to form the Southern DHB.

HHSs. The newly established DHBs followed a population-based funding model and were responsible for the planning and provisions of all healthcare services in their regions.

Following the establishment of the DHBs, a National Health Board was created in 2009, which took on the responsibility of improving the operational performance of DHBs and freeing the MoH up to attend to core policy advice and regulatory functions (Cumming et al., 2014). In 2010, amendments to the Public Health and Disability Services Act 2000 required DHBs to work collaboratively, which led to the establishment of four regional alliances.

Today the health system continues to operate within these institutional frameworks, except the National Health Board, which was dissolved in March 2016. The National Health Board's functions, which included the funding and monitoring DHBs[4], were entrusted back to the MoH.

1.3 New Zealand Healthcare System

The Public Health and Disability Act of 2000, introduced by the Labour-Alliance coalition government in 1999, established the New Zealand healthcare system's current institutional framework. There are five main components in the New Zealand public health system: the MoH, DHBs, PHOs, the Accident Compensation Corporation (ACC) and the Pharmaceutical Management Agency (PHARMAC). Under the Act, the MoH has the general responsibility for the healthcare system in New Zealand. It is the principal advisor to the government on healthcare policy issues. The MoH plays a crucial role in advising, funding, and monitoring health sector Crown Entities and DHBs.

The DHBs play a critical role in the New Zealand public healthcare system. They are responsible for organising and funding health services in their geographically established areas (Ministry of Health, 2020c). The DHBs also fund the PHOs, not-for-profit organisations that deliver primary healthcare services through general practices and clinics. The GPs, practise nurses, pharmacists and other healthcare professionals working within the general practice are contracted by the government to provide primary healthcare services. More recently, a third sector, which is comprised of non-profit and non-governmental organisations, has started offering primary and community-based health and disability support services. For example, many union-based healthcare providers deliver healthcare services for low-income union members and their families.

Similarly, many Māori and Pacific healthcare clinics provide essential primary and disability support services to local communities and are fully or partially funded. There is also a relatively

[4] The current Labour government intends to abolish the 20 DHBs and replace them with a single national health authority known as Health New Zealand.

small private healthcare sector, which provides some specialties in elective surgeries and long-term care.

PHARMAC works on behalf of DHBs in procuring pharmaceutical products and medical equipment (PHARMAC, 2020), while ACC administers no-fault universal injury insurance cover, including accident and rehabilitation funding costs and earnings compensation (ACC, 2020).

The majority of New Zealand healthcare services are currently publicly funded, with health coverage provided through a network of government, non-government and private organisations. The primary source of healthcare funding is taxation. According to 2017 data, public spending accounted for 78.68 per cent of total healthcare spending (The Commonwealth fund, 2020). Public hospitals owned and operated by DHBs provide most secondary and tertiary healthcare services such as general medicine and surgery, specialist treatment services, diagnostic and clinical support, and 24-hour emergency services free of cost. While public hospitals offer healthcare services free of charge, co-payments apply to some community services, pharmaceuticals, primary care and diagnostic tests.

1.3.1 District Health Boards

The public healthcare system in New Zealand has undergone regular and comprehensive changes since 1980, motivated mainly by a desire to increase access to hospital services and enhance financial performance. The New Zealand healthcare system's most comprehensive and significant restructuring occurred in 2000, resulting in 20 DHBs. Under this system, DHBs own public hospitals as their providers and fund healthcare services in their regions. The establishment of DHBs ended the split between purchase and provision of hospital services and aimed at improving the efficiency of the healthcare system through vertical integration.

The DHBs are heterogeneous in terms of the type and speciality of healthcare service they provide. For example, Auckland DHB operates New Zealand’s largest purpose-built children’s hospital and clinical research facility. In contrast, West Coast DHB operates a much smaller hospital with no tertiary level hospital care facility.

Table 1.1 shows the name, population catchment and form of hospital service provided by each DHB. A list of major hospitals and clinics operated by DHBs is provided in Appendix A.

Table 1.1. New Zealand District Health Boards

DHB	Population catchment	Main hospital service
Auckland	460,000	Tertiary
Bay of Plenty	220,000	Secondary
Canterbury	501,425	Tertiary
Capital and	300,000	Tertiary
Counties	512,130	Tertiary
Hawke's Bay	165,000	Secondary
Hutt Valley	140,000	Secondary
Lakes	108,000	Secondary
Mid Central	160,000	Secondary
Nelson	134,500	Secondary
Northland	175,000	Secondary
South	55,000	Secondary
Southern	315,000	Tertiary
Tairawhiti	46,000	Secondary
Taranaki	110,000	Secondary
Waikato	360,000	Tertiary
Wairarapa	40,000	Secondary
Waitemata	560,000	Secondary
West Coast	31,000	Secondary
Whanganui	60,120	Secondary

The reforms of 2000 reintroduced the local governance system, with DHBs gaining considerable autonomy in managing funds for the provision of hospital services. There are currently 20 DHBs in New Zealand, with each being governed by seven locally elected members and up to four MoH appointees plus a Chief Executive (Ministry of Health, 2020c). New Zealand’s health system is the only system in the developed world at present where members are elected locally to the health boards (Stewart et al., 2016). The elected boards are responsible for overseeing their hospitals' financing and organising other public healthcare programmes in their areas. While providing hospital services is the primary function of DHBs, they also fund other critical healthcare services such as primary care, disability support services, and long-term residential care.

A population-based funding formula (PBFF[5]) is used to determine the DHBs’ annual funding allocation. The PBFF aims to allocate resources between DHBs according to their populations' relative needs (Ministry of Health, 2016a). Figure 1.1 displays the nominal annual DHB funding allocation (The Treasury, 2019a) from 2011 to 2018 as a bar graph. This figure shows that there has been a steady increase in DHB funding in the last two decades. While the funding allocations have increased at an annual rate of 5% on average, the growth has slowed more recently.

[5] For an in-depth explanation of the PBFF model, refer to the Ministry of Health (2015d).

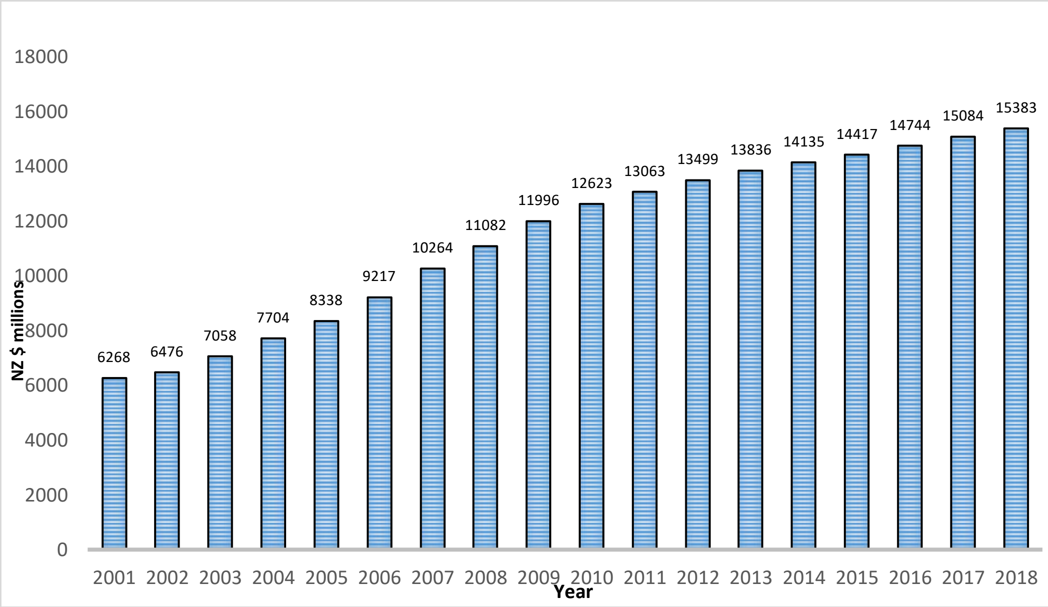

Figure 1.1. Population-based funding of DHBs

The PBFF core model calculates the relative healthcare needs of the population based on the past use of healthcare services. The PBFF model considers the historical average expenditure based on various demographic characteristics to derive ‘cost weights’ calculated using past resource use by different public groups. The cost weight is assumed to represent the average cost of delivering healthcare services to individuals based on their demographical characteristics. In other words, cost weight is the mean cost per person for a service given the demographical feature. Therefore, it is an estimation of future health needs. The mean cost per person includes both users and non-users; it includes people for whom no costs or zero costs were recorded (Ministry of Health, 2015c).

Several concerns have been raised about the data quality used to identify population characteristics in the PBFF model. For example, the data accuracy of an individual's ethnicity is often derived from administrative datasets such as the National Minimum Data Set (NMDS), considered to be unreliable and error-prone (Penno & Gauld, 2013). Similarly, the data quality on overseas visitors also appears to be of low quality, with many DHBs not identifying and recording patients consistently (Ministry of Health, 2015b). The PBFF model is the largest determinant of healthcare funding and is designed to finance DHBs according to their population's relative needs, providing each DHB with the same funding opportunity to respond to health needs. However, significant differences in the funding per capita across 20 DHBs and consistent budget deficits have attracted criticism of the PBFF model (Penno & Gauld, 2013).

1.4 The rationale for the study

Public health costs have continued to increase since the formation of the DHBs, with many DHBs reporting regular budget deficits despite a steady increase in funding over time (The

Treasury, 2017a). In the light of increasing budget deficits, recent public health audit reports have raised serious concerns about the DHBs' management of public funds and their ability to provide hospital services into the future (Controller and Auditor-General, 2014, 2016b, 2018).

The consistent budget deficits posted by DHBs may indicate that New Zealand may be operating with some level of inefficiency. Numerous empirical studies published in the healthcare literature show that rising healthcare costs directly result from inefficient operations (Bentley et al., 2008; Rosko, 2001; Welch, 1987; Zuckerman et al., 1994). However, this assertion may not be relevant to the New Zealand public healthcare system. High budget deficits among New Zealand DHBs maybe merely an indicator of shortcomings in the PBFF model, which does not adequately fund DHBs. Nevertheless, in the interest of policymakers and regulators, budget deficits do raise the issue of whether or not DHBs are using funds efficiently.

The existence of inefficiency in healthcare, ceteris paribus, is often viewed as a by-product of sub-optimal management practices. Although inadequate resource management can contribute to inefficiency, the adjustment cost theory put forward by Penrose (1995), Eisner et al. (1963), Hamermesh and Pfann (1996) and Treadway (1971) provides a unique motivation for the idea of efficiency estimation.

The adjustment cost hypothesis suggests that adjustment costs act as barriers that prevent organisations from adjusting their inputs promptly to achieve full efficiency levels in the short run. According to Argyres et al. (2019), "adjustment costs include the costs associated with acquiring needed (as well as disposing of unneeded) capabilities, assets, and knowledge to support repositioning". In the presence of significant adjustment costs, organisations may sluggishly adopt optimal production decisions, leading to a dynamic system where inefficiencies are slow to disappear over time. It is essential to distinguish between adjustment costs and the concept of 'cost of transacting' that originates from Transaction Cost Economics put forward by Williamson (1975). While transaction costs can be considered a type of adjustment costs, transaction costs refer explicitly to the costs incurred when buying or selling a good or service.

According to the adjustment cost hypothesis, DHBs may not be able to quickly adjust inputs within their operating environment to optimal levels due to high adjustment costs. In other words, due to the existence of adjustment costs, the optimum strategy for DHBs may be to remain partly inefficient in the short run and reach the sector's targeted long-run equilibrium level of efficiency. As a result, DHBs may not only be inefficient at a point in time, but inefficiency may persist from one period to the next (persistence in inefficiency). Therefore, it is essential to recognise the intertemporal nature of healthcare providers' decision processes and distinguish between short-run and long-run efficiency.

To date, no research has differentiated between short-run and long-run efficiency measures resulting from adjustment costs in healthcare efficiency literature. Therefore, the purpose of the first two studies in this thesis is to fill this gap. More specifically, the studies achieve this by relaxing the assumption of inefficiency independence across time. By allowing inefficiency to persist, the short-run efficiency level of each DHB could be compared to the long-run efficiency level, which gives a more reliable efficiency measure given the constraints resulting from the lack of adequate infrastructure.

In addition to measuring efficiency, the measurement of healthcare productivity growth and its components are essential, a measure currently lacking in New Zealand healthcare literature. The Treasury (2005) was one of the earliest reports to highlight the need to develop productivity measures to estimate the value of the money generated in the New Zealand public healthcare sector. More recently, a report by Knopf (2017) raised concerns about the deterioration of the public health sector. The report argued that assessing public health productivity could potentially provide useful policy recommendations. Another study by Fraser and Nolan (2017) highlighted the importance of measuring healthcare productivity to improve health outcomes.

In this thesis, this gap is addressed by estimating the total factor productivity (TFP) change under both primal (production) and dual (cost) specifications while controlling for unobserved heterogeneity.

To summarise, this thesis attempts to answer the following three research questions:

1. Given the data on inputs and outputs, how well did New Zealand’s DHBs perform in the short-run relative to the sector's equilibrium level of long-run technical efficiency? What is the degree of persistence in technical inefficiency among New Zealand DHBs?
2. Given the data on input prices and outputs, how well did New Zealand DHBs perform in the short-run relative to their equilibrium level of cost efficiency while controlling for DHB-level heterogeneity? Is there bias in the cost efficiency scores when heterogeneity is not accounted for in the cost function?
3. Did the New Zealand DHBs’ TFP improve between 2011 and 2018 when accounting for DHB-level unobserved heterogeneity? What are the relative technical changes, efficiency changes, and the scale component’s contribution to the TFP change? Are the results consistent under both primal and dual specifications?

1.5 Organisation of the thesis

This thesis consists of seven chapters:

Following the introductory chapter, Chapter 2 describes some key concepts in efficiency and productivity literature. This chapter sets the scene for the literature review and empirical modelling in the following chapters.

Chapter 3 discusses the two principal methodologies used in healthcare efficiency and productivity studies. The literature review also offers a more in-depth insight into the treatment of inefficiency persistence in the broader efficiency literature. This section also briefly touches on the variety of inputs, outputs and price variables employed to measure efficiency and productivity in healthcare.

Chapter 4 is the first empirical chapter that estimates both the short-run technical efficiency of New Zealand DHBs and the long-run level of efficiency of the sector, using a Bayesian dynamic stochastic frontier model. This chapter focuses on identifying the level of persistence in the technical inefficiency among New Zealand DHBs.

Chapter 5 empirically estimates the cost efficiency of New Zealand DHBs using a dynamic stochastic frontier model while controlling for unobserved heterogeneity. As well as estimating the persistence parameter, the long-run efficiency level is also computed for each DHB, against which their short-run performance is compared. Considerable attention is also paid towards the bias in cost efficiency scores and parameters when the specification ignores heterogeneity.

Chapter 6, the final empirical chapter, employs stochastic frontier analysis to estimate the TFP change and its components between 2011 and 2018 while controlling for unobserved heterogeneity. More specifically, this chapter focuses on the reliability of the parameters by verifying their consistency under both primal and dual approaches.

Finally, Chapter 7, which is the concluding chapter, summarizes the main findings of this thesis, provides some policy implications, identifies shortcomings and offers suggestions for future studies.

Chapter 2 Efficiency and Productivity Concepts

The purpose of this chapter is to provide a brief explanation of various concepts and ideas that are specific to efficiency and productivity. These terms and ideas are used extensively in the next chapter and in subsequent empirical chapters.

The term ‘productivity’ is often confused with the term ‘efficiency’. They are not synonymous in economics but are two distinct but related concepts. According to the classical definition, productivity is the ratio between outputs and inputs (Daraio & Simar, 2007, p. 13). Efficiency, however, includes comparing the observed inputs (or resources) and outputs (or products) with what is optimal. One of the first definitions of efficiency was put forth by Koopmans (1951), who first defined efficiency as a point where an increase in output implies a decrease in at least one additional output or an increase in at least one input. In the same way, efficiency can also be seen as a point where a reduction in any input requires an increase in at least one input or a reduction in at least one output. This form of efficiency is referred to in the literature as 'technical efficiency.'

The first measurement of technical efficiency was undertaken by Debreu (1951), who measured technical efficiency by concentrating on the idea of a maximum equiproportionate reduction of all inputs that still allowed the production of given amounts of outputs. Following Debreu’s work, Farrell (1957) introduced the concept of relative efficiency to Koopmans’ definition of technical efficiency. Farrell’s view of relative technical efficiency provided an opportunity to compare efficient production units with inefficient units based on best-observed practice from the reference units.

Farrell (1957) further extended the work by Koopmans and Debreu by introducing ‘allocative efficiency’. Allocative efficiency stems from the idea of using prevailing input prices to select the mix of inputs that produce a given quantity of output at minimum cost. This led Farrell to redefine productive (cost) efficiency as the product of technical and allocative efficiency (Daraio & Simar, 2007, p. 15)

Since this thesis undertakes a study of the efficiency and productivity analysis of New Zealand DHBs, the term ‘healthcare providers’ is used from hereon instead of ‘firms’ or ‘decision-making unit’.

In healthcare literature, technical efficiency measures a healthcare provider's ability to use inputs in the most technologically efficient way. In other words, technical efficiency relates to the combination of resources (capital, labour, and materials) that minimises the resources used to produce health outcomes or maximise health gain for a given level of inputs (Hollingsworth & Peacock, 2008, pp. 25-26). On the other hand, allocative efficiency measures healthcare providers' ability to use prevailing input prices to select the mix of inputs that produce a given quantity of output at minimum cost. Given this, if a healthcare provider is allocatively efficient, then its marginal cost per unit of its patients' health status improvement must be equal across all inputs (Hollingsworth & Peacock, 2008, p. 25). Moreover, if a healthcare provider employs its resources, both allocatively and technically efficiently, then it can be said that it is cost efficient (Coelli et al., 2005, pp. 53-54).

2.1 Input and Output-oriented technical efficiency

Efficiency can be measured based either on an input-oriented or output-oriented framework. The radial output-oriented efficiency measure can be demonstrated by considering the case where two outputs q_1 and q_2 are produced using a single input, x. In Figure 2.1, the curve ZZ' represents the unit production possibility curve which shows all possible combinations of outputs that can be produced with a given x. Point A corresponds to an inefficient healthcare provider that is operating at a point that lies inside the maximum possible output level, represented by the output possibilities frontier, ZZ'.

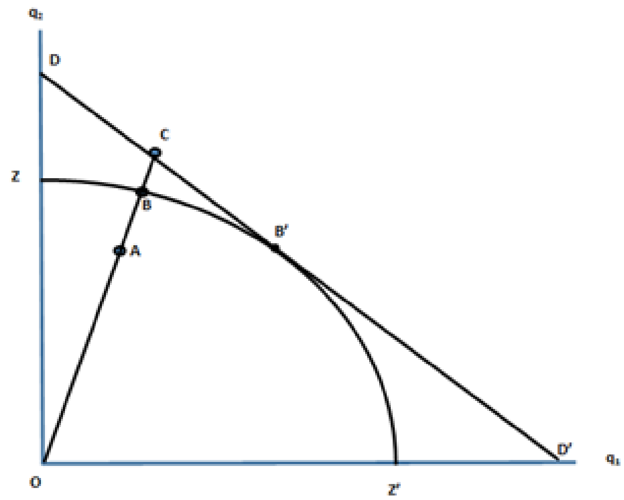

Figure 2.1. Output-oriented measure of technical inefficiency

The distance AB is the amount by which outputs could be radially increased without an increase in the input. In this case, the measure of technical efficiency can be calculated by dividing OA by OB. On the other hand, if it is assumed that the healthcare provider aims to maximise revenue, then given the isorevenue line, DD' as shown in Figure 2.1, the measure of allocative efficiency can be calculated by taking the ratio of OB to OC.

Farrell (1957) illustrated the radial measure of efficiency under an input-oriented approach, using a simple example where a healthcare provider uses two inputs, x_1 and $x_2$to generate one output y. Assuming that the unit isoquant of a fully efficient healthcare provider is known, as illustrated by SS' in Figure 2.2.

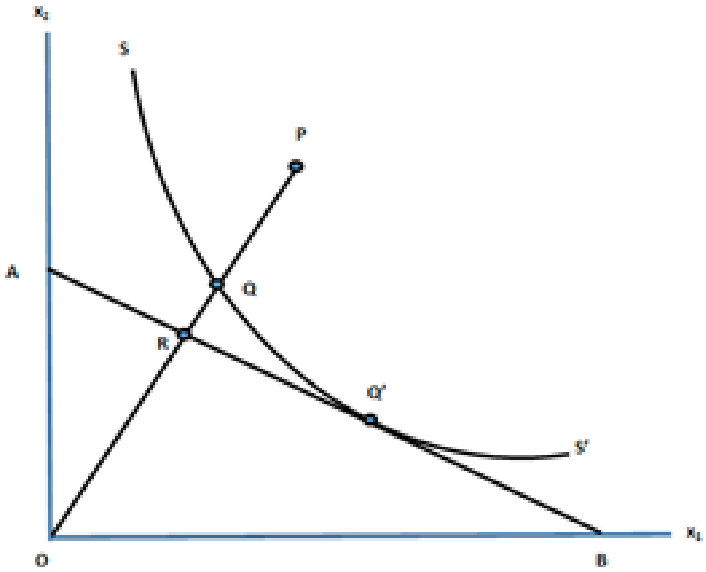

Figure 2.2. Input-oriented measure of technical inefficiency

Farrell (1957) argued that a healthcare provider operating at point P is technically inefficient as this provider could produce the same amount of output by using inputs at point Q. Therefore, the technical inefficiency of this healthcare provider can be represented by the distance QP. In other words, the radial distance QP is the amount by which this healthcare provider can reduce the use of its inputs proportionally, without a reduction in the output. The point Q is technically efficient as it lies on the efficient isoquant, which defines the minimum combinations of inputs for a given level of output. The radial measure of technical efficiency expressed in a percentage can be calculated by taking the ratio of OQ to OP.

2.2 Cost efficiency

The concept of cost-efficiency relates to cost-minimisation theory, which involves choosing an input combination from the bundle of all technically efficient input combinations that minimise total production costs (Coelli et al., 2005, p. 53). This idea is demonstrated in Figure 2.3, where the minimum cost curve/frontier, $c(w^0, y)$ describes the relationship between minimum production cost and output for a given vector of prices w^0. Therefore, if a healthcare provider operates above the minimum cost frontier, it is not operating at technical and allocative efficient levels, and therefore is cost inefficient.

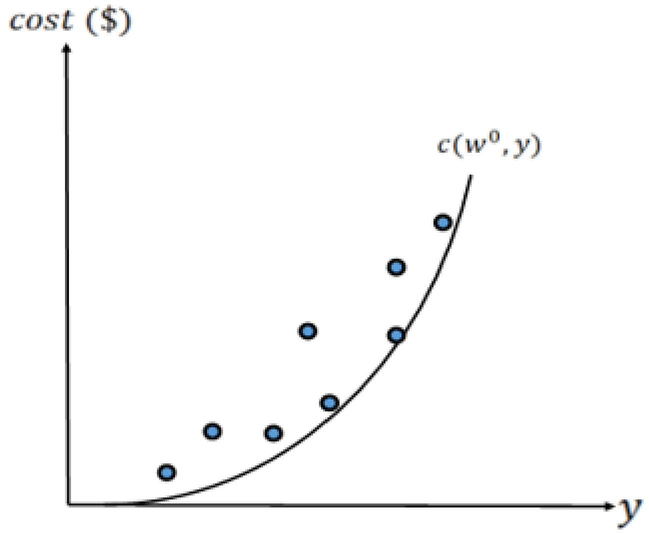

Figure 2.3. Minimum cost curve

On the other hand, a healthcare provider that is on the minimum cost frontier is fully cost efficient. For other healthcare providers that operate above the frontier, the measure of cost efficiency can be computed by the ratio of the minimum cost to the actual cost. For example, if a healthcare provider has a ratio of 0.75, this means it can reduce its costs by approximately 33% without affecting its ability to provide the same level of services.

Figure 2.4 depicts the concept of cost efficiency as a result of combining input-oriented technical and allocative efficiency, which is adapted from Coelli et al. (2005, p. 53). This adaptation assumes that healthcare providers only use two inputs, x_1 and x_2 with market prices of w_1 and w_2 respectively to provide service y^0. The curve IQ is an isoquant with a slope equal to the marginal rate of technical substitution (MRTS), which measures the rate at which one input can be substituted for another while maintaining the same level of services. The curve IC represents all the input combinations that cost, $c = w_1x_1 + w_2x_2$.

The slope of IC represents the market rate at which one input can be purchased in place of the other while holding total cost constant. This ratio of input prices is referred to as the economic rate of substitution. Given the respective isoquant and isocost curves in Figure 2.4, the theory of production (Wetzstein, 2013) states that the total cost is minimised at the point B' where the slope of the isocost curve is equal to the slope of isoquant. In other words, at the point B', the marginal cost of providing one additional service is the same, irrespective of which additional input is used.

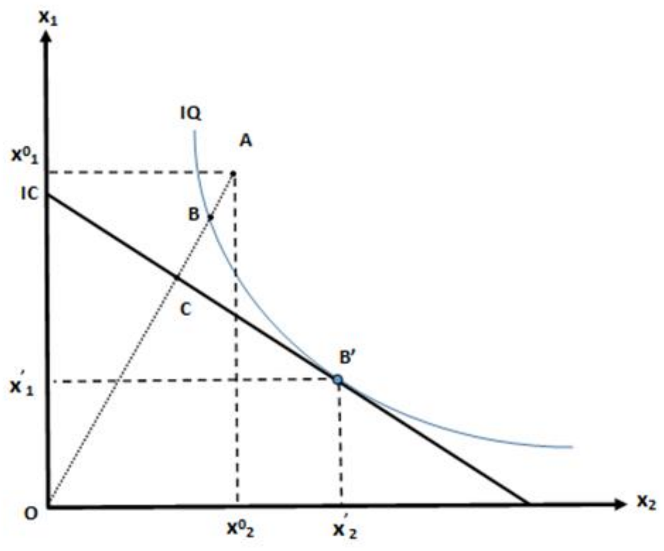

Figure 2.4. Cost efficiency

In Figure 2.4, if a DHB is providing y^0 units of service and is currently operating at point A, then, according to the theory, it can become fully technically efficient if it manages to reduce its input usage to point B on isoquant IQ. Therefore, the measure of the input oriented technical efficiency of the healthcare provider operating at the point A is the ratio of OB over OA, which shows how well the physical resources are utilised. On the other hand, if the healthcare provider can further reduce its input consumption to C, that is, where the cost of inputs is minimised, then the measure of allocative efficiency can be obtained by the ratio of OC over OB. That is the product of technical and allocative efficiency: $\frac{OB}{OA} \times \frac{OC}{OB} = \frac{OC}{OA}$.

It should also be noted that when an estimation of technical and allocative efficiency is obtained using input price and output quantities information, it is commonly referred to as the 'dual approach' (Fuss et al., 1978). On the other hand, if the estimation is carried out using data on input and output quantities, the approach is said to be ‘primal’ (Marschak & Andrews, 1944).

2.3 Total factor productivity

Productivity can be seen as the absolute ratio between production outputs and inputs. It can be measured either in terms of partial productivity or by considering overall productivity. Partial productivity measures often involve the study of the relationship between a firm’s output and a single input. The most common partial productivity measure is labour productivity (Murray, 2016). In general, partial productivity measures could be calculated for any input.

One of the frequently quoted disadvantages of the partial productivity measure is that it does not consider trade-offs between various inputs (Windle & Dresner, 1992). For example, a tertiary healthcare provider with high capital to labour input mix, *ceteris paribus*, may have high labour productivity but not necessarily high overall productivity. TFP, on the other hand, addresses some of the issues associated with partial productivity measures by computing productivity as the ratio of aggregate output to aggregate inputs, also known as multi-factor productivity (Lipsey & Carlaw, 2004).

The TFP measurement theory evolved independently from the seminal works of Tinbergen (1942) and Solow (1957), laid the groundwork for macroeconomic growth accounting. These studies examined the change in TFP in the context of the production function and connected it to economic growth analysis. As a result of these contributions, technological change is quantified as residual, the portion of output growth that cannot be explained by changes in labour or capital inputs. This is frequently referred to in macroeconomic literature as the ‘Solow residual’.

In microeconomic productivity theory, this term has been borrowed to analyse changes in the TFP and its components. In a TFP computation, the overall input and output indices are created by weighting the individual inputs and outputs. Since the indices are constructed compared to a given provider in the industry, it ensures that the resulting TFP metric comparisons are invariant with the provider or the time chosen as the reference (Windle & Dresner, 1992). The resulting TFP measure can be used over time to compare different healthcare providers with TFP growth rates for a given provider. TFP change is often decomposed into sources such as technical change, returns to scale and efficiency changes. These TFP change measures are valuable, as they provide insights into the impact of changes in management and organisational practices over time.

2.4 Summary

This chapter has laid the foundations for the empirical analysis in the upcoming chapters by briefly explaining various concepts and definitions extensively used in efficiency and productivity literature. The next chapter undertakes an extensive literature review on methodology, inputs, outputs and prices used in efficiency and productivity literature.

Chapter 3 Literature Review

This chapter provides a three-part literature review of the efficiency and productivity studies in healthcare. It begins by reviewing the two primary empirical methods used in healthcare efficiency studies, emphasising the treatment of inefficiency persistence in the literature. Second, previous contributions to healthcare productivity research are discussed with a focus on methodology and findings. In the third section, the use of various measures of outputs, inputs and prices in health literature is explored to determine the extent of consensus.

3.1 Empirical methodology in healthcare efficiency

The last 30 years have witnessed considerable momentum in the number of studies published on the topic of healthcare efficiency. The theory of production and cost functions, following the seminal work of Farrell (1957), have heavily influenced the current efficiency estimation methods. Many healthcare literature's empirical methods revolve around estimating either technical or allocative efficiency or both (Worthington, 2004).

Researchers have employed frontier-based efficiency techniques extensively to measure the productivity and efficiency of healthcare units. Frontier techniques are divided into parametric and nonparametric methods. Both methods involve estimating a frontier against which the performance of healthcare providers are compared. A healthcare provider on the frontier is believed to be able to provide a given level of service using the least amount of inputs/minimum cost or the maximum level of services for a given level of inputs/cost (Hollingsworth & Peacock, 2008, p. 2). The degree of deviation from the efficient frontier provides an estimate of the level of inefficiency.

DEA is a nonparametric methodology based on linear programming tools developed by Charnes et al. (1978). It is one of the commonly used frontier-based methodologies in health efficiency studies. The DEA frontier includes a series of linear segments connecting one efficient decision-making unit (DMU[6]) to another. The frontier's construction is based on ‘best-observed practice’, where inefficient DMUs are ‘enveloped’ by the efficiency frontier. A notable feature of the DEA is that all deviations from the frontier are attributed to inefficiency.

One of the earliest applications of efficiency measurement techniques was undertaken by Nunamaker (1983), who used the DEA to estimate the technical efficiency of 16 hospitals in the state of Wisconsin, USA. Soon after, Sherman (1984) and Borden (1988) also employed the DEA methodology to compute the technical efficiency scores of hospitals in the USA.

[6] DMU is a term used for not-for-profit entities by Charnes et al. (1978), in the seminal paper that estimated their efficiency.

A major limitation of using the DEA is that it makes an unverifiable and strong assumption of no measurement error or random variation in output (Newhouse, 1994). In particular, interpretation of DEA-based results may be problematic, as frontiers may be affected by stochastic variance, measurement error, or unobserved heterogeneity of data (Hollingsworth & Peacock, 2008, p. 37).

In the healthcare sector, there are occasions where the healthcare unit's capacity to deliver services is affected by factors outside the healthcare provider's control. For example, a sudden onset of a pandemic in a region, medical equipment break down[7], or errors in measuring the level of resources used. Since the DEA fails to account for random shocks, it can introduce bias to the efficiency scores (Jacobs et al., 2006, p. 153). Nevertheless, the DEA and its variants are still the most widely used tool in healthcare studies, possibly due to its ease of use and versatility (Jacobs et al., 2006, p. 13).

In the last 20 years, various studies have been put forward that can be used in conjunction with the DEA to deal with efficiency scores' sensitivity. One of the most popular among these techniques is the application of the bootstrap methodology introduced by Simar and Wilson (1998) and Simar and Wilson (2007). To some extent, the bootstrap methodology has addressed the sensitivity of efficiency scores to the sampling variation and has provided the statistical properties of the nonparametric estimators. Some of the recent studies in healthcare literature using bootstrap methodology with the DEA include work by Alonso et al. (2015), Chowdhury and Zelenyuk (2016), Jiang and Andrews (2020), Andrews (2020a) and Andrews (2020b).

Stochastic Frontier Analysis (SFA) is, on the other hand, a parametric approach developed independently by Meeusen and Van den Broeck (1977) and Aigner et al. (1977). SFA differs from DEA in its assumption that discrepancies between actual and optimal organisational performance are due to inefficiencies and random shocks.

In order to incorporate the concept of stochastic shocks and inefficiency in SFA, the error term is defined as the sum of two components- a one-sided, non-negative term that represents inefficiency and the second component, which represents random or stochastic fluctuations. In addition to the distributional assumption, the specification of the production function is also required in SFA. On the other hand, DEA requires no specification of the production functions or distributional assumptions where the efficiency frontier is constructed purely based on observed data (Jacobs et al., 2006, p. 90; Nedelea & Fannin, 2013).

Despite the fact that the challenges associated with SFA's assumptions and specifications, its ability to separate random fluctuations beyond a hospital's control have made it very popular.

[7] The failure of equipment in this instance is not assumed to be the result of unmaintained or out-of-date capital stock.

Furthermore, SFA offers researchers the opportunity to estimate the relationships between outputs, inputs and costs. Further, SFA allows researchers to separate healthcare provider-specific effects (heterogeneity) and time-specific effects when longitudinal data is available. Hence, the application of SFA to longitudinal data also allows for a more robust estimate of parameters.

While the majority of studies in healthcare efficiency literature use classical inferences to estimate the model parameters, Koop et al. (1997) employed Bayesian inference to estimate the model parameters and cost efficiency by using longitudinal data on 382 non-teaching US hospitals. More recently, Chen et al. (2016) used Bayesian SFA to estimate hospital cost efficiency in 31 provinces in China.

Although SFA's implementation is more demanding in terms of modelling and interpretive skills (Jacobs et al., 2006, p. 13), it has been gaining more prominence in healthcare productivity and efficiency studies (Worthington, 2004). Some recent healthcare studies that employ SFA include work by Al-Amin et al. (2016), Chen et al. (2016), Colombi et al. (2017) and Jiang and Andrews (2020).

Since the introduction of SFA in efficiency literature, several approaches have been put forward that employ it in longitudinal data in various other sectors. Early research into longitudinal SFA focussed on estimating time-invariant (persistent) or long-run efficiency (Battese & Coelli, 1988; Kumbhakar, 1987; Pitt & Lee, 1981; Schmidt & Sickles, 1984), time-varying (transient) or short-run efficiency (Battese & Coelli, 1992, 1995; Cornwell et al., 1990; Kumbhakar, 1990). Other studies, such as Kumbhakar and Heshmati (1995) and Kumbhakar and Hjalmarsson (1995), estimated persistent and transient efficiency. On the other hand, studies by Greene (2005a), Greene (2005b), Kumbhakar and Wang (2005) and Wang and Ho (2010) estimated transient efficiency while accounting for heterogeneity at the cost of ignoring persistent inefficiency.

Currently, two main approaches exist in the efficiency literature that incorporates the idea of persistence in inefficiency. The difference between these approaches is due to the specific treatment of the adjustment cost hypothesis in efficiency analysis. Studies such as those by Kumbhakar and Heshmati (1995), Kumbhakar and Hjalmarsson (1995), Colombi et al. (2014), Kumbhakar et al. (2014), Tsionas and Kumbhakar (2014), Filippini and Hunt (2015) and Filippini and Greene (2016) employ SFA without incorporating the adjustment cost theory. Instead, they divide total inefficiency into short-run (transient) and long-run inefficiency (persistent inefficiency). In healthcare literature, studies incorporating the persistent nature of inefficiency are scarce. So far, only one study by Colombi et al. (2017) has used SFA to evaluate the transient and persistent efficiency of 133 Italian hospitals.

An important point to note about these studies is that the authors differentiate between transient (short-run) and persistent (long-run) inefficiency by specifying a time-varying and one-sided time-invariant skewed error term, respectively. In such specifications, short and long-run inefficiency are considered independent, and the product of these two types of inefficiency gives the overall inefficiency estimates. Also, the short-run inefficiency estimates in these models are assumed to be independent between different time periods.

The motivation behind the existence of long-run inefficiency in these models fundamentally rests on the idea that there are long-run factors that give time-invariant characteristics to persistent inefficiency. Examples of such factors include obsolete production equipment and technology, substandard buildings, substandard transport systems, the continuous lack of workforce development leading to underexploited technologies, and other management rigidities associated with administrative practices.

In other words, long-run inefficiency stems from structural issues that constrain efficient methods due to operational rigidities over a longer time horizon. These operational rigidities are theorised to be related to physical capacity, infrastructural problems, recurring managerial incompetence, and modern technology availability. Though the motivation behind persistence in inefficiency makes economic sense, none of these studies incorporates dependencies in inefficiency through time.

Another strand of efficiency literature provides a more comprehensive and economically intuitive way of combining the idea of short and long-run inefficiency in SFA through a dynamic process. This approach explicitly highlights the existence of the adjustment costs of quasi-fixed inputs to be the primary reason for persistence in inefficiency over time. As a result, the organisation would prefer to remain partly inefficient in the short run due to high adjustment costs and would instead seek to achieve their targeted long-run efficiency level (i.e., steady-state efficiency level) in the long run. Furthermore, these models are dynamic, as they allow the short-run inefficiency between periods to be dependent.

Ahn and Sickles (2000) pioneered the dynamic stochastic frontier approach by specifying an autoregressive process to accommodate persistence in inefficiency due to adjustment costs. The dynamic models they specified use generalised non-linear methods of moments (GMM) to estimate the parameters. However, recent studies have found that dynamic longitudinal data models estimates from GMM methods may be susceptible to weak instruments, especially near the unit root boundary, leading to a variance ratio of errors that is not unity (Bun & Windmeijer, 2010).

Desli et al. (2003) put forth a version of the dynamic stochastic frontier model estimated using maximum likelihood methods (ML), assuming that the healthcare provider-specific intercept is autoregressive, with a set of covariates that influence a healthcare provider's production frontier over time. However, as Khalaf and Saunders (2016) highlighted, this specification is prone to incidental parameter bias due to the correlation between unobserved heterogeneity and efficiency specific covariates in the latent equation.

Using the Bayesian approach, Tsionas (2006) presented a dynamic model where an autoregressive process was applied to a transformed efficiency that can take any value on the real line, thus, enabling the imposition of a standard autoregressive process. Similarly, Emvalomatis (2012) used the inverse of the logistic function of technical efficiency as a transformation in the autoregressive process using the Bayesian approach. Building on Tsionas (2006), many other Bayesian dynamic model versions have been presented in studies such as those by Emvalomatis et al. (2011), Galán et al. (2015), Lambarraa et al. (2015) and Skevas et al. (2018).

These dynamic models are motivated by the adjustment cost hypothesis, where the short-run efficiency is derived based on the organisation's performance relative to the production possibility frontier. In contrast, the long-run efficiency corresponds to the long-run equilibrium value of efficiency specified by the autoregressive process. Hence, the dynamic model is more flexible, as it accommodates the relationship between transient efficiency between different periods. However, no such relationship is found in the models where transient efficiency is assumed to be a one-sided time-varying error component. Further, in the non-dynamic model, short-run efficiency is obtained from a system that is always assumed to be in equilibrium. The assumption of constant equilibrium is unrealistic in the presence of adjustment costs and other rigidities arising from the sector's regulatory framework.

To the best of current knowledge, no studies have incorporated the idea of dynamic models in assessing healthcare providers' efficiency or productivity performances. Jacobs et al. (2006, pp. 174-176) argue that in the short-run, healthcare providers might only be able to perform relative to the various constraints imposed by infrastructure and available inputs (for example, quality of clinical equipment and technology). Therefore, short-run efficiency levels should only be assessed based on the configuration of the inputs that a healthcare provider has available. On the other hand, healthcare providers may reconfigure their resources to bring about efficiency improvements in the long run. This implies that the healthcare production process should be modelled through a dynamic link between its present and past performances Jacobs et al. (2006, pp. 177-178).

Specifying a dynamic link makes it possible for the current output of a healthcare provider to depend on the ease in which the inputs can be reconfigured or through which technology may be adopted in the presence of adjustment costs. Given the prevalence of public finance as a fundamental source of healthcare services in the majority of developed countries, and the existence of a highly regulated operating environment (Jacobs et al., 2006, p. 3), it is surprising how little attention is paid to this dynamic link in healthcare studies.

A possible reason for this might be the complexity associated with the estimation of dynamic longitudinal models and the small data sizes that are prevalent in healthcare efficiency studies (Jacobs et al., 2006, pp. 37-38). Nevertheless, Hollingsworth and Street (2006) and Colombi et al. (2017) argue that identifying the nature and the form of inefficiency in healthcare systems is critical for formulating appropriate policy measures. For example, if a high degree of persistence in inefficiency exists, especially among public healthcare providers, then unless there is a reconfiguration of current organisational structure or/and a significant change of government policy towards the overall system, efforts to improve efficiency will not yield expected outcomes.

The application of efficiency measurement techniques to the New Zealand healthcare sector is very recent. There are currently three studies in the field of New Zealand healthcare efficiency and productivity. Jiang and Andrews (2020) performed the first efficiency study using longitudinal data on 20 New Zealand DHBs from 2011 to 2017. Their study used both SFA and DEA to estimate technical and cost efficiency. However, DHB level heterogeneity or persistence in inefficiency was not considered in the analysis. The other two studies, Andrews (2020a) and Andrews (2020b), used the same data but applied DEA with bootstrapping to estimate technical efficiency.

A selective list of healthcare efficiency studies from the early 1990s to 2020 that have used frontier-based approaches is presented in Appendix B. While not a complete list, it provides a fair representation of the methodology used in the last three decades. A comprehensive list of frontier-based healthcare efficiency studies can be found at Hollingsworth and Peacock (2008, pp. 102-117) and Worthington (2004).

It is also worth noting that, based on the studies listed in Appendix B, 36 of the 40 studies that applied DEA, with or without bootstrapping, 17 of them exclusively used longitudinal data with no control for unobserved or unit-specific heterogeneity. This is likely to result in a substantial bias in the measure of efficiency. Additionally, of the 13 studies that used SFA on longitudinal data, only Koop et al. (1997), Barros et al. (2013), Chen et al. (2016) and Colombi et al. (2017) controlled for unobserved heterogeneity. The three New Zealand studies by Jiang and Andrews (2020), Andrews (2020a) and Andrews (2020b), while using longitudinal data, failed to account for unobserved heterogeneity.

3.2 Previous contribution to TFP studies in healthcare

When longitudinal data are available, it is insightful to investigate the changes in productivity over time and decompose them into its components to examine the relative contributions. In the healthcare sector, such a study will help analyse the effect of targeted policies on the provision of health services and ultimately determine the impact of various initiatives on the population's health outcomes. For example, suppose the intention is to examine the productivity of a group of healthcare providers. In that case, one could determine whether productivity change for a specific healthcare provider is driven by improved relative efficiency, scale improvement, or technological progress.

In practice, TFP can either be estimated by using index number methods or econometric techniques. Examples of index number methods include the Malmquist productivity index, the Hicks-Moorsteen productivity index, the Törnqvist productivity index, and the Fisher productivity index (Jacobs et al., 2006, p. 129). In the econometric approach, regression analysis and the SFA are often used to estimate a production or cost function with distributional assumptions to estimate the TFP change and its components.

A selective list of healthcare literature studies focusing on TFP change and its components is provided in Appendix C. Among others, this list summarises the methodology, variables, and results of several healthcare studies related to the assessment of TFP and components. While the studies in Appendix C decompose the TFP changes in efficiency, scale and technological components, they tend to concentrate on the relative contribution of efficiency and technological change to changes in the TFP.

The list of studies in Appendix C shows the Malmquist productivity index (Malmquist, 1953) as the most common healthcare productivity approach. Malmquist's productivity index was introduced into the literature through the seminal study by Caves et al. (1982), which adopted Malmquist's approach to constructing quantity indices as distance function ratios.

Färe et al. (1992) undertook one of the earliest applications of the Malmquist productivity index in healthcare. The study analysed the productivity changes of a group of pharmacies in Sweden and concluded that most of the improvements in the TFP were due to technological progress. The healthcare studies that followed (see, for example, Linna (1998); Maniadakis et al. (1999); Ng (2011); Tambour (1997)) that used the Malmquist productivity index also found positive technological progress.

However, following the study by Färe et al. (1992), another application of the Malmquist productivity index was undertaken by Burgess and Wilson (1995). Their study found that technological decline dominated the effect of technical efficiency on TFP for a group of 137 hospitals in the USA. Other studies, such as those by Giuffrida (1999), Jiménez et al. (2003) and González and Gascón (2004), have also either reported technological regress or no significant impact of technological change on the TFP.

As for the effect of efficiency changes on TFP, studies by Linna (1998), Dismuke and Sena (1999), Maniadakis and Thanassoulis (2000) and Gannon (2008) found that both efficiency and technological progress contributed towards the increase in the TFP. On the other hand, Giuffrida (1999), who assessed the TFP growth of 90 English family health service authorities over 1991-1995, found that only technical and scale efficiency contributed to TFP growth while there was no noticeable technological progress. Further, the study highlighted that improvements in the TFP were minimal and expressed a limited scope of productivity growth in the healthcare sector.

Two Malmquist index studies have incorporated the quality of healthcare outputs in the assessment of the TFP. The earliest study was by Färe et al. (1995), which showed that the incorporation of quality significantly affects the measure of TFP change. More recently, Karmann and Roesel (2017) found that for a sample of German hospital data, quality improvements contributed more growth towards TFP than just output volumes.

While Malmquist is widely used in healthcare studies, its application requires data on inputs and outputs to be consistently measured over time (Jacobs et al., 2006, p. 137). This requirement is often challenging in healthcare due to regular changes in policies or inconsistent data collection across different units. Another disadvantage of the Malmquist index is that it requires the assumption of constant returns to scale to estimate TFP changes, which in turn assumes there are no scale efficiency effects (Coelli et al., 2005, p. 293).

However, very few healthcare studies use econometric approaches to assess improvements in productivity and its components. Morikawa (2010) used a fixed-effects panel-data model to estimate the effects of increasing hospital size on TFP, based on data from 239 Japanese medical facilities. The study found that TFP increases more than 10% when the size of a hospital doubles. Using time-series regression analysis, Blank and Eggink (2014) used Dutch hospital data for the period from 1972–2010 to analyse productivity improvements. Their studies looked into the effects of regulations on changes in the TFP and found that hospital competition reform failed to improve productivity among hospitals. Both of these studies excluded inefficiency in the cost/production functions. Only one study by Dismuke and Sena (1999) used the SFA to decompose the TFP change for a group of hospitals in Portugal. Their result found technical progress for most of the hospitals.

One of the advantages of using SFA is that it allows for the control for unobserved time-invariant heterogeneity when computing costs and input elasticities. Further, it offers an opportunity to decompose productivity changes into parts that have a straightforward economic interpretation. Despite numerous advantages, currently, SFA is not widely used in the healthcare sector to assess changes in the TFP and its components.

Another noteworthy point is that all the studies in Appendix C, except for Linna (1998), have used the primal approach to estimate the TFP changes and their components. No study has undertaken a TFP analysis under both the primal and dual approaches. According to the duality theory, both approaches should produce the same consistent results (Jorgenson & Griliches, 1967). However, the results differ in practice due to the lack of an accurate measure of variables and imperfect market conditions (Kee, 2004). Therefore, it is helpful to adopt both approaches for the sake of consistency and the sources of discrepancies in the TFP estimates.

3.3 Variables used in healthcare efficiency and productivity studies

3.3.1 Output variables

The measurement of output in the healthcare sector is not straightforward, as the demand for healthcare services arises from the need to improve health status. A healthcare institution combines resources such as labour and capital to provide healthcare services, which individuals then consume, leading to improved health (Hollingsworth & Peacock, 2008, p. 21). Therefore, production and efficiency analysis should ideally be based on improving the population's health status (Jacobs et al., 2006, p. 22).

Proponents of using health outcomes when studying effectiveness and performance analyses claim that outcome metrics are the primary purpose of delivering health services. While the argument is convincing, it lacks consistency in practical applications. Quality-of-life measures are often formulated using different key indicators and methodologies (Hollingsworth & Peacock, 2008, p. 24). Furthermore, healthcare outcomes may take years to be realised, and the collection of healthcare outcome data may impose impractically high costs on the health system (Jacobs et al., 2006, p. 27). Additionally, the expected improvement in an individual’s health status depends on other factors, which may be outside the healthcare providers' control.

Due to the practical difficulties involved in measuring healthcare outcomes and the associated costs of collection, various measures of healthcare activities are used as proxies for healthcare outcomes (Jacobs et al., 2006, p. 27). These proxies measure healthcare outputs in inpatient care episodes, outpatient visits and the length of inpatient stay (Hollingsworth & Peacock, 2008, p. 24). For example, measures of healthcare activities can include a count of the patients admitted, surgical procedures performed, outpatient numbers or immunisations given.

The list of the studies in Appendices B and C shows that almost all healthcare productivity and efficiency studies use healthcare activities to measure healthcare outputs. However, the exceptions are studies that focus on measuring healthcare productivity at the regional or cross-country level. For example, Cozad and Wichmann (2013) used state-level data from US hospitals, including the survival rates, health status and population share without disabilities as outputs to measure technical efficiency. Similarly, Kinfu (2013) used data on under-five-year-old mortality rates for 52 districts in South Africa. In a cross-country analysis, Cetin and Bahce (2016) used DEA to measure life expectancy and infant mortality rates from 26 OECD countries to assess their relative technical efficiency using DEA.

From Appendices B and C, it is also evident that most studies used inpatient admissions or discharges as one of the measures, along with some version of outpatient visits. A handful of studies also used ancillary services, such as the number of X-rays taken Pilyavsky and Staat (2008), laboratory tests performed (Athanassopoulos & Gounaris, 2001; Pilyavsky & Staat, 2008) and ambulatory visits (Ancarani et al., 2009; Burgess & Wilson, 1995; Chowdhury & Zelenyuk, 2016) as a measure of healthcare outputs.

The number of inpatients can be considered the most critical measure of hospital output in resource consumption. The measuring of inpatient services can further be divided into the number of admissions, the number of inpatient bed-days, and the number of separations[8]. While the majority of studies use separation as a measure of output, there are a few studies such as those by Pilyavsky et al. (2006), Pilyavsky and Staat (2008) and Mutter et al. (2008) that use inpatient admissions as a measure of output.

In an attempt to incorporate both case complexity and severity into the measurement of healthcare outputs, studies often use the number of inpatient days to account for case complexity and resource use. One of the earliest studies to use this variable is by Grosskopf and Valdmanis (1987). They used acute and intensive care inpatient bed-days along with other variables to assess the efficiency of 80 hospitals in California, USA. More recently, Jiang et al. (2017) and Giménez et al. (2019) included measuring inpatient days as one of the output variables in evaluating efficiency levels.

However, the use of inpatient days still does not capture the case complexity in full and can be only considered to be a crude measure (Hollingsworth & Peacock, 2008, p. 24). For example, a one-day inpatient stays in the geriatric ward cannot be counted as equal to a one-day stay by a newborn in a paediatric ward. The treatments and costs differ greatly depending on the health conditions and characteristics of patients. Nevertheless, the use of inpatient days and treatments do provide some reliability in terms of output measurement but do not fully reflect the heterogeneity of outputs (Hollingsworth & Peacock, 2008, p. 25).

[8] Separation occurs when a patient leaves a healthcare facility due to death, discharge or leaves without authorisation

In so far as admissions or separations are concerned, each inpatient stay often varies according to the complexity and severity of the individual's condition (Hollingsworth & Peacock, 2008, p. 24). The inconsistency around the measurement of healthcare outputs has led to the development of 'Case-Mix' adjusted outputs, which consider the severity of different patients' conditions. The most common measure used in case-mix adjusted measures of output are based on Diagnosis Related Groups (DRGs) (Hollingsworth & Peacock, 2008, p. 24).

The DRG system was pioneered by Fetter et al. (1980), who stated that “the primary objective in the construction of the DRGs was a definition of case types, each of which could be expected to receive outputs or services from a hospital” (p.5). In other words, DRG is essentially a statistical system of classifying any inpatient stay by taking into account the diagnosis involved and the hospital resources necessary to treat the condition. Each DRG is assigned a specific price based on at least five characteristics: the person’s age, their primary and secondary diagnosis, the primary and secondary surgical procedures and, in some cases, the gender of the patient (Fetter et al., 1980).

A study by Rosko and Chilingerian (1999) found that the inclusion of case-mix output variables reduces the mean efficiency score by more than 50 per cent. Another study by Björkgren et al. (2004) showed that the efficiency scores vary considerably, depending on the case-mix adjustments used for inpatient services. The popularity of case-mix output measures has grown since it was first used by Wagstaff (1989) to assess the efficiency of 49 Spanish hospitals.

Similarly, using DRG based case-mix measures, Brown (2003) separated discharges into three classes to account for relative resource use and the complexity of treatments. Soon after, Linna et al. (2006) used DRG-based output measures to assess hospitals' efficiency in Norway and Finland. In more recent work, Chowdhury and Zelenyuk (2016) study on hospitals in Ontario used case-mix adjusted weighted inpatient bed-days and ambulatory visits as outputs. In New Zealand, studies by Jiang and Andrews (2020), Andrews (2020a) and Andrews (2020b) have used DRG-based case-weighted inpatients and price-weighted outpatient visits as a measure of outputs.

3.3.2 Inputs and price variables

In healthcare literature, the measurement of inputs tends to be relatively less challenging than outputs, as physical inputs can often be measured more precisely than outputs (Jacobs et al., 2006, p. 29). In its simplest form, the production of healthcare services involves combining resources such as labour, capital and other intermediary inputs to produce healthcare services, which the individuals then consume to improve their health status (Hollingsworth & Peacock, 2008, p. 21).

As healthcare is a labour-intensive sector, medical and non-medical staff's contribution is crucial in providing services to the population. The use of measures of labour input in efficiency and productivity studies varies significantly. Of the 40 studies presented in Appendix B on technical efficiency, 18 used the staff numbers, and 15 used FTEs to account for labour consumption. The use of counts may not be appropriate as the number of labour units does not account for actual workforce use; most importantly, they do not reflect the actual time spent doing tasks. Moreover, counts obscure the mix of staff who are employed on a part-time or casual basis or who work overtime (Peacock et al., 2001). In such cases, compared to headcounts, the FTE measure is more appropriate in accounting for the mix of various types of staff time.

Another consideration in the healthcare efficiency literature relates to the level of labour disaggregation, based on the skill level deemed appropriate. Jacobs et al. (2006, p. 30) argue that unless there is a particular interest in analysing the input relationships or addressing specific policy-related questions, it may be reasonable to aggregate labour inputs by weighting according to their relative wages. However, such data on labour prices might not always be available. Studies such as Mitropoulos et al. (2015) and Sommersguter-Reichmann (2000) appear to have used an unweighed aggregated measure of labour inputs.

In New Zealand based studies, while Andrews (2020b) used disaggregated labour data on medical, nurses, allied, support and management staff, Jiang and Andrews (2020) and Andrews (2020a) weighted and aggregated the FTEs of nurses, allied, support and management staff, based on their relative price.

If the research interest is to extract the input elasticities or measure how each labour group’s input interacts with each other or with outputs, then it may be appropriate to use disaggregated data. This may be particularly important when the SFA is used to estimate the efficiency and relationships between various inputs and outputs.

According to the studies in Appendices B and C, most hospital-based efficiency and productivity studies have disaggregated labour inputs into doctors, nurses, and all other staff. On the other hand, studies such as those by Alonso et al. (2015), Ancarani et al. (2016), and Ahmed et al. (2019) have aggregated only the labour inputs into doctors and nurses while completely ignoring the contribution of administration and other labour groups. Once again, this might be due to the unavailability or inconsistency of data for various non-medical skill groups.

Jacobs et al. (2006, p. 30) suggest that labour inputs can also be measured in terms of expenditure, as physical inputs fail to capture variations in the wage rates between different labour groups and organisations. Studies Giokas (2001) and Steinmann and Zweifel (2003) used labour expenditure data as a proxy for input consumption to estimate technical efficiency.

However, due to commercial and political sensitivity, access to financial data may be limited in many cases.

The second crucial input factor needed to undertake any kind of productivity and efficiency study is capital. However, measuring capital in the healthcare sector is more complicated than labour input. This is due to the difficulty in distinguishing and measuring the flow of capital services from the capital stock at any given time. As a result, in practice, researchers often rely on very rudimentary measures, such as hospital beds, depreciation or hospital floorspace. Ideally, the best indicator of capital input is the flow of capital services from capital stock (Jacobs et al., 2006, pp. 31-32). However, such services are hard to measure in practice, and the associated data is challenging to obtain.

In the healthcare literature, the number of beds is the most widely used proxy for the measure capital stock (Worthington, 2004). Similarly, based on the studies listed in Appendices B and C, 26 out of 40 studies on technical efficiency and nine out of 19 studies on TFP decomposition use beds to measure capital stock. Some recent studies that use hospital beds include those by Ahmed et al. (2019), Sultan and Crispim (2018) and Colombi et al. (2017). Though widely used, the use of hospital beds is far from ideal and can lead to an overestimation of capital use, which may result in biased estimates of efficiency (Jacobs et al., 2006, p. 32).

Another rarely used measure of capital is the ‘capital charge’, which was first used by Parkin and Hollingsworth (1997) to evaluate the technical efficiency levels of 75 Scottish hospitals. According to The Treasury (2001), the capital charge is a cost levied on the Crown’s investment in various government agencies. It implies that capital is not costless and should be managed in the same manner as any other cost of production. The capital charge is usually levied on the net worth of the organisation (assets minus liabilities). A New Zealand study by Jiang and Andrews (2020) also used the capital charge as a measure of capital input to estimate the technical efficiency of 20 DHBs.

While the incorporation of capital in efficiency and productivity analysis can take various forms, Coelli et al. (2005, pp. 149-150) recommend that conducting a sensitivity analysis of efficiency scores to various choices of capital can assist in providing some reliability of the chosen capital measure.

According to the studies in the healthcare literature in Appendix B, while the majority undertake technical efficiency analysis, a handful evaluates the cost and allocative inefficiency. The estimates of cost and allocative efficiency can offer insights into how successfully healthcare providers can minimise cost. However, the evaluation of cost/allocative efficiency requires information on input prices for labour and capital.

The measure of labour price in healthcare productivity and efficiency studies takes different forms, given that researchers are often required to work with the data where availability is either limited or may even vary significantly across healthcare providers. Based on the studies listed in Appendix A and B, the most common way of computing the price of labour is to divide the labour expenditure by their respective FTEs. Some recent cost efficiency studies that use price per FTE as a proxy for labour price include Jiang and Andrews (2020), Al-Amin et al. (2016) and Widmer (2015).

Another set of studies, such as Vitaliano and Toren (1994), Friesner et al. (2008) and Araújo et al. (2014), used the average wages paid to the staff as a measure of labour price. In contrast, Koop et al. (1997), Blank and Valdmanis (2005) and Medin et al. (2011) used wage indices as a proxy for labour price. Further, whether labour price should be disaggregated by skill mix once again depends on the research question and the context of the study.

As with the capital input, the incorporation of capital price into the efficiency analysis is more problematic than the labour price (Folland & Hofler, 2001). Ideally, the price of capital should estimate the price of the flow of capital services, which is not straight- forward to measure. Further, according to the neoclassical theory of investment, the price of capital is the rental price of capital, which, under a profit-maximization assumption, is equal to the marginal product of capital (Eisner & Nadiri, 1968). Therefore, the rental price or price of capital can be considered to be the sum of the interest rate or the borrowing cost of capital and the depreciation rate (Harcourt & Riach, 1997b). Surprisingly, the neoclassical concept of the rental price is seldom used in healthcare studies as a proxy for the capital price. The only exception was the study by Chen et al. (2016), where the ratio of depreciation over total assets (depreciation rate) is used to estimate the capital price. The standard approach in healthcare studies appears to be dividing the value of the capital stock or expenditure by the real value of capital.

According to Webster et al. (1998), the user cost of capital is often reflected in the depreciation and the opportunity cost of capital (capital charge and interest expenditure). Following the idea of the user cost of capital to compute capital, Rosko (2001), Mutter et al. (2008), Nedelea and Fannin (2013) and Al-Amin et al. (2016) used the sum of depreciation and interest costs per bed to estimate the capital price. Another study by Friesner et al. (2008) used the sum of depreciation and interest costs divided by the hospital building area in square footage to estimate the price of capital. Similarly, in New Zealand, Jiang and Andrews (2020) used both depreciation and the capital charge per inpatient discharge to estimate capital price and conduct a sensitivity analysis of the two measures of price.

The third category of the price needed to estimate cost efficiency is intermediate inputs such as supplies (clinical and non-clinical) and other operating costs. Since the data on the volume of intermediate inputs is often unavailable, the standard way is to divide the aggregate expenditure by the number of hospital beds Webster et al. (1998). Herr (2008) used the cost of clinical expenditure per installed bed to measure the price of clinical materials. On the other hand, Widmer (2015) computed the operating price per hospital admission, whereas Jiang and Andrews (2020) estimated the price per inpatient discharge. In another study, Friesner et al. (2008) used a producer price index to estimate the price of hospital supplies.

3.4 Summary

The literature review shows that while the DEA and the SFA have been used extensively in healthcare productivity and efficiency studies, their application in the context of longitudinal data is limited. Further, no study currently undertakes the measurement of the TFP changes and their components under both primal and dual approaches. There is also a considerable variation in the use of inputs, outputs and price variables in the literature, perhaps partly due to the difficulties in obtaining detailed and consistent data. Therefore, it is fair to say that using variables in healthcare productivity and efficiency literature rests on the balance between data availability and the research scope.

To sum up, the current literature on healthcare productivity and efficiency studies point towards the three main literature gaps:

1. While various studies use longitudinal data, only a minimal number of studies control for cross-sectional unobserved heterogeneity. This is most likely to produce bias in the measure of efficiency, particularly in the healthcare sector, as demonstrated by Greene (2004).
2. Currently, only one study by Colombi et al. (2017) explicitly differentiates between the short-run and long-run inefficiency in healthcare. Furthermore, no study to date has estimated efficiency in the dynamic context where inefficiencies are not independent over time.
3. There is currently no study in the healthcare literature that uses both the primal and dual approaches to demonstrate the model's consistency and, more importantly, to identify sources of discrepancies if they exist.

Chapter 4 Estimating the technical efficiency of New Zealand District Health Boards in providing hospital services: A Bayesian Dynamic Stochastic Frontier Approach

Abstract

In longitudinal stochastic frontier studies, the measure of short-run technical efficiency only reveals how successful organisations are in minimising their input usage relative to the efficient input frontier, ignoring any dependencies in inefficiency over time. However, the assumption of dependence in efficiency performance over time is valid due to the persistence in inefficiency resulting from the long-term structural and environmental constraints in the operating environment that are difficult to reorganise without high adjustment costs. In the presence of such high adjustment costs, the optimal strategy for health care providers may be to remain partly inefficient over time, leading to a dynamic process where inefficiencies are slow to disappear.

While incorporating dynamic links between short-run efficiency performances due to high adjustment costs has gained popularity in other sectors, its application to healthcare remains unexplored. Using quarterly longitudinal data on 20 New Zealand District Health Boards (DHBs) during the period 2011-2018, this chapter uses a dynamic stochastic frontier model that incorporates the persistence in inefficiency over time. A well established Bayesian stochastic frontier model is used to estimate technical efficiency scores and model parameters, including the degree of persistence in inefficiency.

The findings indicate that while, on average, New Zealand DHBs operated close to the sector's equilibrium level of technical efficiency in the short run, they face high adjustment costs in the long run. As a result of long-run technical inefficiency, on average, DHBs used 32% more inputs between 2011 and 2018.

4.1 Introduction

In the past three decades, public healthcare expenditure in New Zealand has increased substantially. The real dollar amount spent on public healthcare has risen from $1,952 in 1996 to $3,381 per capita in 2016 (2016 dollars[9]). A crucial part of the New Zealand public healthcare system revolves around its 20 DHBs. The DHBs are entrusted with a substantial portion of the public healthcare budget in order to provide various public health services, including primary care, hospital care, and aged care services in their regions. In the year 2017/18, approximately 75.6% of the total public healthcare budget of 12.7 billion was distributed to DHBs to meet the regional healthcare demand, including hospital services (The Treasury, 2017b).

Though hospitals have historically been allocated a higher proportion of DHB funding, this allocation has been gradually growing over time (The Treasury, 2017a). A New Zealand Treasury report emphasised that over the last few years, DHBs have steadily diverted substantial portions of their funds to their hospitals at the cost of other services, such as primary and mental health services (The Treasury, 2017a). The report argues that the pressure to meet hospital output targets[10] introduced in 2007/08 and a push to reduce budget deficits has been the driving force behind the increased channelling of funding to hospitals.

A report by the Controller and Auditor-General (2016a) argued evidence of a severe lack of investment by the DHBs in hospital infrastructure. The same report also suggests that a significant portion of clinical equipment used by DHBs is outdated and past its useful life, leading to low asset utilisation, leading to further inefficiencies. For example, estimates show that close to $300 million worth of clinical equipment in hospitals has reached the end of its useful theoretical life (Controller and Auditor-General, 2016a).

More recently, a report by ASMS (2018) has argued that the capital charge[11] has disincentivised DHBs from investing in critical hospital infrastructure. The report highlighted that DHBs engage in minimal investment in medical technology and other vital clinical infrastructure or even defer it for a prolonged period to avoid paying the capital charge to the government. A New Zealand Treasury report estimates that it will take close to $222 million every year for the next ten years to bring the current DHB infrastructure up to date (The Treasury, 2010).

The target-driven measures, substandard hospital infrastructure and other regulatory policies such as capital charges can be linked to the adjustment cost theory put forward by Penrose (1995), Eisner et al. (1963), Hamermesh and Pfann (1996) and Treadway (1971). The

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[9] As per The Treasury (2013a) this study uses the Consumer Price Index to inflate the 1996 nominal dollar value to the 2016 real dollar value.
[10] For more information on Health Targets refer to the Ministry of Health (2018c).
[11] Capital charge is a payment that DHBs make to the Crown every six months for the Crown's investment in the hospital infrastructure. More information on capital charge can be found in The Treasury (2016b).

adjustment cost theory states that if it is costly for organisations to improve their working conditions, they will continue to operate under sub-optimal working conditions, albeit inefficiently.

The adjustment costs[12] faced by DHBs may include, among other things, expenses associated with the procurement of new clinical equipment and technologies, expansion of current hospital capacity, and target-driven constraints. As the MoH places considerable pressure on the DHBs to remain within their budgets, DHBs either delay or reduce their investment in critical infrastructure and continue to operate with a level of inefficiency. In the presence of such adjustment costs, there will always be a long-run equilibrium level of inefficiency that DHBs aim to achieve in the short run. A naïve short-run efficiency analysis completely ignores adjustment costs and treats each period's production decisions in isolation.

This study extends the previous contribution by Jiang and Andrews (2020), which used quarterly balanced data from 2011 to 2018 by explicitly allowing technical inefficiencies to be serially correlated due to the presence of adjustment costs. A Bayesian dynamic stochastic frontier model proposed by Tsionas (2006) was used to estimate the parameters. To the best of the author's knowledge, this is the first study in the healthcare literature to use dynamic stochastic frontier analysis to account for the persistence in technical inefficiency as healthcare providers adjust to the long-run equilibrium in the sector.

4.2 Econometric specification

The empirical analysis in the healthcare sector often involves multiple inputs and outputs. Econometric studies often employ distance functions to represent the relationship between inputs and outputs. As highlighted by Kumbhakar et al. (2015, pp. 27-29), the flexibility of a distance function comes from the fact that it does not require information on input prices or behavioural assumptions to estimate a multiple output and input production technology. Studies often choose between the input or output distance functions within the standard distance function approach, depending on the study's context and sector under consideration.

In this chapter, an input distance function (IDF) is used to account for the multiple inputs and outputs in the production of healthcare services. The IDF enables the estimation of the efficiency scores by determining how much the input vector can be proportionally contracted for a given output vector. As DHBs are expected to treat a specified number of patients in a given period while at the same time meeting the demand of acute hospital care, the managerial problem is better formulated by considering how much input quantities can be reduced while still meeting the demand for hospital services. Furthermore, as PBFF is used to allocate funds

[12] It is acknowledged that there may be other factors that contribute to high adjustment costs; however, in this thesis, policy and infrastructural issues have been used to motivate the estimation of efficiency under a dynamic system.

every year, DHBs are expected to minimise input usage and provide the contracted healthcare services to the public (Knopf, 2017)

Following Kumbhakar et al. (2015), an IDF can be represented as:

$$D_I(y,x) = max\{\theta : (x/\theta) \in V(y)\}, \tag{4.1}$$

where $V(y)$ represents the set of all non-negative input vectors $x = (x_1, \ldots, x_M) \in \mathbb{R}_+^M$ that can produce the non-negative output vectors $y = (y_1, \ldots, y_N) \in \mathbb{R}_+^N$; and $\theta \geq 1$, which measure the maximum proportional reduction of the input vector x given the output vector y. To satisfy economic regularity conditions, an IDF must be concave, homogenous of degree one in inputs, and increase in each input level and decrease in each output level.

From Eq. (4.1), it is clear that $D_I(.) \geq 1$, where a value equal to one identifies the respective input vector x used by a DHB to be fully efficient. This is located on the frontier of the input set. Values greater than one represent an inefficient use of inputs. Using the measure of technical efficiency in Farrell (1957), the measure of input-oriented technical efficiency (TE) can be calculated by the inverse of the input distance function:

$$TE(y,x) = \frac{1}{D_I(y,x)} \tag{4.2}$$

In order to estimate a production process, a functional form for IDF needs to be specified. This study adopts a translog functional form put forward by Christensen et al. (1973). The translog functional form is a second-order Taylor approximation that is used to estimate unknown functions (Intriligator et al., 1996). Unlike the Cobb-Douglas function, the translog function does not impose assumptions about constant elasticities of inputs nor elasticities of substitution between inputs and outputs (Coelli et al., 2005).

The translog IDF on a longitudinal data set with M inputs and N outputs can be written as:

$$\begin{aligned} \log D_{it}^I = {} & \alpha + \sum_{n=1}^{N} \alpha_n \log y_{nit} + \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{N} \alpha_{nk} \log y_{nit} \log y_{kit} \\ & + \sum_{m=1}^{M} \beta_m \log x_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{l=1}^{M} \beta_{ml} \log x_{mit} \log x_{lit} \\ & + \sum_{m=1}^{M}\sum_{n=1}^{N} \delta_{mn} \log x_{mit} \log y_{nit} + \gamma_t\, t + \frac{1}{2}\vartheta_{tt} t^2 \end{aligned} \tag{4.3}$$

where the subscripts i and t denote the organisation and time, respectively; whereas, $ln\, y_{nit}$ and $ln\, x_{mit}$ represent the natural logarithm of quantities for outputs and inputs, respectively. Furthermore, $t = 1, \ldots, T$ is a linear time trend and t^2 captures the quadratic trend in the IDF.

To impose linear homogeneity in inputs, the distance term D_{it}^{I} and the inputs in Eq. (4.3) are divided by one of the inputs (Kumbhakar et al., 2015, p. 99).

Once linear homogeneity in inputs is imposed by using an input, in order to carry out the empirical estimation the $\log D_{it}^{I}$ term is moved to the right-hand side of the translog function and treated as a non-negative random variable, $u_{it} \equiv \log D_{it}^{I}$. Finally, another component, v_{it}, is added to the right-hand side of the equation to capture statistical noise.

Therefore, the estimable form of the translog IDF can be represented as:

$$\begin{aligned} -\log x_{Mit} = {} & \alpha + \sum_{n=1}^{N} \alpha_n \log y_{nit} + \frac{1}{2} \sum_{n=1}^{N} \sum_{k=1}^{N} \alpha_{nk} \log y_{nit} \log y_{kit} \\ & + \sum_{m=1}^{M-1} \beta_m \log x_{mit}^{*} + \frac{1}{2} \sum_{m=1}^{M-1} \sum_{l=1}^{M-1} \beta_{ml} \log x_{mit}^{*} \log x_{lit}^{*} \\ & + \sum_{m=1}^{M-1} \sum_{n=1}^{N} \delta_{mn} \log x_{mit}^{*} \log y_{nit} + \gamma_t t + \frac{1}{2} \vartheta_{tt} t^2 + v_{it} \\ & - u_{it} \end{aligned} \tag{4.4}$$

where $x_{mit}^{*} = \frac{x_{mit}}{x_{Mit}}$, with x_{Mit} is the normalising input and the parameters $\alpha, \beta, \delta, \gamma\ and\ \vartheta$ are unknowns to be estimated. The term $u_{it} \equiv \log D_{it}^{I} = -\log TE_{it}$, is the measure of the technical inefficiency of the organisation i at time t and is also an unknown to be estimated.

The model in Eq. (4.4) can be written compactly for the sake of brevity and clarity as:

$$q_{it} = p_{it}'\beta + v_{it} - u_{it} \tag{4.5}$$

where q_{it} represents the dependent variable and p_{it}' is a row vector of the independent variables in Eq. (4.4), β is the vector of corresponding parameters to be estimated, v_{it} is an idiosyncratic error capturing the random disturbances to the production process where $v_{it} \sim N(0, \sigma_v^2)$ and u_{it}, being the measure of technical efficiency, can take a user-defined distribution.

If in Eq. (4.5), the dynamic part is denoted by $s_{it} = f(u_{it})$, then according to Tsionas (2006), the inefficiency component u_{it} follows a log-normal distribution conditional on s_{it-1} specified as $s_{it} = \log(u_{it})$. The dynamic specification controls the autoregressive process of inefficiency. This autoregressive (AR) process of order one can be represented as:

$$s_{it} = \omega + \rho s_{it-1} + \eta_{it}, \quad \eta_{it} \sim N(0, \sigma_\eta^2), \quad t = 2 \dots T \tag{4.6}$$

where s_{it} represents the dynamic component, ω is a constant, ρ is the persistence parameter measuring the proportion of the dynamic part of inefficiency that is transmitted from one period to the next and η_{it} represents the unobserved random shocks to the dynamic component representing the 'unexpected log-inefficiency sources' that follows a normal distribution with variance σ_η^2.

Stationarity in the dynamic process requires the persistence parameter to satisfy $|\rho| < 1$, which is imposed by the specification of s_{it} in the first period that initialises the dynamic process:

$$s_{i1} = \frac{\omega}{1-\rho} + \eta_{i1}, \;\; \eta_{it} \sim N\left(0, \frac{\sigma_\eta^2}{1-\rho^2}\right), \quad t = 1. \tag{4.7}$$

Stationarity ensures that s_{it} does not diverge to positive or negative infinity, which may lead to efficiencies being equal to one or zero in the long run. Further, divergence also contradicts the presence of adjustment costs that motivate the model's dynamic structure (Galán et al., 2015).

In the dynamic part of the model, a value of ρ close to 1 indicates high persistence in the inefficiency component from one period to the next, highlighting high adjustment costs in the sector. On the other hand, ρ close to zero implies a static model with no adjustment costs.

Solving for TE from the equation, $\frac{\omega}{1-\rho} = \log(\log(TE))$ gives the measure of long-run technical inefficiency, whereas the measure of short-run technical efficiency can be found by solving the transformation equation $s_{it} = log(-log(TE_{it})$ for TE_{it}.

An alternative and more flexible distributional specification for inefficiency was put forward by Emvalomatis (2012) where s_{it} follows a normal distribution:

$$s_{it} = \log\left(\frac{e^{-u_{it}}}{1 - e^{-u_{it}}}\right) \tag{4.8}$$

where the efficiency score, $e^{-u_{it}}$ conditional on s_{it-1} follows a logit-normal distribution. With this specification, the measure of long-run technical efficiency can be found using the same formula, $\frac{\omega}{1-\rho}$, whereas the measure of short-run technical efficiency is found by solving Eq. (4.8) for $TE_{it} = e^{-u_{it}}$. In this chapter, we use this specification to estimate model parameters.

4.3 Model estimation

This study uses Bayesian techniques to estimate the model described in Eq. (4.5) - (4.8). To demonstrate the likelihood of the structural parameters and latent states, let us define s_i to be a $T \times 1$ vector of the latent state variable in the dynamic equation for a healthcare provider i. Next, collect all structural parameters to be estimated to a vector $\theta = [\beta, \sigma_v^2, \rho, \sigma_\eta^2]'$. Thus, the complete data likelihood of the structural parameters and latent states is:

$$p\big(q,\{s_i\}\,\big|\,\theta,P\big) = p\big(q\,\big|\,\{s_i\},\beta,\sigma_v\,,P\,\big) \times p\big(\{s_i\}\,\big|\,\omega,\rho,\sigma_\eta\big) \tag{4.9}$$

$$= \frac{1}{(2\pi\sigma_v^2)^{\frac{NT}{2}}}\,exp\left\{-\frac{\sum_{i=1}^{N}\sum_{t=1}^{T-1}\,(q_{it} - p'_{it}\beta + u_{it})^2}{2\sigma_v^2}\right\}$$

$$\times \frac{1}{\big(2\pi\sigma_{u_1}^2\big)^{\frac{N}{2}}}\,exp\left\{-\frac{\sum_{i=1}^{N}(s_{i1} - \omega_1)^2}{2\sigma_{u_1}^2}\right\}$$

$$\times \frac{1}{(2\pi\sigma_u^2)^{\frac{N(T-1)}{2}}}\,exp\left\{-\frac{\sum_{i=1}^{N}\sum_{t=2}^{T-1}\,(s_{it} - \omega - \rho s_{it-1})^2}{2\sigma_u^2}\right\}$$

where q and P are, respectively, the stacked vector and matrix, over both i and t, of the dependent and independent variables as in Eq. (4.5). The parameters ω_1 and $\sigma_{u_1}^2$ are the mean and variance in the specification of s_{it} in the first period as in Eq. (4.7). It is straightforward then to see that the resulting likelihood function in Eq. (4.9) is due to the normality assumption of error terms in Eq. (4.5), (4.6) and (4.7).

Using Bayes' rule, the joint posterior density of the model parameters and latent states is:

$$\pi\,\big(\theta,\{s_i\}\,\big|\,q,P\big) \propto p\big(q,\{s_i\}\,\big|\,\theta,P\big)\;\times p(\theta) \tag{4.10}$$

where $p\big(q,\{s_i\}\,\big|\,\theta,P\big)$ is given by Eq. (4.9) and $p(\theta)$ corresponds to the prior density of the parameters.

The priors imposed on the parameters in this chapter are the following:

1. For the prior of vector, β is a multivariate normal density with prior means zero and diagonal prior covariance matrix with diagonal values of 1,000. This is a proper but vague prior, which will have minimal effect on the results. This prior is also conjugate.
2. A Gamma prior is used for both $\frac{1}{\sigma_v^2}$ and $\frac{1}{\sigma_\eta^2}$. For $\frac{1}{\sigma_v^2}$ shape and scale hyper-parameters of 0.001 are used. However, the shape and scale hyper-parameters of $\frac{1}{\sigma_\eta^2}$ are set to 0.1 and 0.01. The prior on $\frac{1}{\sigma_\eta^2}$ is slightly more informative than the one imposed on $\frac{1}{\sigma_v^2}$ as it corresponds to latent-state equations.
3. For the persistent parameter ρ a beta prior with shape parameters 4 and 2 is used in order to restrict ρ on the unit interval.
4. For the constant ω a normal prior with mean zero and variance of 1,000 is used.

4.4 Data and descriptive statistics

The MoH provided the administrative data used in this study. The data set includes quarterly observations for the period from 2011 to 2018 (T=32) of each DHB's labour, capital, and clinical input usage, along with the respective number of inpatients and outpatients treated by each DHB. In line with the consensus in healthcare efficiency studies, the count of the FTEs of each labour group is used to account for labour inputs (Hollingsworth & Peacock, 2008; Hussey et al., 2009; Jacobs et al., 2006; Worthington, 2004). The labour inputs consist of the quarterly count of the number of full-time equivalents (FTEs[13]) employed by each DHB as medical, nursing, allied, support, and management staff.

To reduce the number of parameters to be estimated and avoid the issues associated with high multicollinearity[14], the FTEs of nursing, allied, support and management staff are combined to form a single labour group, other staff FTEs. Based on microeconomic theory, if it is assumed that a cost-minimising healthcare provider pays its staff at their marginal products[15], then the price of any labour group can be used as a weight when aggregating different types of FTEs.

For the weighting process, first, the average price per FTE for support staff[16] is obtained by dividing a DHBs expenditure on support staff by its FTE in each period. Then, this average price of support staff is used to weight nursing, allied and management FTEs. Thus, the total weighted measure of other staff FTEs is calculated by adding all the weighted FTEs.

In terms of capital inputs, the commonly used proxy in the healthcare literature is the number of hospital beds [see, for example, studies by Aletras et al. (2007), Herr (2008), Cozad and Wichmann (2013), Asmild et al. (2013) and Mitropoulos et al. (2015)]. The use of beds as a measure of capital use is not because of its appropriateness but rather because of the difficulty in obtaining data on other capital measures (Jacobs et al., 2006).

In this chapter, a more comprehensive measure of capital input proxied by capital asset value is used (see Chattopadhyay and Ray (1996); Grosskopf and Valdmanis (1993); Hu et al. (2012); Valdmanis (1992)). The value of capital assets represents a broad range of capital that healthcare providers consume. For example, many DHBs in New Zealand own outpatient clinical centres where patients come for diagnostic procedures without necessarily getting admitted. These clinics may not have many beds but may have highly expensive medical equipment that performs procedures such as magnetic resonance imaging (MRI), computed

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13 One FTE refers to 40 hours of labour per week and is calculated based on accrual. However, a person working more than 40 hours is only counted as one FTE. For more information on the calculation of FTEs please refer to the Nationwide Service Framework Library (2016).
14 A substantial correlation (close to 0.97) is observed between the FTEs of various labour groups.
15 It is recognised that when an unionised workforce is prevalent, employees may not always be paid at their marginal product rate. Nonetheless, given the limited availability of detailed compensation data, it is reasonable to make this assumption in the context of this research.
16 The price of any labour group can be used as a weighting factor.

tomography scans (C T Scan) and 3-D Mammography. In such cases, using the number of beds as a proxy of capital may not account for all the capital inputs used by DHBs, thereby underestimating the capital use.

In this chapter, the end of year capital asset values of buildings, equipment (clinical and non-clinical), information technology and motor vehicles reported by DHBs are used as a proxy for capital input. To remove the effect of inflation, the value of capital assets is deflated by the yearly capital goods price index produced by Statistics New Zealand[17]. Other inputs used in this chapter include outsourced labour and clinical costs and clinical supplies costs that are also deflated by using the healthcare producers index produced by Statistics New Zealand.

Another important decision in specifying the production process is the selection of appropriate outputs. As the healthcare sector is a multi-output industry, a wide range of proxies can be used to account for the heterogeneous nature of healthcare services offered to the public. In this chapter, case-weighted inpatient discharges and price-weighted outpatient visits are used as outputs.

The inpatient discharge volumes used in this chapter are weighted by case weights to account for relative resource consumption and case complexity. In New Zealand, as a standard practice, every inpatient stays in a hospital is assigned a code based on AR-DRGs (Australian Refined Diagnostic Related Groups)[18]. The AR-DRGs groups for each inpatient stay are based on similar clinical conditions and resources. A Weighted Inlier Equivalent Separation (WIES) weight within each group is calculated based on the length of stay to derive case-weighted inpatient discharges (Ministry of Health, 2019c). The WIES system is updated annually by MoH to recognise changes in clinical practices and the cost of inputs.

Similarly, outpatient visits are price-weighted to account for the differences in relative resource consumption. The price-weighted outpatient visits are calculated by multiplying the outpatient volumes by the price of respective purchase units[19] then dividing the total figure by the national case-weight price (Ministry of Health, 2018a). The price-weighted measure enables a consistent valuation of outpatient services across all DHBs.

The use of weighted outputs is critical as it considers the complexity and heterogeneity in the healthcare services delivered by hospitals (Asmild et al., 2013; Friesner et al., 2013; Mutter et al., 2008; Rosko, 2001). The summary statistics are shown in Table 4.1, while the definitions of the corresponding variables are presented in Appendix D.

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[17] The price index for various goods and services can be accessed at Statistics New Zealand. (2019).
[18] For more information refer to The Australian Institute of Health and Welfare (2019).
[19] The purchase unit is essentially a classification system used to measure and quantify a healthcare service . For more information refer to the Ministry of Health (2018b).

Table 4.1 Summary statistics of variables

Variable	Statistics	
Labour inputs (FTEs)		
Medical staff *(med)*	Minimum	96.84
	Maximum	5,230.16
	Mean	1,264.05
	Standard deviation	1,219.92
other staff *(other_staff)*	Minimum	1,077.84
	Maximum	24,068.66
	Mean	7,794.98
	Standard deviation	6,110.73
Capital and other inputs[§]		
Capital asset values *(capital)*	Minimum	39,440.88
	Maximum	1,994,221.00
	Mean	610,812.50
	Standard deviation	504,227.90
Outsourced labour and clinical costs *(out_cost)*	Minimum	1,238.56
	Maximum	28,243.90
	Mean	6,546.95
	Standard deviation	5,780.26
Clinical supplies costs *(clinical_cost)*	Minimum	1,078.47
	Maximum	66,263.76
	Mean	15,611.06
	Standard deviation	14,092.50
Outputs		
Case-weighted inpatients *(inpatients)*	Minimum	797.73
	Maximum	36,574.26
	Mean	10,334.19
	Standard deviation	8,794.45
Price-weighted outpatient visits *(outpatients)*	Minimum	610.23
	Maximum	8,369.72
	Mean	3,378.82
	Standard deviation	2,171.94

[†] Based on the Ministry of Health (2015a). Author's compilation.

[§] Reported in thousands of New Zealand dollars

4.5 Empirical results

Based on the first application of simulation techniques to stochastic frontier models by Van den Broeck et al. (1994), and Koop et al. (1995), Markov Chain Monte Carlo (MCMC) simulation is used to derive the posterior moments of the model parameters. When drawing samples from the posterior of $\{\boldsymbol{s_i}\}$ along with the parameters of the model, data augmentation techniques put forward by Tanner and Wong (1987) have also been used. As the priors specified for $\boldsymbol{\beta}$ and ω and the inverses of the variances are conjugate, Gibbs sampling is used. However, the complete conditionals for ρ and s_{it} do not belong to any known distributional families; therefore, random-walk Metropolis-Hastings updates were used.

The MCMC sampling involves 50 independent Markov chains, with each chain contributing 10,000 draws from the posterior distributions of model parameters. A burn-in phase of 50,000 iterations is used to remove the influence of initial values. Since the random walk Metropolis-Hastings algorithm has the potential to generate correlated draws, one in every three draws in each chain is retained. The results reported are therefore based on 500,000 retained samples. Although this makes sampling slightly computer-intensive, this process substantially reduces the relative inefficiency factors[20].

Before estimating a translog function, inputs and outputs are normalised by their geometric mean, whereas the trend variable by its arithmetic mean which allows the interpretation of parameters associated with the first-order terms directly as distance elasticities, evaluated at the geometric mean of the data. The homogeneity restriction on the IDF was imposed by using the variable *med* as numeraire.

In Table 4.2, the posterior means, standard deviation, 90%credible intervals and the structural parameters are displayed. Results show that all the first-order parameter means have the expected signs. In other words, since the output elasticities are negative at the geometric mean, the estimated IDF is decreasing in outputs. In contrast, the positive input elasticities state that IDF is increasing in inputs. With the expected signs of input and output elasticities, the monotonicity condition is also strongly satisfied at the sample means.

The input distance elasticities reflect the measure of the curvature of the input distance frontier. For example, the elasticity of *log_other_staff* is 0.08, which implies that a 1% increase in all other staff FTEs will lead to a 0.08% increase in the input distance function, signifying that DHBs will move away from the efficient frontier**.** It can also be seen that the 90% credible intervals of all first-order input and output elasticities at their respective geometric means do not contain zero.

The scale elasticity is -1.09, which reveals that DHBs operate at decreasing returns to scale, signifying that a 1% increase in all inputs leads to an approximately 0.9% increase in the number of inpatients and outpatients treated by DHBs. The first order coefficient of time (*trend*) is -0.004, implying an extremely low magnitude of technical regress at the sample mean between 2011 and 2018.

[20] The relative inefficiency factor of a parameter is computed by using the formula $1 + 2\sum_{\varphi=1}^{\infty} g(\varphi)$, where $g(\varphi)$ is the sample autocorrelation of the draws on the parameter at lag φ.

Table 4.2 Posterior means, standard deviations and 90% credible intervals

Variable	Posterior Mean	Standard Deviation	90% credible interval
log_inpatients	-0.81	0.03	[-0.86, -0.77]
log_outpatients	-0.28	0.03	[-0.33, -0.23]
log_other_staff	0.08	0.02	[0.04, 0.12]
log_clinical_cost	0.19	0.03	[0.15,0.23]
log_out_cost	0.08	0.01	[0.06,0.09]
log_capital	0.06	0.02	[0.03, 0.09]
log_other_staff ^{2}	-0.01	0.09	[-0.17, 0.14]
log_clinical_cost ^{2}	0.27	0.12	[0.07, 0.47]
log_out_cost ^{2}	0.02	0.02	[-0.02, -0.05]
log_capital ^{2}	0.11	0.09	[-0.04, 0.26]
log_inpatients ^{2}	-0.98	0.12	[-1.18, -0.78]
log_outpatients ^{2}	-1.24	0.19	[-1.54, -0.94]
log_other_staff × *log_clinical_cost*	0.01	0.10	[-0.15, 0.18]
log_other_staff × *log_out_cost*	-0.09	0.04	[-0.16, -0.03]
log_other_staff × *log_capital*	0.08	0.07	[-0.03, 0.19]
log_other_staff × *log_inpatients*	-0.15	0.10	[-0.32, 0.01]
log_other_staff × *log_outpatients*	0.11	0.13	[-0.09, 0.31]
log_clinical_cost × *log_out_cost*	-4.8×10^{-3}	0.04	[-0.08, 0.06]
log_clinical_cost × *log_capital*	0.13	0.06	[0.02, 0.23]
log_clinical_cost × *log_inpatients*	-0.03	0.10	[-0.20, 0.12]
log_clinical_cost × *log_outpatients*	0.10	0.12	[-0.10, 0.30]
log_out_cost × *log_capital*	-0.04	0.03	[-0.09, 3.7×10^{-3}]
log_out_cost × *log_inpatients*	-0.01	0.04	[-0.08, 0.05]
log_out_cost × *log_outpatients*	-0.03	0.05	[-0.10, 0.05]
log_capital × *log_inpatients*	-0.14	0.07	[-0.26, -0.02]
log_capital × *log_outpatients*	0.20	0.10	[0.04, 0.37]
log_inpatients × *log_outpatients*	1.09	0.15	[0.84, 1.33]
quarter 1	0.06	3.7×10^{-3}	[0.05, 0.06]
quarter 2	0.01	3.7×10^{-3}	[5.4×10^{-3}, 0.02]
quarter 3	-0.03	4.1×10^{-3}	[-0.04, -0.02]
trend	-4.0×10^{-3}	7.6×10^{-4}	[-5.3×10^{-3}, -3.0×10^{-3}]
trend ^{2}	1.9×10^{-4}	5.8×10^{-5}	[9.8×10^{-5}, 2.9×10^{-4}]
constant	0.26	0.04	[0.20, 0.34]
Dynamic parameters			
constant	0.03	0.01	[0.01, 0.05]
$\boldsymbol{\rho}$	97.61 %	7.3×10^{-3}	[96.30 %, 98.66 %]
Precision parameters			
$\boldsymbol{\tau}$	1719.60	284.80	[1340.12, 2249.80]
$\boldsymbol{\phi}$	79.82	24.88	[46.85, 126.05]
Standard deviations			
$\boldsymbol{\sigma_v}$	0.02	1.9×10^{-3}	[0.02, 0.03]
$\boldsymbol{\sigma_s}$	0.12	0.02	[0.09, 0.15]
Long-run TE	0.76		
Log marginal likelihood (Lewis & Raftery, 1997)	846.43		

The posterior mean of the autoregressive equation shows that the persistence parameter, $\boldsymbol{\rho}$ is close to 97.61%. With a minimal standard deviation of 0.01, this value of $\boldsymbol{\rho}$ implies that technical inefficiency is highly persistent among New Zealand DHBs. This high persistence shows the existence of significant adjustment costs in the New Zealand public healthcare sector, which prevents DHBs from operating at a technically efficient level in the short run. In other words, the high persistence parameter highlights the fact that New Zealand DHBs operate in an environment where certain factors are costly to adjust to optimum levels for the efficient delivery of hospital services.

Furthermore, in the presence of these high adjustment costs, DHBs will choose to remain inefficient in the short run and instead aim to reach the sector's long-run technical efficiency (LRTE[21]) over time. Based on the estimated IDF, the LRTE for New Zealand DHBs is calculated to be 0.76. This value of LRTE implies that New Zealand DHBs use 32% more inputs on average in providing hospital services due to their inability to adjust their operations instantaneously.

Given the long-run equilibrium efficiency level of 0.76, the measure of short-run technical efficiency (SRTE) shows how each DHB performs against this equilibrium value. The overall average of the national SRTE is estimated to be 0.76, which is equal to the LRTE. The average measure of short-run technical efficiency (SRTE) scores for each DHB are listed with their coefficient of variation (CV) and ranking[22] in Table 3.

The equality between the average SRTE and the sector's LRTE indicate that during the period 2011-2018, most DHBs remain close to the long-run equilibrium or steady-state level of performance. This implies that there were no noticeable structural changes between 2011 and 2018 in the New Zealand public healthcare sector that would make DHBs more or less efficient.

The full year by year average measure of SRTE for each DHB is listed in Appendix E. The kernel density plot of the SRTE is also displayed in Appendix F. The time series plot of the SRTE scores for each DHB is plotted in Appendix G.

[21] The LRTE corresponds to the expected value of LRTE calculated as $\left[1 + exp\{\omega_j/(1-\rho_j)\}\right]^{-1}$, where j indicates the jth draw from the posterior density.

[22] DHBs with the same average efficiency scores and CVs are assigned the same ranking. On the other hand, a DHB with low CV but same average efficiency compared to its counterpart is given a high ranking. A low CV indicates low variability in efficiency signifying consistent performance.

Table 4.3 Estimates of yearly mean SRTE scores

DHB	Rank	Mean	CV
Wairarapa	1	0.87	0.03
Bay of Plenty	1	0.87	0.03
South Canterbury	2	0.87	0.05
Canterbury	3	0.84	0.03
Waikato	4	0.83	0.01
Southern	5	0.83	0.02
Lakes	6	0.79	0.03
Hutt Valley	7	0.78	0.02
Taranaki	8	0.77	0.02
Nelson Marlborough	9	0.76	0.05
Whanganui	10	0.75	0.02
Counties Manukau	11	0.75	0.03
Northland	11	0.75	0.03
Waitemata	12	0.73	0.07
Hawke's Bay	13	0.72	0.03
Mid Central	14	0.69	0.02
Auckland	15	0.67	0.03
West Coast	16	0.67	0.10
Capital & Coast	17	0.65	0.03
Tairawhiti	18	0.65	0.05
Grand Mean		0.76	

4.6 Discussion

The results from Table 4.3 show that six (30%) of DHBs are operating between overall mean efficiency of 0.72-0.76; i.e., close to the long-run equilibrium performance level, whereas nine DHBs are performing above the long-run equilibrium. The time series plot of the SRTE scores for each DHB in Appendix G shows that most DHBs posted steady performance around their average technical efficiency scores, except Northland, South Canterbury, Mid Central and Nelson Marlborough, which showed signs of a deteriorating efficiency performance between 2011 and 2018. Furthermore, Nelson Marlborough and South Canterbury also have a relatively high coefficient of variation in their performances, indicating weak and unstable performance.

The empirical results also show that over the period from 2011-2018, New Zealand DHBs witnessed a small technological regress. However, this is not surprising as there has been long and overdue underinvestment in modern clinical and information technology among DHBs in New Zealand (Controller and Auditor-General, 2016a). Another reason for low technological progress may be the absence of fee-for-service payments to medical staff, which offer a much greater incentive to adopt new technologies (Allsopp, 2006).

From the measure of the SRTE in Table 4.3, it is clear that most New Zealand DHBs are operating close to or above the LRTE value. In comparison to Jiang and Andrews (2019), who estimated the average technical efficiency (i.e., SRTE) of 0.86 without inefficiency persistence, this study reveals that most DHBs are performing exceptionally well relative to the long-run equilibrium efficiency level in the sector. Instead, a more pressing issue is the existence of high adjustment costs that restrict DHBs ability to become more efficient in the long run. Though some part of persistence in technical efficiency will always remain, based on DHBs expenditure in the 2017/18 financial year (Ministry of Health, 2018d), a 1% reduction in long-run technical inefficiency would have saved approximately 165 million NZ dollars in the 2017/2018 fiscal year.

Concerning the SRTE, as seen earlier, four out of the five DHBs that posted the lowest SRTE scores operate in urban areas. Of the four lowest-performing urban DHBs, Auckland (0.67) and Capital & Coast DHBs (0.65) stand out as the only tertiary DHBs to fall to the bottom of the efficiency performance rankings. All other tertiary and urban DHBs, such as Canterbury (0.84), Waikato (0.83), Southern (0.83), operate above the LRTE level (0.76), except Counties Manukau (0.75), which operates just under the LRTE level. This points towards the fact that Auckland and Capital & Coast DHBs are not effective in utilising their inputs efficiently in providing hospital services and, therefore, need to review their management practices by measuring themselves against the top urban and tertiary DHBs.

Of the two poorest operating DHBs, Tairawhiti and West Coast deserve some attention. Tairawhiti DHB posted the worst performance with an average technical efficiency of 0.65. The Tairawhiti DHB operates the Gisborne hospital in a region with close to a 50 per cent Maori population and a very high proportion of people living in poverty (Ministry of Health, 2019b). Many people in Tairawhiti experience significant housing, education, and economic inequality compared to the rest of New Zealand and witness a high proportion of patients with long-term conditions such as heart disease and stroke (Robson et al., 2015). The Māori population in Tairawhiti also experience an early onset of long-term conditions such as cardiovascular disease and diabetes. This implies that the management of patients with such chronic and long-term conditions requires greater resources at the hospitals, a metric that may not be adequately reflected in the hospital outputs.

The West Coast DHB, which posted the second-lowest average technical efficiency score of 0.67, operates one secondary care hospital in Greymouth. Unlike any other New Zealand DHB, the West Coast DHB operates in one of the most isolated and geographically spread out parts of New Zealand. Being the sole provider of hospital services in the area, the West Coast DHB is bound to have some degree of excess resources available at all times so that hospital services can be provided readily to the local population. This argument is supported by Färe et al. (1989), who point towards the unexpected nature of the demand for hospital services that result in a level of inefficiency at all times.

Further, due to the isolation of the West Coast, the region has experienced an acute shortage of medical and allied staff in its hospitals over a long period due to the difficulty in recruiting and retaining medical staff (Health Workforce New Zealand, 2015; West Coast District Health Board, 2017). To meet the demand in the hospitals, DHBs rely heavily on expensive outsourced staff and medical locums (West Coast District Health Board, 2018b). High reliance on locums and external staff raise expenditure and, as a result, has caused persistent budget deficits for West Coast DHBs over the past few years (West Coast District Health Board, 2014a, 2015, 2016, 2018a).

The West Coast DHB also has the highest proportion of patients who miss hospital specialist and outpatient appointments (West Coast District Health Board, 2014b, 2018b). This contributes to a high degree of inefficiency by wasting medical staffs time and other resources. Additionally, this leads to patients' condition worsening in the future and increases avoidable admissions and the length of stay in the hospitals (West Coast District Health Board, 2014b), leading to high resource use per admission. The West Coast region also has one of the highest proportions of people over 65 (14.5%), contributing to a high hospital admission rate and length of stay (West Coast District Health Board, 2014b).

4.7 Concluding remarks

For the first time in the healthcare literature, this chapter has applied the dynamic stochastic frontier model proposed by Tsionas (2006) to account for the persistence in technical efficiency due to the existence of adjustment costs. In contrast to the static model, this dynamic model recognises that DHBs may partly choose to remain inefficient in the short run and instead aim to reach the sector's long-run equilibrium efficiency.

This chapter's results show the inefficiency persistence parameter to be 97.61 %, which provides compelling evidence that significant adjustment costs exist among New Zealand DHBs. The high adjustment costs may be related to government regulations and target-driven incentives. The empirical findings of this chapter can be summarised as follows:

1. The LRTE of New Zealand DHBs is estimated to be 0.76, which suggests that New Zealand DHBs used on average 32% more inputs due to the high adjustment costs in the sector.
2. While all large and tertiary DHBs operated close to the LRTE, Auckland and Capital & Coast DHBs, two of the largest tertiary hospital service providers appear to be operating below the LRTE at 0.67 and 0.65, respectively. Similarly, Tairawhiti, West Coast and Mid Central posted the lowest SRTE scores among secondary hospital service providers.

3. The national average SRTE is also found to be 0.76, which indicates that most DHBs performed close to the long-run efficiency level. Therefore, future policy-related research should focus on understanding adjustment costs that are restricting the DHBs ability to be more efficient in the long run.

Chapter 5 Estimating the cost efficiency of New Zealand District Health Boards in providing hospital services: A Bayesian Random-Effects Dynamic Stochastic Frontier Approach

Abstract

In healthcare literature, input-oriented technical efficiency measures the degree to which inputs are fully utilised under the available technology to provide a given amount of healthcare services. However, it is also essential for policymakers to evaluate the health care providers' ability to choose a mix of inputs that minimize the cost of providing a given amount of healthcare services. Using longitudinal data on 20 New Zealand DHBs between 2011 and 2018, this study aims to evaluate the cost efficiency of DHBs in the presence of adjustment costs while controlling for heterogeneity at the DHB level. A random-effects dynamic stochastic cost frontier model is estimated and compared to three other specifications where either observed/unobserved heterogeneity or both are ignored to demonstrate the existence of bias in the cost function parameters and cost efficiency scores.

The results indicate that ignoring heterogeneity in the cost function induces not only a downward bias in cost efficiency scores but also biases the estimates of cost function slopes, particularly the economies of scale elasticity. This highlights the fact that it is crucial to control for heterogeneity in cost functions as the robustness of parameters and efficiency scores provides regulatory authorities insights into performance levels to design incentive mechanisms to improve the healthcare system's overall productivity. Furthermore, cost efficiency estimates from the random-effects dynamic specification indicate that New Zealand DHBs spent approximately 7.50% more on average in 2011-2018 due to the high persistence in cost inefficiency. Rural[23] DHBs, on the other hand, face higher levels of long-run cost inefficiency resulting in over-spending by around 15% of annual budgets. All four dynamic stochastic frontier specifications indicate that most DHBs operated very close to their average long-run equilibrium level of cost-efficiency.

[23] Rural DHBs in this context does not mean that DHBs have acute hospitals that are physically located in rural area, but rather it is used to denote DHBs that have a substantial number of the population under its coverage living in rural and remote areas. Often main hospitals are located in the main town or city where people commute to seek hospital treatments.

5.1 Introduction

Public health costs have continued to increase since the formation of DHBs, with many DHBs reporting regular budget deficits despite a steady increase in funding over time (The Treasury, 2017a). In the light of increasing budget deficits, recent public health audit reports have raised serious concerns about the DHBs' management of public funds and their ability to provide hospital services at a low cost (Controller and Auditor-General, 2014, 2016b, 2018). The findings of audit reports point towards the existence of some level of inefficiency that may be contributing to the rising budget deficits. Several empirical studies in the healthcare literature have suggested that the direct result of inefficient operations is increasing healthcare costs (Bentley et al., 2008; Rosko, 2001; Welch, 1987; Zuckerman et al., 1994).

The structural reforms of 2000 reintroduced the local governance system, which gave DHBs considerable autonomy in managing funds. Specifically, DHBs are required to provide quality hospital services at the lowest cost, subject to their annual budgets (Knopf, 2017). However, since the establishment of DHBs, their performances have been continuously debated among policymakers (Knopf, 2017; Maniparathy, 2008; The Treasury, 2005). According to the public sector accountability, disclosure and transparency standards of New Zealand (Webster et al., 1998), DHBs are required to publish detailed accounts throughout the financial year and are expected to implement remedial measures to control costs and increase access to hospital services.

The information in the financial statement is closely related to cost-effectiveness, which can be thought of as a metric that measures the healthcare system's capability to produce desired health outcomes in the population. Cost-effectiveness is often used to compare alternative healthcare interventions by estimating how much it costs to gain additional health outcomes or life-year (Centers for Disease Control and Prevention [CDC], 2019). Although a financial statement may indicate whether or not a DHB is cost-effective, it does not in any way address whether hospital services are offered at the least cost (Jacobs et al., 2006, pp. 2,10).

The measure of "cost efficiency" can provide a meaningful measure of the extent to which healthcare services are provided at the minimum possible cost. The cost efficiency measure is often considered as a combination of input-oriented technical and allocative efficiency (Coelli et al., 2005, pp. 53-54). Input-oriented technical efficiency measures a healthcare unit's ability to provide healthcare service(s) with minimum input(s). In contrast, allocative efficiency measures the ability to provide service(s) with input combinations that cost the least given current prices and outputs. According to Knopf (2017), since 2009, public authorities have placed considerable weight on reducing inefficiency to free up resources for more front-line hospital services.

When stochastic frontier analysis (SFA) is used to assess cost efficiency using longitudinal data on healthcare providers, unit-specific differences must be taken into account for cost-influencing unit-specific heterogeneity. Failure to adjust for unobserved heterogeneity can result in heterogeneity bias (Hsiao, 2003, pp. 8-9), which may substantially underestimate or overestimate cost efficiency measures, frontier slope estimates, such as input elasticities, scale, and scope effects. Furthermore, as healthcare providers often maintain a reserve or standby capacity to meet unanticipated health needs (Friedman, 1999; Gaynor & Anderson, 1995), estimates of actual marginal treatment costs may be distorted if considerations such as excess capacity remain hidden in unobserved heterogeneity has not been captured by the cost functions.

As shown in the previous chapter, the application of the dynamic stochastic frontier is vital as it accounts for the persistence in inefficiency. While it is necessary to account for persistence in cost inefficiency, it is equally important to consider the heterogeneity related to capacity, speciality, demographics and size that affects costs that DHBs cannot alter. These influences of these factors must be isolated from other parameters to obtain unbiased estimates of cost function parameters and efficiency (Jacobs et al., 2006). While using electricity data, Emvalomatis (2012) extended the original dynamic stochastic frontier model by Tsionas (2006) by including random effects to account for unobserved heterogeneity. Its application in healthcare studies remains to be explored.

Using quarterly balanced data on 20 New Zealand DHBs from 2011 to 2018, this study uses a dynamic stochastic frontier model (Tsionas, 2006) and a random effects dynamic stochastic frontier (Emvalomatis, 2012) with varying specifications of heterogeneity to compare and contrast parameter estimates of the cost function, and long and short-run cost efficiencies.

The results indicate that omitting DHB-specific effects from the specification results in significant heterogeneity bias in the estimation of cost efficiency and other parameters due to high variations in costs between DHBs. The results emphasize that both observed and unobserved heterogeneity across healthcare providers must be considered when estimating cost functions in healthcare to obtain more accurate estimates of cost function parameters and cost efficiency scores.

5.2 Stochastic cost frontier

A simple stochastic frontier model with cost inefficiency can be represented as:

$$c_{it}^{a} = c\left(w_{1it}, w_{2it}, \cdots, w_{Kit}, y_{1it}, y_{2it}, \cdots y_{Jit}\,; \beta\right) exp\,\{v_{it} + u_{it}\} \qquad (5.1)$$

where the subscripts i and t denote the organisation and time, respectively, c_{i}^{a} is the observed or actual cost of DHB i; w_{ki} is the k-th input price of the i-th DHB; y_{ji} is the number of the j-

the healthcare services provided by DHB i and β are the vector of parameters to be estimated that captures the relationship between the total expenditure and explanatory variables in the cost specification.

Following the SFA's fundamental assumptions, the error term is denoted by v_i which represents random events and measurement errors, whereas u_i captures cost inefficiency. Once the stochastic cost frontier is estimated based on the observed data, the measurement of cost efficiency(ce) can be computed by the ratio of stochastic expenditure to the actual cost. This can mathematically be represented as:

$$ce_{it} = \frac{c(w_{1it}, w_{2it}, \dots\dots, w_{Kit}, y_{it}; \beta)\ exp\{v_{it}\}}{c(w_{1it}, w_{2it}, \dots\dots, w_{Kit}, y_{it}; \beta)\ exp\{v_{it}\}\ exp\{u_{it}\}} = exp\{-u_{it}\} \tag{5.2}$$

The measurement of cost efficiency using the SFA involves estimating the cost function based on data on observed total expenditure, prices of inputs and amount of healthcare services. When longitudinal data are available, and a translog cost specification in input prices and outputs with a linear and quadratic trend can be used to approximate the cost function and can be written as:

$$\begin{aligned} \log c_{it}^{a} = {} & \alpha + \sum_{j=1}^{J} \alpha_j \log y_{jit} + \frac{1}{2} \sum_{j=1}^{J} \sum_{h=1}^{J} \alpha_{jh} \log y_{jit} \log y_{hit} \\ & + \sum_{k=1}^{K} \beta_k \log w_{kit} + \frac{1}{2} \sum_{k=1}^{K} \sum_{p=1}^{K} \beta_{kp} \log w_{kit} \log w_{pit} \\ & + \sum_{k=1}^{K} \sum_{j=1}^{J} \delta_{kj} \log w_{kit} \log y_{jit} + \gamma_t\, t + \frac{1}{2} \vartheta_{tt} t^2 + v_{it} \\ & + u_{it} \end{aligned} \tag{5.3}$$

where the subscripts i and t denote the DHB and time, respectively, whereas, $ln\, y_{jit}$ and $ln\, w_{kit}$, represent the natural logarithm of quantities for healthcare services and input prices, respectively. Furthermore, $t = 1, \dots, T$ is a linear time trend and t^2 captures the quadratic trend in the cost specification. According to Kumbhakar et al. (2015, pp. 105-107), a well-behaved cost function is homogeneous of degree one in the input prices, monotonically increasing in input prices and outputs, and concave in input prices.

If the subscript t is dropped from Eq. (5.3) for the sake of concision, the requirement of the homogeneity of degree one in input prices (i.e., $w_1, w_2, \dots, w_K$) is satisfied if the following parameter restrictions hold:

$$\sum_k \beta_k = 1, \quad \sum_k \beta_{kp} = 0 \,\forall\, p, \quad \sum_k \delta_{kj} = 0 \,\forall\, j\,. \tag{5.4}$$

In practice, the homogeneity condition is often imposed by using w_{ki} for an arbitrary choice of k to normalise c_i^a and other input prices. For the monotonicity condition to be satisfied for the cost function, the cost must be nondecreasing in input prices and healthcare services. If the first derivate of the actual cost is c_i^a with respect to the input price w_{ki} can be represented as:

$$\frac{\partial c_i^a}{\partial w_{ki}} = \frac{\partial \log c_i^a}{\partial \log w_{ki}} \times \frac{c_i^a}{w_{ki}} \tag{5.5}$$

and if both c_i^a and w_{ki} are positive, then, according to Kumbhakar et al. (2015, p. 106):

$$sign\left(\frac{\partial c_i^a}{\partial w_{ki}}\right) = sign\left(\frac{\partial \log c_i^a}{\partial \log w_{ki}}\right) \tag{5.6}$$

Using Shephard's Lemma, the partial derivate on the right-hand side of Eq. (5.6) is simply the cost share of the input w. Therefore, the monotonicity condition on input prices can be checked by merely looking at the estimated cost shares at each observation.

In the case of the translog cost function in Eq. (5.3), the partial derivatives with respect to input prices (i.e., the input shares) are:

$$\frac{\partial \log c_i^a}{\partial \log w_{fi}} = \beta_f + \sum_k \beta_{fk} \log w_{ki} + \sum_k \delta_{fj} \log y_{ji} \qquad f = 1, \dots, K \tag{5.7}$$

Similarly, the monotonicity of output can be checked by the sign of $\partial \, ln\, c_i^a / \partial \, ln\, y_{ji}$.

$$\frac{\partial \log c_i^a}{\partial \log y_{gi}} = \beta_g + \sum_j \beta_{gj} \log y_{ji} + \sum_j \delta_{gk} \log w_{ki} \qquad g = 1, \dots, J \tag{5.8}$$

When the variables in the translog cost function are normalised by their respective geometric means, the parameters of first-order terms can be compared against the actual input expenditure shares to test the adherence to theory at the mean of the data.

Once a translog cost function is estimated, the measure of global[24] economies of scale and scope can be computed. If a cost function has more than one output, the concept of ray scale

[24] Global economies of scale relates to the change in cost as a result in proportional changes in all the healthcare services.

economies can be used, which is defined as the proportional increase in total costs resulting from a proportional increase in all outputs. Baumol (1982) showed that for a multi-product cost function, the economies of scale (ES) of the output vector y_j could be calculated using the cost elasticities as:

$$ES = \frac{c^a(y_1, y_2, \dots, y_J)}{\sum_{j=1}^{J} y_j \frac{\partial c^a}{\partial y_j}} = \frac{1}{\sum_{j=1}^{J} \frac{\partial \log c^a}{\partial \log y_j}} \tag{5.9}$$

The ES estimation in Eq. (5.9) calculates total economies of scale given that the product bundle composition stays constant, i.e. every output is expanded in the same proportion (Smet, 2007). If $ES < 1$, the costs rises higher in proportion to the set of healthcare services, i.e., the DHB's operate with diseconomies of scale. Similarly, if $ES > 1$, the cost function implies DHBs benefit from global economies of scale, whereas $ES = 1$ implies constant returns to scale.

The estimated translog cost function in Eq. (5.3) can also be used to estimate the economies of scope (ESC), which occur if the cost of jointly delivering a collection of healthcare services together is lower than the cost of providing such services separately (Panzar & Willig, 1981). However, the translog cost function cannot be used to estimate ESC directly as it does not permit zero values of any output in estimation or prediction (Pulley & Humphrey, 1993).

An alternate approach to testing the ESC's presence is to use sufficient conditions based on weak cost complementarities (WCC) put forward by Baumol (1982) and Baumol (1986). The WCC condition for ESC for two products y_j and y_h can be formally written as follows:

$$\frac{\partial^2 c^a}{\partial y_j \partial y_h} \leq 0; \text{ for all } j \neq h. \tag{5.10}$$

At the translog approximation point, the WCC condition can be tested by checking the following condition:

$$\frac{\partial^2 \log c^a}{\partial \log y_j \, \partial \log y_h} + \frac{\partial \log c^a}{\partial \log y_j} \times \frac{\partial \log c^a}{\partial \log y_h} \leq 0; \text{ for all } j, h, \text{ with: } j \neq h. \tag{5.11}$$

Complementarity economies rely on the existence of the complementary of costs between two separate outputs, which means that an output's marginal cost decreases or at least does not increase when the quantity produced of the other output increases (Baumol et al., 1983). As the cost complementarity condition is a marginal condition, the existence of high fixed costs does not affect the measure of ESC.

5.3 Econometric specification and model estimation

As seen earlier, the estimated translog cost function should be homogenous of degree one in the input price, which can be easily imposed by normalising input prices and total costs by dividing by one common input price. Once the homogeneity is imposed, Eq. (5.3) can be written as:

$$\begin{aligned}\log\left(\frac{c_{it}^{a}}{w_{1it}}\right) = {} & \alpha_0 + \sum_{j=1}^{J} \alpha_j \log y_{jit} + \frac{1}{2}\sum_{j=1}^{J}\sum_{h=1}^{J} \alpha_{jh} \log y_{jit} \log y_{hit} \\ & + \sum_{k=2}^{K} \beta_k \log\left(\frac{w_{kit}}{w_{1it}}\right) + \frac{1}{2}\sum_{k=2}^{K}\sum_{p=2}^{K} \beta_{kp} \log\left(\frac{w_{kit}}{w_{1it}}\right) \log\left(\frac{w_{pit}}{w_{1it}}\right) \\ & + \sum_{k=2}^{K}\sum_{j=1}^{J} \delta_{kj} \log\left(\frac{w_{kit}}{w_{1it}}\right) \log y_{jit} + \gamma_t\, t + \frac{1}{2}\vartheta_{tt} t^2 + v_{it} \\ & + u_{it}\end{aligned} \quad (5.12)$$

where parameters $\alpha, \beta, \delta, \gamma \ and\ \vartheta$ are unknowns to be estimated. Further, in Eq. (5.12), the following constraints are also satisfied $\sum_{k=1}^{K} \beta_k = 1,\ \sum_{k=1}^{K} \beta_{kp} = 0,\ \sum_{p=1}^{K} \beta_{kp} = 0$ and $\sum_{k=1}^{K} \delta_{kj} = 0$. The term $u_{it}$is the measure of the short-run cost inefficiency of DHB i at time t.

The model in Eq. (5.12) can be written compactly for the sake of brevity as:

$$c_{it} = x_{it}'\beta + v_{it} + u_{it} + \tau_i, \quad \tau_i \sim N(0, \sigma_\tau^2) \quad (5.13)$$

where c_{it} represents the dependent variable and x is a vector of the independent variables, including a constant term in Eq. (5.12), where β is the vector of corresponding slope parameters to be estimated, v_{it} is an idiosyncratic error that captures random disturbances to the DHB expenditure and u_{it}, is the measure of short-run cost inefficiency.

To separate the effect of unobserved heterogeneity, a random effect variable τ_i is specified to capture DHB-specific effect or heterogeneity that affects the costs and have zero mean since there is a constant in x_{it}. The independent variables are assumed to be uncorrelated with the cost inefficiency.

Taking into account the persistence in cost inefficiency due to high adjustment costs, following Skevas et al. (2018), the dynamic nature of cost inefficiency is specified in an autoregressive process. This specification recognises DHB-specific inefficiency persistence that results from the heterogeneity in adjustment costs, as suggested by Galán et al. (2015).

The autoregressive process on s_{it} can be defined as:

$$s_{it} = \omega + z_i'\varphi + \rho s_{it-1} + \eta_{it}, \quad \eta_{it} \sim N(0, \sigma_\eta^2), \quad t = 2 \ldots T \quad (5.14)$$

where ω is a constant, z_i' is the vector of time-invariant DHB-specific variables that affects the long-run cost inefficiency and ρ is the persistence parameter measuring the proportion of the dynamic part of cost inefficiency that is transmitted from one period to the next. The variable η_{it} represents the unobserved random shocks to the dynamic component representing the 'unexpected log-cost inefficiency sources' and follows a normal distribution with variance σ_η^2.

Stationarity in the dynamic process of Eq. (5.14) is imposed by the specification of s_{it}in the first period that initialises the dynamic process:

$$s_{i1} = \frac{\omega + z_i'\varphi}{1-\rho} + \eta_{i1}, \;\; \eta_{it} \sim N\left(0, \frac{\sigma_\eta^2}{1-\rho^2}\right), \quad t = 1. \tag{5.15}$$

Following the specification inefficiency distribution put forward by Emvalomatis (2012) where s_{it} follows a normal distribution can be written as:

$$s_{it} = \log\left(\frac{e^{-u_{it}}}{1-\ e^{-u_{it}}}\right) \tag{5.16}$$

where efficiency score, $e^{-u_{it}}$ conditional on s_{it-1} and z_i follows a logit-normal distribution. The short-run cost efficiency score is found by solving Eq. (5.16) for $CE_{it} = e^{-u_{it}}$. From Eq. (5.14) the measure of the long-run expected value of cost efficiency s_i for each DHB can be also found by using the equation $[1 + exp\{\boldsymbol{z_i'\varphi}/(1-\rho)\}]^{-1}$.

Bayesian techniques are used to estimate the model described in Eq. (5.13)- (5.15). To demonstrate the likelihood of the structural parameters and latent states, s_i is defined to be a $T \times 1$ vector of the hidden state variable in the dynamic equation for DHB i. Next, collect all structural parameters to be estimated to a vector $\theta = \left[\beta, \sigma_v, \varphi, \rho, \sigma_\eta, \sigma_\tau\right]'$.

Therefore, the complete data likelihood of the structural parameters and latent states based on Eq. (5.13)- (5.15) is:

$$p\left(c, \{\tau_i\}, \{s_i\} \,\middle|\, \theta, X, Z\right) = p\left(c \,\middle|\, \{\tau_i\}, \{s_i\}, \beta, \sigma_v, X\right) \times p\left(\{s_i\} \,\middle|\, \omega, \rho, \sigma_\eta, Z\right) \times p(\{\tau_i\} \,|\, \sigma_\tau) \tag{5.17}$$

$$= \frac{1}{(2\pi\sigma_v^2)^{\frac{NT}{2}}} exp\left\{-\frac{\sum_{i=1}^{N}\sum_{t=1}^{T-1} (c_{it} - \tau_i - p_{it}'\beta - u_{it})^2}{2\sigma_v^2}\right\}$$

$$\times \frac{1}{\left(2\pi\sigma_{u_1}^2\right)^{\frac{N}{2}}} exp\left\{-\frac{\sum_{i=1}^{N}(s_{i1} - \omega_1 - z_i'\varphi)^2}{2\sigma_{u_1}^2}\right\}$$

$$\times \frac{1}{(2\pi\sigma_u^2)^{\frac{N(T-1)}{2}}} exp\left\{-\frac{\sum_{i=1}^{N}\sum_{t=2}^{T-1} (s_{it} - \omega - z_i'\varphi - \rho s_{it-1})^2}{2\sigma_u^2}\right\}$$

$$\times \frac{1}{(2\pi\sigma_\tau^2)^{\frac{N}{2}}} exp\left\{-\frac{\sum_{i=1}^{N}\tau_i^2}{2\sigma_\tau^2}\right\}$$

where c and X are, respectively, the stacked vector and matrix, over both i and $t,$ of the dependent and independent variables as in Eq. (5.13), and Z is the matrix of covariates in Eq. (5.14) and (5.15).

Using Bayes' rule, the posterior joint density of the model parameters and latent states is:

$$\pi\left(\theta, \{s_i\}, \{\tau_i\} \,\middle|\, c, X, Z\right) \propto p\left(c, \{\tau_i\}, \{s_i\} \,\middle|\, \theta, X, Z\right) \times p(\theta) \qquad (5.18)$$

where $p\left(c, \{\tau_i\}, \{s_i\} \,\middle|\, \theta, X, Z\right)$ is given by Eq. (5.17) and $p(\theta)$ corresponds to the prior density of parameters.

All the priors are the same as in the previous chapter. The new variables φ and τ_i are also assumed to have multivariate normal density with prior means zero and prior covariance matrix with diagonal values of 1,000.

5.4 Data and descriptive statistics

The data set includes balanced quarterly observations for the period 2011-2018 (T=32) on each DHB's expenditure, prices, outputs and other DHB indicators such as size and speciality. The total DHB expenditure is the sum of the expenditure on labour, clinical supplies, outsourced labour and clinical services, depreciation, interest and capital charges[25]. Since the price of labour, capital, and other inputs are not directly available, they are computed using data on expenditure, FTEs and various available price indexes. The prices of all the different labour groups are computed by dividing each DHB's labour costs by the respective FTEs in each period. Apart from the price of medical staff, the price of nursing, allied, support and management staff were aggregated by weighing them based on their share of total labour expenditure for these categories to form a weighted price measure for other staff.

Unlike the labour price, it is more difficult to estimate the cost of capital in healthcare. Under the neoclassical theory of investment, the price of capital is the rental price of capital, which is equal to the marginal product of capital (Eisner & Nadiri, 1968). Therefore, the rental price, or the price of capital, is considered to be the sum of the interest rate or the borrowing cost of capital and the depreciation rate (Harcourt & Riach, 1997a). In this study, following the neoclassical approach, the price of capital is estimated as the sum of the depreciation rate[26], the capital charge rate[27] and the treasury bond rate[28].

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[25] DHBs pays capital charges to the crown every six months. The charge is based on the previous six months actual closing equity balance at 31 December and 30 June. The capital charge represents the opportunity cost of money – what the government can expect to earn in alternative investments entailing similar risk. It may be thought of as an internal rate of return on the government's investment in its own entities.

[26] The depreciation rate is calculated by dividing the depreciation expenditure by the total value of capital assets.

[27] The data on capital charge rates was obtained from The Treasury (2018).

[28] The data on treasury bond rates was obtained from the Reserve Bank of New Zealand (2019).

The input indices from the producer price index[29] are used to approximate the price of clinical supplies and outsourced labour and clinical services, as no direct measure of prices is available. The Pharmaceutical Products Index is used to approximate the price of clinical supplies. A weighted index was also constructed to approximate the price of outsourced labour and clinical services to reflect variations in the price of outsourced labour and clinical services. The aggregate input price of outsourced labour and clinical services is thus the sum of the Healthcare Wages Index and the Healthcare Provider Index, weighted based on their share of overall outsourced spending.

The case-weighted inpatient discharges and price-weighted outpatient visits are used as the measure of outputs in this study. Information on the average number of beds for each DHB, size and a rurality indicator was also collected. The summary statistics of all the variables used in this chapter are shown in Table 5.1.

Table 5.1 Summary statistics of variables

Variable	Statistics	
Input Prices‡		
Medical staff price *(med_ price)*	Minimum	11.61
	Maximum	31.42
	Mean	17.86
	Standard deviation	3.18
Other staff price *(other_ price)*	Minimum	17.53
	Maximum	33.69
	Mean	21.57
	Standard deviation	1.52
Price of capital *(capital_ price)*	Minimum	0.07
	Maximum	0.12
	Mean	0.09
	Standard deviation	0.01
Price of outsourced labour and clinical services *(out_price)*	Minimum	101
	Maximum	114
	Mean	103
	Standard deviation	2
Price of clinical supplies *(clinical_price)*	Minimum	101
	Maximum	111
	Mean	106
	Standard deviation	3

[29] The price index can be accessed at can be accessed at Statistics New Zealand (2019).

Outputs		
Case-weighted inpatients *(inpatients)*	Minimum	797.73
	Maximum	36,574.26
	Mean	10,334.19
	Standard deviation	8,794.45
Price-weighted outpatient visits *(outpatients)*	Minimum	610.23
	Maximum	8,369.72
	Mean	3,378.82
	Standard deviation	2,171.94
Average DHB beds *(beds)*	Minimum	102
	Maximum	1685
	Mean	590
	Standard deviation	462
Expenditure‡		
Total expenditure (*total expenditure*)	Minimum	12,702.00
	Maximum	408,669.40
	Mean	98,232.97
	Standard deviation	82,298.66
DHB specific characteristics indicator		
Medium (1 = Medium, 0 = all others)	Frequency	256
	Proportion	0.40
Small (1 = Small, 0 = all others)	Frequency	160
	Proportion	0.25
Rural (1 = Rural, 0 = Urban)	Frequency	288
	Proportion	0.45

‡ Reported in thousands of New Zealand Dollars

5.5 Empirical results and discussion

The MCMC sampling process involved five independent Markov chains. Each chain contributed 100,000 iterations towards the posterior distributions of the model parameters. A burn-in phase of 70,000 iterations is used to remove the influence of initial values. Since the random walk Metropolis-Hastings algorithm can generate correlated draws, one in every 45 draws in each chain was retained. The results reported are therefore based on 500,000 retained samples.

Once again, before the estimation of translog cost functions, the prices and outputs are normalised by their geometric means, whereas the trend variable by its arithmetic mean. This allows the first-order cost frontier parameters of the translog cost functions to be interpreted as cost elasticities, evaluated at the geometric mean of the data.

The price of outsourced labour and clinical services *(out_price)* was used to normalise total costs and other input prices to impose homogeneity in the cost function. The indicator variable for small, medium and rural DHBs is included in the cost function to detect discrepancies in technology and geographic characteristics.

In order to allow for different degrees of persistence in cost inefficiency, average hospital beds for each DHBs are used to parameterise the short-run cost efficiency level in the dynamic equation. The hospital beds are time-variant for each DHB, as there has been little or no significant rise in hospital capacity, resulting in a more or less stable number of hospital beds for each DHB between 2011 and 2018. Such parametrisation of short-run cost efficiency will allow each DHB to have its long-run efficiency level.

In order to easily compare and contrast the various parameters obtained through different specifications, in Table 5.2, only the first-order terms along the measure of average short-run (SRCE) and long-run cost efficiency (LRCE) scores are presented. These parameters are based on four different specifications: the dynamic stochastic frontier (DSF), the dynamic stochastic frontier with DHB specific indicators (DSF_IND), the random-effects dynamic stochastic frontier (REDSF) and the random-effects dynamic stochastic frontier with DHB specific indicators (REDSF_IND). Appendices H to K list the complete set of parameter values for all four specifications.

Since each variable is in its natural logarithm and is normalised by its sample mean, the first-order coefficients can be interpreted as cost elasticities at the sample means. Table 5.2 shows that all the first-order cost frontier elasticities from all specifications are positive and significant at the point of approximation. This implies that the estimated cost frontiers are increasing in outputs and input prices, implying that the monotonicity condition is satisfied in all the specifications at the geometric mean of the independent variables.

According to the results in Table 5.2, the first-order coefficient of time (trend) ranges from 0.3% to 0.45%, which quantifies the measure of technical change. This positive coefficient suggests that there has been a modest technological regress among New Zealand DHBs. The negative and significant parameter estimates of small, medium and rural indicators imply that lower costs exist for these DHBs compared to large and urban DHBs. The low relative costs of the small, medium and rural DHBs reflect the fact that these DHBs only provide non-tertiary hospital services to relatively small population numbers. Also, large and urban DHBs, which provide the majority of tertiary hospital services in New Zealand, attract the most complicated hospital cases (Shin et al., 2017), which are costly to treat.

Table 5.2 Posterior means of the first-order terms and other structural parameters

Variable	Posterior Mean			
	DSF	DSF_IND	REDSF	REDSF_I
log_med_ price	0.13	0.18	0.17	0.17
log_other_ price	0.49	0.38	0.41	0.40
log_clinical_ price	0.26	0.16	0.20	0.19
log_capital_ price	0.11	0.08	0.07	0.06
log_inpatients	0.69	0.23	0.17	0.17
log_outpatients	0.30	0.09	0.08	0.07
trend	3.0×10^{-3}	4.0×10^{-3}	4.4×10^{-3}	4.5×10^{-3}
small	-	-1.52	-	-1.69
medium	-	-0.85	-	-0.83
rural	-	-0.32	-	-0.23
Dynamic parameter				
$\boldsymbol{\rho}$	98.78%	96.51%	96.38%	91.68%
small	-	-0.22	-	-0.26
medium	-	-0.12	-	-0.12
rural	-	-0.03	-	-0.07
log_beds	-	-0.10	-	-0.10
Standard deviations				
$\boldsymbol{\sigma_v}$	0.03	0.01	0.01	0.01
$\boldsymbol{\sigma_s}$	0.07	0.08	0.02	0.22
$\boldsymbol{\sigma_\alpha}$	-	-	0.77	0.18
Average SRCE	0.68	0.74	0.92	0.92
Average LRCE	0.69	0.75	0.92	0.93
Log marginal likelihood	880.01	1110.00	1153.16	1175.30

The first-order coefficients of inputs represent the estimated factor shares that can be compared to the actual cost share to check the consistency of the cost function with the theory. Table 5.3 reports the estimated cost shares from all four specifications where, except for the DSF specification, the cost share estimates are closer to the actual share. However, the cost share of outsourced labour and clinical services is overestimated, perhaps due to the high volatility in the outsourced expenditure data. Furthermore, if there is no allocative inefficiency, and the cost function is precisely estimated, the cost shares estimates should be equal to the actual share. In other words, the differences between the actual and observed cost shares may be either due to incorrect specifications, or to an allocative inefficiency, or both.

Table 5.3 Estimates of cost shares

Input	Actual share	Estimated Cost Shares			
		DSF	DSF_IND	REDSF	REDSF_IND
med	0.20	0.13	0.18	0.17	0.17
other	0.48	0.49	0.38	0.41	0.40
clinical	0.16	0.26	0.16	0.20	0.19
capital	0.08	0.11	0.08	0.07	0.07
outsourced	0.08	0.01	0.20	0.15	0.17

In line with this paper's focus, the measurement of the economies of scale obtained in Table 5.2 through various econometric specifications deserves a detailed explanation. The concept of economies of scale aims to identify the extent to which DHBs exploit average potential cost reductions with a higher level of hospital services. From Table 5.3, the estimate of 0.99 as the scale economy from the DSF specification suggests that New Zealand DHBs are operating very close to constant returns to scale.

However, when DHB specific indicators are taken into consideration, as in the DSF_IND specification, the magnitude of scale economies decreases substantially to 0.32, implying that a 1% rise in inpatients and outpatients increases costs by only 0.32%, demonstrating the presence of substantial unexploited economies of scale among New Zealand DHBs. Similarly, the cost specifications with random effects, and the random effects with indicator variables that are displayed under the REDSF and the REDSF_IND, respectively, also show high economies of scale, ranging from 0.25 and 0.24.

The upward bias in the magnitude of scale economies in the DSF specification is the result of heterogeneity bias (Hsiao, 2003, pp. 8-9). Heterogeneity bias is a direct consequence of misspecification in the cost function as in the DSF, which collapses individual DHB effects into the cost function by masking DHB-level variations. In other words, the DSF specification combines different DHBs at different times, camouflaging any heterogeneity and uniqueness that exists among them. Therefore, compared to the other specifications, the DSF places too much weight on the variability across DHBs, as it considers all the variation in costs rather than apportioning some of them into differences across the DHBs, which is attributable to observed or unobserved sources of cost variability. Ignoring the individual-specific effects among DHBs that are not captured by the explanatory variables leads to biased and inconsistent results (Hsiao, 2003, pp. 8-9). Accounting for such DHB-specific effects ensures that individual DHBs have heterogenous intercepts that are entirely ignored in the pooled specifications, such as the DSF. Accounting for such DHB-specific effects means that individual DHBs have heterogeneous intercepts that are ignored in pooled specifications like the DSF.

Assuming that all other variables that influence costs remain constant, except for hospital services (inpatients and outpatients), the relationship between costs and hospital services can be demonstrated in Figure 5.1. The solid line from the origin in Figure 5.1 shows the estimates of scale economies where pooled DSF specifications have been used. This places too much weight on the variations between DHBs and thus identifies a very high magnitude of scale economies, indicated by the steep slope.

The broken lines between each point scatter show regressions of individual DHBs and reflect a specification where heterogeneity is taken into account. The low value of the measure of scale economies from the DSF_IND, REDSF and REDSF_IND specifications shows that the cost increases from treating additional inpatients and outpatients are not as high (steep) as those obtained from the DSF specifications. More specifically, the flat slopes of individual DHBs in Figure 5.1 indicate that DHBs operate at a very high level of economies of scale when DHB-specific variations are considered in the cost specification.

The presence of such high economies of scale points towards the existence of substantial spare capacity in New Zealand public hospitals. The presence of excess capacity does not necessarily indicate consistent low occupancy rates in New Zealand public hospitals. Instead, it suggests that given the number of staff and the other hospital infrastructure, the treatment of additional patients does not substantially increase costs. Therefore, matching healthcare demand, especially elective services with excess capacity in hospitals, can enhance the existing capacity utilisation and improve productivity. In practice, however, any attempt to better use existing hospital capacity will depend on priorities and targets set by policymakers at the time. Nevertheless, a certain level of unused capacity will always remain, as excess capacity is necessary to provide healthcare services.

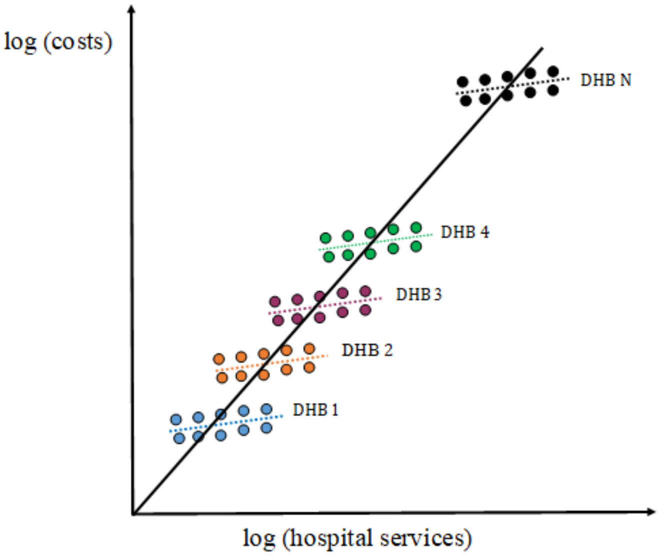

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Figure 5.1. Heterogeneity bias

Similarly, the parameter of *log_inpatients* × *log_outpatients* [see: Appendices (H – K)], which shows that the presence of the economies of scope is severely overestimated in magnitude (-0.69) for DSF specifications while it is consistent in all other specifications with an average -0.24. This further demonstrates the bias as a consequence of ignoring heterogeneity in the cost function.

Another result of ignoring DHB heterogeneity is the upward bias in the estimate of the persistence parameter, ρ, which is overestimated to be 98.78% in the DSF model, as it captures the effect of unobserved heterogeneity (Emvalomatis, 2012). On the other hand, when observed and unobserved heterogeneity, as specified in REDSF_IND, is considered in the cost function, the persistence parameter drops to 91.68%. Nonetheless, given the persistent parameter value of 91.68 %, there is evidence that adjustment costs exist among New Zealand DHBs.

Similarly, input price elasticities hardly change between REDSF and REDSF_IND specifications; however, they differ significantly from the DSF specification due to heterogeneity bias. Likewise, due to the inclusion of DHB-specific indicators that partially account for heterogeneity in the DSF_IND specification, its input elasticities are slightly closer to those of the REDSF and REDSF_IND specifications.

In addition to the bias in estimating the cost function parameters, the omission of unobserved heterogeneity also biases the estimate of SRCE scores. The Spearman rank correlation in Table 5.4 indicates that the correlations of cost efficiency scores between the DSF and other specifications are very low and negative in some cases. In contrast, a high correlation of 0.92 between REDSF and REDSF_IND were observed when unobserved heterogeneities are taken into consideration. This further demonstrates that ignoring heterogeneities in healthcare produces bias, not only the parameter estimates but also generate a biased and inconsistent estimate of efficiency scores.

Table 5.4 Spearman Rank Correlation Coefficients

Specification	DSF	DSF_IND	REDSF	REDSF_IND
DSF	1.00			
DSF_IND	0.10**	1.00		
REDSF	-0.12***	0.51***	1.00	
REDSF_IND	-0.14***	0.72***	0.92***	1.00

***,**,* indicate significance at the 1%, 5%, and 10% confidence levels,respectively.

Of the four specifications shown in Table 5.2, the REDSF_IND specification has the highest log-likelihood of 1175; thus, the estimates of SRCE, LRCE, scale and scope economies are displayed in Table 5.5 are based on the REDSF_IND. In Table 5.5, DHBs are ranked in ascending order based on their long-run efficiency scores. The yearly average SRCE scores for each DHB are listed in Appendix L, whereas the kernel density plot is displayed in Appendix

M. The time series plot for the SRCE and LRCE scores for each DHB are plotted in Appendix N.

Table 5.5 shows that most DHBs are operating at or very close to their LRCE levels, indicating that between 2011 and 2018, no significant structural changes in the form of policy change or technological investment influenced these DHBs’ short-run efficiency performances. This also implies that most New Zealand DHBs performed close to the long-run cost-efficiency average of 0.93, except for the South Canterbury and Wairarapa DHBs. These two DHBs operated above their long-run equilibrium level before gradually tapering off towards their equilibrium levels, as shown in Appendix N. This indicates the temporal nature of DHB performances when a significant policy change or substantial investment in modern technology temporarily raises productivity above the long-run equilibrium level of cost efficiency.

It is noticeable from Table 5.5 that all seven DHBs with the lowest LRCE scores provide hospital services to rural areas, whereas nine high performing DHBs operate in urban areas. The low relative LRCE scores of rural DHBs point to the existence of the high cost of adjustment, due to which they choose to remain cost inefficient in the short run and instead aim to reach their long-run equilibrium level of cost efficiency. With an overall LRCE score of 0.87, these seven rural DHBs essentially overspent their budget by approximately 15% on average between 2011 and 2018 due to the persistence in cost inefficiency resulting from high adjustment costs.

The low long-run equilibrium level of cost efficiency among rural DHBs may be related to the fact that these DHBs provide hospitals services to some of the most remote and isolated parts of New Zealand. Therefore, in the absence of modern communication technology, inefficiency may persist in terms of high travel costs for patients and medical staff and other inefficient practices that are difficult to eliminate unless advanced technology is used to manage and provide services to rural patients. It is also evident from a report by the West Coast District Health Board (2018b) that patients living in rural and remote areas have some of the highest proportions of patients that miss specialist and outpatient appointments, thereby contributing further to persistence in inefficiencies.

Table 5.5 Estimates of yearly mean SRCE, LRCE, Scale and Scope economies

DHB	LRCE	SRCE	Scale	Scope
Whanganui	0.81	0.67	0.21	-0.24
West Coast	0.85	0.85	0.17	-0.24
South Canterbury	0.86	0.90	0.24	-0.23
Northland	0.89	0.89	0.25	-0.23
Wairarapa	0.89	0.91	0.21	-0.23
Hawke's Bay	0.91	0.82	0.21	-0.23
Nelson Marlborough	0.91	0.94	0.26	-0.22
Auckland	0.94	0.94	0.27	-0.24
Bay of Plenty	0.94	0.93	0.26	-0.23
Lakes	0.94	0.93	0.21	-0.23
Southern	0.94	0.93	0.27	-0.23
Tairawhiti	0.94	0.93	0.22	-0.23
Canterbury	0.95	0.95	0.22	-0.25
Mid Central	0.95	0.95	0.26	-0.23
Waitemata	0.95	0.94	0.27	-0.22
Counties Manukau	0.96	0.96	0.28	-0.22
Hutt Valley	0.96	0.94	0.23	-0.23
Waikato	0.96	0.95	0.27	-0.23
Capital & Coast	0.97	0.96	0.24	-0.23
Taranaki	0.97	0.97	0.26	-0.22
Grand Mean	0.93	0.92	0.24	-0.24

The experience of using the Telehealth and virtual health network in the province of British Columbia in Canada has shown a significant reduction in travel costs, thereby reducing cost inefficiencies. It has consistently been shown to have increased rural patient access to hospital services (OECD, 2016). Furthermore, technological improvements can play a vital role in delivering cost efficient hospital services to the elderly, who are generally less mobile and may require long-term care (Cornwall & Davey, 2004).

Another practical solution for DHBswhen providing hospital services to communities living in rural areas will be to invest in mobile surgical units[30]. An MoH's commissioned report on the feasibility of mobile surgical services by Blick et al. (2015) pointed towards improvement in access times for rural communities, with some efficiency benefits. However, to date, no significant actions have been taken by authorities following the report.

The three poorest performing DHBs – Whanganui, West Coast and South Canterbury with the lowest LRCE scores of 0.81, 0.85 and 0.86 respectively, are small DHBs providing rural areas hospital services. While the West Coast and South Canterbury DHBs operate at and above their LRCE level, the Whanganui DHB consistently performed below its LRCE level (0.67 against the LRCE of 0.81), as shown in Appendix N. This suggests that the Whanganui DHB needs to

[30] More information on Mobile Health. (2019).

review its management practices and address the source of short-run cost inefficiencies. Similarly, Hawke's Bay, a rural DHB, has an SRCE of 0.82 against its LRCE of 0.91, which points towards inefficient management practices.

The scale economies presented in Table 5.5 indicate that small DHBs have an average scale elasticity of 0.21, compared to an average of 0.25 for large and medium DHBs. Since small DHBs mostly operate in rural areas where healthcare demand is often unpredictable and low, these DHBs must maintain standby staff and facilities to meet unanticipated demands. Consequently, the additional increase in average costs due to extra hospital admissions or outpatient visits is negligible. Given that DHBs were specifically established to provide hospital services to specific regions, it is not practical to close small hospitals to exploit economies of scale. Nevertheless, given that large DHBs already provide a substantial number of specialist hospital services to small DHBs through inter-district patient flows (Krieble & Siddharth, 2017), closer cooperation between DHBs in managing patients, sharing staff, the joint procurement of pharmaceuticals and other resources may lead to better utilising the existing economies of scale.

The estimated parameter of *log_inpatients* × *log_outpatients* in Appendix K is close to -0.24 and is significant. Thus, the complementary cost test demonstrates the presence of economies of scope, which implies that the marginal cost of providing an inpatient service decreases when the quantity of an outpatient service is increased. The DHB level calculation of the economies of scope in Table 5.5 shows no significant variation in their measure across DHBs. This is expected because the economies of complementarity depend on the marginal costs between inpatients and outpatients, rather than the concept of spreading fixed costs that would have shown higher economies of scope for the larger DHBs.

5.6 Conclusion and policy implications

This study uses the dynamic stochastic frontier model with four different specifications to estimate the cost function, cost efficiency, and associated parameters. From a modelling perspective, the findings of this study reinforce the fact that ignoring either observed or unobserved heterogeneity in a cost function can lead to biased estimates of parameters, particularly in the measure of economies of scale and scope. Further, the model that ignores heterogeneity also severely underestimates the short-run cost efficiency scores.

The persistence parameter measure is close to 92% when controlling for unobserved and observed heterogeneity, proving that significant adjustment costs exist among New Zealand DHBs. Results show that the average long-run cost efficiency is 0.93, which implies that New Zealand DHBs spent approximately 7.50 % more on average in 2011-2018 due to high adjustment costs.

The main findings of this study and the associated policy implications can be summarised as follows:

1. The results from the cost specification used in this study show no evidence of technological progress among New Zealand DHBs between 2011 and 2018. However, the absence of technological progress may be associated with the improvement in the quality of hospital services, which may have masked the cost savings associated with technology over time.
2. There is a substantial amount of economies of scale among DHBs to be exploited by carefully matching spare capacities and healthcare demand. Further, improved collaboration among DHBs inpatient care, and the sharing of healthcare personnel and diagnostics tests, may lead to the better use of existing economies of scale.
3. The DHBs providing hospital services to rural areas are associated with high persistence in cost inefficiency and therefore overspent approximately 15% more between 2011 and 2018 due to high adjustment costs relative to urban DHBs. Investing in state-of-the-art communication technology such as virtual healthcare will improve patient access to healthcare and lower the inefficiencies associated with staff time and transportation. Further, DHBs should seriously consider investing in mobile clinics and surgical units to improve patient access and reduce missed appointments.
4. While the majority of DHBs performed very close to their respective long-run equilibrium levels of cost efficiency, Whanganui and Hawke’s Bay DHBs consistently operated below their equilibrium level; this points towards the existence of potential inefficient management practices, which should be addressed. These two DHBs can substantially improve their short-run cost efficiency by following the best-practice techniques adopted by some of the top-performing DHBs, such as South Canterbury, Wairarapa, Tairawhiti, Hutt Valley and Mid Central, which operate at a similar size and scale.

Chapter 6 Total Factor Productivity decomposition of New Zealand District Health Boards: An application of Primal and Dual approaches using Bayesian Stochastic Frontier Analysis

Abstract

Using the longitudinal data on New Zealand DHBs for the period 2011-2018, the total factor productivity (TFP) change and its components are evaluated using an input distance function and a cost function. The empirical results indicate that TFP decreased at an average rate of between 0.73 and 0.98 per cent annually, mainly due to the deterioration of the technical component, which averaged close to -2 per cent between 2011 and 2018. However, contrary to the technological component, the scale component improved every year at an average rate of 1 to 1.16 per cent, thus cushioning some of the effects of the deteriorating technological component of the TFP. The TFP also posted a one-off positive growth in 2016, following the nationwide implementation of an 'elective initiative' programme in the 2015-2016 year, which raised both the scale and efficiency (technical and cost) components to their highest levels. Furthermore, the study also demonstrates the consistency in the effect of scale and technological change components on the TFP under both primal and dual approaches.

6.1 Introduction

Productivity growth among public healthcare providers has the potential to deliver additional healthcare services and shorten waiting times without increasing the demand on constrained public resources. However, measuring healthcare productivity growth is challenging as multiple inputs are used to provide a wide variety of healthcare services under a highly regulated environment. TFP is one of the most widely used metrics of overall productivity. TFP allows for the estimation of overall productivity by incorporating the relationship between all outputs and inputs. Most importantly, the changes in the TFP can be decomposed into sources such as technical change, returns to scale, and changes in efficiency using stochastic frontier models (Kumbhakar et al., 2015, pp. 286-288). From a policy perspective, TFP and its components can offer insights into such questions as to whether consumers are getting enough value for public funds through productivity improvement.

With the establishment of DHBs in 2001, the New Zealand government continued to invest extensively in public healthcare to expand access to public healthcare services and improve health outcomes. While the first concerns relating to the lack of DHB productivity measures were raised by The Treasury (2005) more than a decade ago, no significant progress has been made in this area. To date, New Zealand public health authorities have yet to adopt a well-established method of assessing health productivity or its components. More recently, a report by Knopf (2017) reiterated the same concerns and argued that assessing public healthcare productivity is crucial in formulating policy recommendations.

The conventional approach of measuring the TFP and its components follows a primal growth approach that is closely related to the productivity growth model put forth by Solow (1957). The primal approach adopts the growth accounting framework based on the estimated production function (Kumbhakar et al., 2015, pp. 286-287). As evident from the list of studies in Appendix C, nearly all studies in healthcare use a primal approach to estimate the TFP and its components.

Alternatively, a dual approach, which is calculated based on weighted growth in input prices by estimating a cost function, can also be used (Kumbhakar et al., 2015, pp. 294-295). While according to the microeconomic theory, both primal and dual approaches should produce the same results, this is seldom the case (Crafts & Woltjer, 2019). The inconsistencies in results between these approaches are usually attributed to how prices and quantities are measured (Hsieh & Klenow, 2009). Nevertheless, the application of both primal and dual approaches can serve as a robustness check for any TFP related studies and is very valuable in situations where the divergences between primal and dual approaches are significant (Aiyar & Dalgaard, 2005).

This chapter undertakes the first such attempt in the healthcare literature to measure and decompose the TFP change using both the primal and dual approaches. While this study's novel feature is the application of primal and dual approaches, this study also accounts for time-invariant heterogeneity among healthcare providers to obtain a more robust measure of parameters. The methodology developed by Denny et al. (1981), Bauer (1990), and Kumbhakar et al. (2000) is employed to measure not only the changes in the TFP but also decompose the contributions that stem from efficiency changes, technological changes and scale effects. This study will be the first to measure and quantify TFP changes among New Zealand DHBs using observed data on inputs, prices and outputs for the period 2011-2018. Further, this study will also provide valuable insights into the drivers of TFP change and can guide policymakers to make informed decisions.

6.2 TFP decomposition: Primal and Dual approaches

As mentioned in section 3.2, the nonparametric DEA-Malmquist index is the most widely used technique for calculating TFP growth and its components. This may be because the DEA and indices do not require an estimation of either cost or production functions. Although the DEA can also decompose TFP growth into sources such as technological, efficiency and scale changes, the main advantage of using a parametric approach such as the SFA is that estimation can be carried out while simultaneously controlling for unobserved heterogeneity and random shocks.

The primal approach to TFP decomposition states that the growth in TFP is the residual from the difference between the real output growth and the weighted average growth of real physical and human resources (Crafts & Woltjer, 2019). Since the parametric approach requires the estimation of the production function, the translog IDF in Chapter Four is borrowed, in part, to demonstrate a brief derivation of TFP change and its components.

Using Eq. (4.3), an estimable form of the translog IDF with N outputs and M inputs can be expressed as:

$$
\begin{aligned}
-\ln x_{Mit} = {} & \alpha_0 + \sum_{n=1}^{N} \alpha_n \ln y_{nit} + \frac{1}{2} \sum_{n=1}^{N} \sum_{k=1}^{N} \alpha_{nk} \ln y_{nit} \ln y_{kit} \\
& + \sum_{m=1}^{M-1} \beta_m \ln x^*_{mit} + \frac{1}{2} \sum_{m=1}^{M-1} \sum_{l=1}^{M-1} \beta_{ml} \ln x^*_{mit} \ln x^*_{lit} \\
& + \sum_{m=1}^{M-1} \sum_{n=1}^{N} \delta_{mn} \ln x^*_{mit} \ln y_{nit} + \gamma_t t + \frac{1}{2} \vartheta_{tt} t^2 \\
& + v_{it} - u_{it} + \alpha_i
\end{aligned}
\tag{6.1}
$$

where the subscripts i and t denote the DHB and time, respectively, whereas, $ln\, y_{it}$ and $ln\, x_{it}$ represent the natural logarithm of quantities for outputs and inputs, respectively. The variable $x^*_{mit} = \frac{x_{mit}}{x_{Mit}}$, with x_{Mit} is the normalising input. To account for technological progress, a linear trend t and its square are included in the IDF. Furthermore, the variable u_{it} captures the technical inefficiency, v_{it} the stochastic noise and α_i captures DHB-specific random effects to account for unobserved heterogeneity. To impose linear homogeneity in inputs, the distance term D^I_{it}, and the inputs in equation (1) can be divided by one of the inputs, termed as the normalizing input (Kumbhakar et al., 2015, p. 99).

From the translog IDF in Eq. (6.1) based on Kumbhakar et al. (2015, p. 303), the returns to scale (RTS) can be computed as:

$$RTS = -\left[\sum_{n=1}^{N} \frac{\partial\, ln\, D^I_{it}}{\partial\, ln\, y_{nit}}\right]^{-1} \quad (6.2)$$

whereas the technological change component[31] $(\dot{TC})$ and technical efficiency change component $(\dot{TE})$ as shown by Kumbhakar et al. (2015, p. 307) can be found by:

$$\dot{TC} = \frac{\partial\, ln\, D^I_{it}}{\partial\, t} = \gamma_t + \vartheta_{tt} t + \sum_{n=1}^{N} \omega_n\, ln\, y_{nit} + \sum_{m=1}^{M} \theta_m\, ln\, x_{mit} \quad (6.3)$$

$$\dot{TE} = \frac{\partial\, ln\, TE_{it}}{\partial\, t} \approx lnTE_{it} - lnTE_{it-1} \quad (6.4)$$

Once the components in Eqs. (6.3), (6.4) and (6.5) are computed the growth rate of total factor productivity$(\dot{TFP}$[32]$)$ can be expressed as:

$$\dot{TFP} = \dot{TC} + \dot{TE} + \left(1 - \frac{1}{RTS}\right)\dot{y}_c \quad (6.5)$$

where according to Kumbhakar et al. (2015, p. 307), $\dot{y}_c = \frac{1}{\sum_{n=1}^{N}\lambda_n}(\sum_{n=1}^{N}\lambda_n \dot{y}_n)$ and $\lambda_n = -\frac{\partial\, ln\, D^I{}_{it}}{\partial\, ln\, y_{nit}}$.

[31] Where a "dot" over a variable indicates its rate of change
[32] Full derivation of individual components can be found at Kumbhakar et al. (2015, pp. 300-308)

Similarly, under the dual approach, a translog cost function can be represented as:

$$\begin{aligned} \ln C_{it}^{a} = \ & \alpha_0 + \sum_{j=1}^{J} \alpha_j \ln y_{jit} + \frac{1}{2} \sum_{j=1}^{J} \sum_{h=1}^{J} \alpha_{jh} \ln y_{jit} \ln y_{hit} \\ & + \sum_{k=1}^{K} \beta_k \ln w_{kit} \\ & + \frac{1}{2} \sum_{k=1}^{K} \sum_{p=1}^{K} \beta_{kp} \ln w_{kit} \ln w_{pit} \\ & + \sum_{k=1}^{K} \sum_{j=1}^{J} \delta_{kj} \ln w_{kit} \ln y_{jit} \\ & + \sum_{j=1}^{J} \omega_j \ln y_{jit}\, t + \sum_{k=1}^{K} \theta_k \ln w_{kit}\, t + \gamma_t\, t \\ & + \frac{1}{2} \vartheta_{tt} t^2 + v_{it} + u_{it} + \alpha_i \end{aligned} \tag{6.6}$$

where $\ln C_{it}^{a}$, $\ln y_{jit}$ and $\ln w_{kit}$ represent the natural logarithm of total observed costs, output quantities and input prices, respectively.

As the estimated translog cost function must satisfy the condition of homogeneity of degree one in the input prices, this can be imposed by selecting an arbitrary input price and normalising C_{it}^{a} and other input prices by it.

Once the translog cost function in Eq. (6.6) is estimated, using the method in Kumbhakar et al. (2015, p. 295), the RTS or scale economies can be computed as:

$$RTS = \left[\sum_{j=1}^{J} \frac{\partial \ln C_{it}^{a}}{\partial \ln y_{jit}} \right]^{-1} \tag{6.7}$$

Similarly, the technological change component ($\dot{TC}$) and cost efficiency change component ($\dot{CE}$) can be found by:

$$\dot{TC} = -\frac{\partial \ln C_{it}^{a}}{\partial t} = -\gamma_t - \vartheta_{tt} t - \sum_{j=1}^{J} \omega_j \ln y_{jit} - \sum_{k=1}^{K} \theta_k \ln w_{kit} \tag{6.8}$$

$$\dot{CE} = \frac{\partial \ln CE_{it}}{\partial t} \approx \ln CE_{it} - \ln CE_{it-1} \tag{6.9}$$

Once the components in Eq.(6.7), (6.8)and (6.9) are computed, the change in total factor productivity($\dot{TFP}$) can be expressed as:

$$\dot{TFP} = \dot{TC} + \dot{CE} + \left(1 - \frac{1}{RTS}\right) \dot{y}_c \tag{6.10}$$

Where according to Kumbhakar et al. (2015, p. 298), $\dot{y}_c = \frac{1}{\sum_{j=1}^{J}\lambda_j}\left(\sum_{j=1}^{J}\lambda_j\dot{y}_J\right)$ and $\lambda_j = \frac{\partial \ln C^a{}_{it}}{\partial \ln y_{jit}}$

6.3 Model estimation

Bayesian techniques are used to estimate the models described in Eq. (6.6) and (6.6). The inefficiency in both the IDF and cost function is assumed to have a half-normal distribution[33]. In this section, an IDF function is used to demonstrate the estimation process, while the estimation of the cost function is relatively straightforward.

For succinctness, in Eq. (6.1) is rewritten as

$$q_{it} = p'_{it}\beta + v_{it} - u_{it} + \alpha_i, \tag{6.11}$$

$$v_{it} \sim N(0, \sigma_v^2)$$

$$u_{it} \sim N^+(0, \sigma_u^2)$$

$$\alpha_i \sim N(0, \sigma_\alpha^2)$$

where q_{it} represents the dependent variable and p'_{it} is a row vector of the independent variables in Eq. (6.11), and β is the vector of corresponding parameters, including the intercept that is to be estimated. The parameter α_i captures the unobserved time-invariant heterogeneity specified as random effects. If all of the parameters in Eq. (6.11) are collected into a vector $\theta = [\beta, \sigma_v, \sigma_u, \sigma_\alpha]'$, the complete data likelihood is:

$$p(q, \{\alpha_i\}, \{u_{it}\} \,|\, P, \theta) = p(q \,|\, \{\alpha_i\}, \beta, \sigma_v^2, P) \times p(\{\alpha_i\} \,|\, \sigma_\alpha^2) \times p(\{u_{it}\} \,|\, \sigma_u^2) \tag{6.12}$$

$$= \frac{1}{(2\pi\sigma_v^2)^{\frac{NT}{2}}} \exp\left\{-\frac{\sum_{i=1}^{N}\sum_{t=1}^{T-1}(q_{it} - p'_{it}\beta - \alpha_i + u_{it})^2}{2\sigma_v^2}\right\}$$

$$\times \frac{1}{(2\pi\sigma_\alpha^2)^{\frac{N}{2}}} \exp\left\{-\frac{\sum_{i=1}^{N}\alpha_i^2}{2\sigma_\alpha^2}\right\}$$

$$\times \left(\frac{2}{\pi\sigma_u^2}\right)^{\frac{NT}{2}} \exp\left\{-\left(\frac{\sum_{i=1}^{N}\sum_{t=1}^{T}u_{it}^2}{2\sigma_u^2}\right)\right\}$$

where q, u and P are the stacked vector and matrix, over both i and t as in Eq. (6.11), respectively. Using Bayes' rule, the posterior joint density of the model parameters and latent variables is:

[33]At first the dynamic model was used to estimate IDF with random effects, however the value of scale elasticity and efficiency was too extreme to be consistent with the theory, therefore a static model was used instead.

$$\pi\left(\theta,\{\alpha_i\},u_{it}\,\middle|\,q,P\right) \propto p\left(q,\{\alpha_i\},u\,\middle|\,\theta,P\right) \times p(\theta) \qquad (6.13)$$

where $p\left(q,\{\alpha_i\},u\,\middle|\,P,\theta\right)$ is given by Eq. (6.11) and $p(\theta)$ corresponds to the prior density of parameters.

The priors imposed on the parameters are the same as used in Chapters four and five, except for parameter σ_u^2 which is assumed to be gamma distributed with weakly informative priors where the shape and scale hyperparameters are set to 7 and 0.5, respectively.

6.4 Data and descriptive statistics

The data set on inputs, outputs, input prices and expenditures used in this chapter are the same as those used in the previous two chapters, including balanced quarterly observations for the period 2011-2018 (T=32) for each of the 20 DHBs. As the descriptive statistics are already provided in previous chapters, in this section, a summary of yearly percentage changes in variables is provided in Table 6.1.

According to the figures in Table 6.1, the change in inpatient numbers is steadier over time compared to the outpatient numbers. A possible reason for this behaviour may be because DHBs often have less control over inpatient numbers and are usually constrained by the hospital bed capacity. On the other hand, the change in outpatient numbers is more volatile, as DHBs may have some degree of flexibility in scheduling outpatient visits, particularly in elective surgeries. The expenditure figures in Table 6.1 show that the average rate of increase in expenditure is 4.62 per cent over the period 2011-2018, which is again higher than the growth in either inpatient or outpatient numbers. As for the price[34] increases, the highest increase is observed as being the price of other staff, followed by medical staff. However, the price of capital has decreased by 0.25 percentage points, primarily driven by the drop-in capital charge rate and treasury bond rate between 2011 and 2018.

[34] The prices of all inputs are deflated as described in Chapter 5.

Table 6.1 Summary of percentage changes in inputs, outputs and prices

Variables	2012	2013	2014	2015	2016	2017	2018	Mean
Medical staff *(med)*	3.14%	4.36%	4.33%	2.29%	1.33%	2.48%	3.89%	3.12%
Other staff *(other_staff)*	-3.95%	6.75%	-0.79%	4.40%	4.29%	-0.87%	2.41%	1.75%
Capital asset values *(capital)*	3.53%	7.60%	7.06%	3.27%	2.30%	4.44%	0.31%	4.07%
Outsourced labour and clinical costs *(out_cost)*	12.89%	2.25%	0.46%	9.36%	5.97%	5.36%	7.39%	6.24%
Clinical supplies costs *(clinical_cost)*	3.17%	1.20%	-1.94%	8.53%	-1.16%	3.32%	2.71%	2.26%
Case-weighted inpatients *(inpatients)*	2.82%	1.87%	1.51%	1.80%	2.70%	2.02%	2.76%	2.21%
Price-weighted outpatient visits *(outpatients)*	3.35%	-5.26%	-4.20%	4.39%	9.50%	-2.20%	6.57%	1.74%
Medical staff price *(med_ price)*	1.86%	2.49%	0.80%	0.77%	2.66%	1.14%	1.86%	1.65%
Other staff price *(other_ price)*	2.75%	1.17%	2.57%	1.73%	1.59%	1.72%	3.52%	2.15%
Price of capital *(capital_ price)*	-0.14%	-0.08%	0.11%	-0.09%	-0.09%	-0.09%	0.11%	-0.26%
Price of outsourced labour and clinical services *(out_price)*	1.66%	0.27%	0.56%	0.80%	0.83%	2.83%	1.59%	1.22%
Price of Clinical supplies *(clinical_price)*	1.84%	0.17%	4.53%	-3.48%	1.89%	1.31%	2.73%	1.28%
Total expenditure *(total_exp)*	5.04%	3.10%	3.59%	4.50%	3.21%	3.50%	9.39%	4.62%

6.5 Empirical results and discussion

The MCMC sampling involved five independent Markov chains, with each chain contributing 100,000 iterations towards the posterior distributions of model parameters. A burn-in phase of 50,000 iterations is used to remove the influence of initial values. To reduce the effect of correlated draws, one in every five draws in each chain is retained. The results reported are therefore based on 500,000 retained samples

Before the estimation of translog cost and input distance functions, the inputs, prices and outputs were normalised by their geometric means, whereas the trend variable by its arithmetic mean. The IDF's homogeneity constraint was imposed by using variable med as a numeraire.

The posterior means, standard deviation and 90% credible intervals of parameters estimated from the IDF are displayed in Appendix O. The first-order coefficient of *log_inpatients* and *log_outpatients* sum to -0.47, which indicates the existence of a substantial level of economies of scale. The summary of TFP changes and its components estimated from IDF are presented in Table 6.2.

Table 6.2 Yearly TFP change and its components from IDF

Variable	2012	2013	2014	2015	2016	2017	2018	Mean
Scale	0.57%	0.39%	0.12%	1.15%	2.64%	0.11%	2.19%	1.03%
Technical	-2.18%	-1.97%	-1.70%	-1.90%	-2.00%	-1.94%	-2.01%	-1.96%
Efficiency	0.16%	-0.17%	0.12%	-0.32%	0.43%	-0.03%	-0.43%	-0.03%
TFP Change	-1.45%	-1.75%	-1.46%	-1.07%	1.07%	-1.86%	-0.25%	-0.96%

The results in Table 6.2 indicate that the TFP decreased by 0.96 per cent on average between 2011 and 2018. The component breakdown of TFP change illustrates the fact that the TFP has deteriorated on average every year primarily driven by technological regress, except in 2016, where the scale portion recorded its highest growth of 2.64 per cent, driving TFP up by 1.07 per cent. Even though technological regress is the driving force of the decline in TFP for the period under analysis, the yearly positive scale component and some improvement in the technical efficiency component counteracted some of its impact on the overall TFP.

The spike in the scale component in 2016 could be due to additional funding made available to DHBs under the 'elective initiatives' (Ministry of Health, 2015b), starting in 2015-2016. The elective initiative was an incentive-based model where extra funding was made available to DHBs for any additional elective volumes achieved that were negotiated in principle. This extra funding increase saw an overall growth of approximately 9.5 per cent (Table 6.1) in outpatient visits compared to previous periods, where growth ranged close to zero. Similarly, the number of inpatients rose by around 2.70 per cent in 2016, compared to an average rise of 2 per cent in previous years. This indicates that the elective initiative, to some extent, has enabled hospital management to exploit existing economies of scale in the year 2016. However, the following year, the scale components fell by 0.11 per cent. In 2018, the scale component again increased by 2.19 per cent; however, the declining technology and technical efficiency component decreased TFP by about 0.80%.

Similarly, in 2016, the sector witnessed its highest average technical efficiency growth of 0.43 per cent compared to other periods. This may be because the impetus for additional funding under the elective initiative programme temporarily motivated DHBs to boost their level of technical efficiency. However, more recently, in 2019, the elective initiative's policy was replaced with 'Planned Care' (Ministry of Health, 2019a), where DHBs were now required to provide planned volumes of care from their annual allocated budgets.

For each DHB, the TFP change and its components are presented in Appendix Q. The scale component figures in Appendix Q show that, contrary to the positive scale component posted by most DHBs, Nelson Marlborough, South Canterbury and Whanganui DHBs appear to have exhausted their gains from increasing the scale of operations between 2011 and 2018. Further to that, the figures in Appendix S also indicate that the Nelson Marlborough and Whanganui DHBs experienced a 0.23 per cent decline in their respective technical efficiencies, while Lakes DHB posted the largest drop of 0.25 per cent. On the other hand, West Coast (0.23 per cent), Tairawhiti (0.20 per cent) and Canterbury (0.18 per cent) DHBs seem to have made the most significant improvements in their average technical efficiency performance between 2011 and 2018.

According to the figures in Appendix Q, while all DHBs have undergone technological deterioration, the Waikato (-3.02 per cent), West Coast (-2.92 per cent), Canterbury (-2.72 per cent) and Southern (-2.61 per cent) DHBs posted the highest decline in the technical change component. On the other hand, Hutt Valley (-0.85 per cent), Tairawhiti (-0.86 per cent), Whanganui (-0.95 per cent), and Lakes (-0.96 per cent) experienced the lowest technological regress. A dot plot of technological change for each DHB over time is plotted in Appendix R, which indicates that although technological growth was negative in the period 2011-2018, technology improved marginally until 2014 when it reached its peak and subsequently plateaued for most DHBs except for Wairarapa, which has consistently experienced a decline in technology since 2011. However, bucking the overall trend, Capital and Coast DHB posted one of the consistent improvements in the technology.

This phenomenon of technological regress among New Zealand DHBs deserves some attention. According to Folland et al. (2016), in the healthcare sector, technological progress can either reduce healthcare spending by improving healthcare resource productivity or may increase costs while improving healthcare quality. Folland et al. (2016) further argue that technological change in the healthcare sector often raises costs, increasing overall healthcare expenditure. It may well be possible that improved quality of hospital services has driven the rise in expenditure between

2011 and 2018, manifesting itself in technological regress among New Zealand DHBs. At present, due to data limitations, it is not possible to incorporate a reliable quality measure into this study.

Turning now to the estimation of the cost function, the outsourced labour and clinical services price (out_price) was used to normalise total costs and other input prices and impose homogeneity. The posterior means and all other parameters from the estimated cost function are provided in Appendix P. The first-order coefficient of *log_inpatients* and *log_outpatients* in Appendix C2, sum to 0.46, is very close to the absolute value of returns to the scale parameter of 0.47 obtained from the IDF function. This provides some evidence to support the consistency of the scale parameter obtained through the IDF and cost function.

Table 6.3 shows the summary of the TFP change and its components estimated from the cost function. This also provides an opportunity to compare the results between the dual and primal approaches, which should be coherent theoretically.

Table 6.3 Yearly TFP change and its components based on cost function

Variable	2012	2013	2014	2015	2016	2017	2018	Mean
Scale	1.20%	0.38%	0.20%	1.18%	2.58%	0.27%	2.32%	1.16%
Technical change	-1.69%	-1.61%	-2.67%	-1.43%	-1.80%	-1.59%	-1.63%	-1.73%
Efficiency change	0.02%	0.08%	0.74%	-1.46%	1.65%	-0.41%	-2.31%	-0.24%
TFP Change	-0.47%	-1.15%	-1.73%	-1.71%	2.43%	-1.73%	-1.62%	-0.81%

The directions of scale and technical changes for each period shown in Table 6.3 are consistent with the corresponding figures in Table 6.2, wherein 2016 reported its highest increase in the scale component of 2.58 per cent and a cost-efficiency improvement of 1.65 per cent. Similarly, the TFP growth was negative in every year except for 2016, where scale and cost efficiency improvements led to a TFP growth of 2.43 per cent. The average TFP change between 2011 and 2018 shows a drop of 0.81 per cent, which is very close to the average of 0.96 per cent obtained using the IDF.

Both the primal and dual specifications show a one-off growth in the TFP in 2016, which were aided by the positive scale and efficiency change components. The growth in 2016 shows that DHBs responded to the incentive-based funding, particularly in terms of efficiency and scale improvement.

Appendix Q presents the DHB level TFP change and components from the dual approach, alongside the results obtained from the primal approach. From Appendix T, the TFP performance of Nelson Marlborough DHB stands out, as it posted the highest decline in the TFP, both in the DF (-3.09 %) and cost (-2.67%) function estimations. On the other hand, Waitemata DHB posted the highest positive average TFP growth both in the IDF (0.70 %) and cost (1.64 %) estimations.

Each DHB's scale and technical change components displayed in Appendix Q from the IDF and cost function appear to have the same sign. However, according to Appendix Q, there are some differences in the direction of technical efficiency and cost efficiency change. This is not surprising, as both these types of efficiency measure different forms of efficiency. Therefore, the measured TFP change for some DHBs, as outlined in Appendix Q, differ in the direction between the IDF and cost function estimates due to the impact of their respective efficiency components. Nevertheless, the consistency between scale and cost components from the IDF and cost function provides credibility to the results obtained in this study.

6.6 Concluding remarks

In this study, the SFA is used to estimate and decompose the TFP growth of New Zealand DHBs for the years 2011-2018 while controlling for DHB level heterogeneity. From a modelling perspective, this study's findings are consistent, whether the dual or primal approach is used.

The main findings can be summarised as follows:

1. TFP has declined at an average rate of 0.96 per cent (IDF) and 0.73 per cent (cost) between 2011 and 2018. While Nelson Marlborough DHB posted the largest average decline in TFP, Waitemata recorded the most considerable improvement in TFP between 2011 and 2018.
2. The deterioration of the technological component is the primary factor contributing to the decline of TFP overall years, except for 2016, when the increase in the scale component resulted in a one-off positive growth in TFP. The positive scale component posted every year, in addition to the occasional improvement in the inefficiency component, to some degree reduced the influence of negative technological growth on TFP.
3. Although all DHBs have experienced technological deterioration, Waikato, West Coast, Canterbury, and Southern DHBs reported the highest technological decline, whereas Hutt Valley, Tairawhiti, Whanganui and Lakes, experienced the lowest technological regress.
4. The implementation of the performance-based funding model - 'elective initiative' in 2016 appears to have briefly enabled DHBs to exploit the existing economies of scale and improve efficiency in the policy's first year, resulting in a one-off growth in TFP.

Chapter 7 General Conclusions

7.1 Summary of findings

The first two empirical chapters of this thesis depart from the commonly held assumption in conventional efficiency studies where inefficiency is considered to be independent over time. Healthcare providers often operate in an environment where some inputs are difficult to adjust to optimum levels, leading to a long-run inefficiency level. As a result, healthcare providers may choose to remain inefficient in the short run and continue to provide healthcare services while simultaneously aiming to reach the long-run equilibrium level of efficiency. The integration of dynamic decision-making takes into account the long-run objective of healthcare providers while recognising their failure to fully optimise their input usage in the short-run fully.

The New Zealand public healthcare system, particularly DHBs, offer an interesting avenue for measuring healthcare efficiency in the dynamic context. Since its inception, New Zealand DHBs have been operating under budget deficits. In particular, the current regulatory framework has appeared to incentivise DHBs to prioritise short-term operational needs at the expense of long-term capital investment. This is evident from the substantial underinvestment in hospital infrastructure over the past decade. Furthermore, while constant budget deficits may indicate inefficiency, the sub-optimum operating environment reflects that DHBs may be operating with a long-run level of inefficiency.

The third empirical chapter adds to the current healthcare productivity literature by undertaking the TFP growth measurement and decomposition. With the reliable data on DHBs' inputs and their prices and outputs, the New Zealand public health context provides an excellent opportunity to undertake the analysis of TFP change and its decomposition to various components under both primal and dual approaches. While each approach has its strengths and weaknesses and often results in mixed findings, they each provide a cohesive framework for assessing the overall robustness of the results and, to some extent, identify the sources of inconsistencies.

This thesis has attempted to answer three research questions. The first research question was concerned with estimating the persistence in technical inefficiency and the corresponding long-run equilibrium level of technical efficiency in the sector. A well-established Bayesian dynamic stochastic frontier model was used to answer this question in Chapter 4. The empirical results found the technical inefficiency persistence parameter to be 97.61 %, which provides compelling evidence of substantial persistence in the sector. While most DHBs performed well relative to the long-run equilibrium level of technical efficiency of 0.76, two tertiary DHBs, Auckland and Capital & Coast, consistently operated below the long-run levels. Similarly, there was also evidence that Tairawhiti and West Coast DHBs also operated well below the long-run efficiency level. The result of this study highlights the importance of incorporating the dynamic nature of inefficiency, especially in the public healthcare sector, where highly constrained funding and the regulatory environment is expected to present conflict between short-run operational and long-term investment needs.

While keeping to the spirit of inefficiency persistence, the second research question also controls for observed and unobserved DHB-specific heterogeneity, as shown in Chapter 5, to obtain a more robust measure for parameters. While the bias due to group-specific heterogeneity is well known in the healthcare literature, the literature review highlights that very few studies are available to control heterogeneity when using longitudinal data. The findings in Chapter 5 reveal substantial bias in the cost function parameters and short-run cost efficiency scores, which can lead to incorrect policy implications if not addressed. The overall cost inefficiency persistence parameter is estimated to be 92%, reinforcing the findings from Chapter 4 that substantial persistence also exists in cost inefficiency due to high adjustment costs. The corresponding long-run equilibrium level of cost efficiency was estimated to be 0.93, translating to an average of a 7.50% loss of public funds due to high persistence in cost inefficiency. Again, most DHBs performed well relative to their respective long-run equilibrium level of cost-efficiency, except for Whanganui and Hawke's Bay DHBs, which consistently performed well below their equilibrium. The DHBs providing hospital services to the rural area appear to have a lower level of short-run equilibrium of 0.87.

Chapter 6 deals with the third research question that is related to the productivity of New Zealand DHBs for the period 2011-2018. It undertakes the total factor productivity decomposition from both primal and dual perspectives yet to be undertaken in applied healthcare productivity literature. The empirical estimation was once again undertaken while controlling for DHB level heterogeneity to address any group-specific effects. In general, the empirical results from both primal and dual approaches are consistent and showed an average decline of total factor productivity between 0.73 - 0.96%, primarily driven by a decline in the technical component of approximately 2 %. However, an exception was noted in 2016, when a nationwide implementation of a performance-based elective funding model temporarily raised total factor productivity to between 1.07-2.43 %. It appears that during this period, DHBs were temporarily incentivised to utilise their spare hospital capacity, which counterbalanced the negative effect of technological regress, resulting in a one-off growth in productivity. Additionally, positive scale effects were observed for every year, indicating the existence of spare capacity among DHBs. The Nelson Marlborough DHB reported the largest average decrease in TFP. In contrast, Waitemata recorded the most significant improvement in TFP between 2011 and 2018. All tertiary DHBs except Auckland reported the highest decline in the technical change component.

7.2 Limitations

There are some limitations in this thesis that are worth a mention. The estimation of input distance and the cost function is built on the assumption that the quality of hospital services provided by DHBs are identical. However, this presumption may prove too restrictive, given that DHBs offer a wide variety of speciality services to different population groups where quality can differ significantly. With this view, this thesis's omission of quality can have two main implications for measuring efficiency and total factor productivity.

First, a DHB that appears to use more inputs than its peers may be erroneously deemed inefficient where its relative output quality is better than its efficient peers. Second, although the empirical findings in Chapter 6 point to technological stagnation, there might be a possibility that, while costs and inputs usage may seem to have risen, the public may be experiencing better health outcomes due to the improved quality of hospital services. In other words, the rate of improvement in the quality of hospital services may be higher than the rate of cost increases over time, which the empirical model in Chapter 6 does not fully capture. Unfortunately, there is currently no reliable measure of quality that could be used in this study.

In Chapters 4 and 5, although models specifically allow for inefficiency persistence, only one common value of persistence is assumed. This assumption may be too rigid, given the existence of significant heterogeneity associated with population, geography and specialities among DHBs. It is more likely that each DHB has its own inefficiency persistence that completely captures the heterogeneity variations between them.

Another drawback of the empirical results obtained through Chapters 4, 5 and 6 is the absence of spatial dependency among DHBs. This may be particularly important for New Zealand, as DHBs work closely with each other in managing patient flow, particularly for specialist consultations and diagnostic tests. In such instances, DHBs that are located in close proximity may influence each other's decisions. For example, a modern technological investment by one DHB may have an effect on the decisions of its neighbours or vice versa. As a result, the inefficiency of one DHB may depend not only on its own past inefficiency but also on the inefficiency of its neighbours.

Despite the limitations mentioned above, this thesis provides evidence that a significant persistence in inefficiency exists among New Zealand DHBs, resulting in a substantial waste of public funds that policymakers need to address.

7.3 Synthesized results

Although each research question's findings are described in detail in the respective chapters, it is useful to summarise them here just for visual convenience.

In both Chapters 4 and 5, inefficiency persistence and the resulting long-run equilibrium level of inefficiency is found to be high. Table 7.1 presents the persistence level and average short and long-run levels of efficiency.

Table 7.1 Summary of the main findings from chapter 5 and 6

Measure	Persistence	Short-run	Long-run
Technical efficiency	97.61%	0.76	0.76
Cost efficiency	91.68%	0.92	0.93

Many more findings could be derived from Chapters 5 and 6 and summarized in Table 7.1; however, only the measures of persistence, short-run and long-run efficiency scores have been reported, as these are in line with the first two research questions. A key point to be noted is that when heterogeneity is incorporated into the cost function, as discussed in Chapter 5, the persistence parameter decreases, and the efficiency estimate increases. Further, in the model where heterogeneity is not controlled, the persistence parameter and efficiency measure also capture group effects, leading to heterogeneity bias.

In Chapter 6, the total factor productivity change and its components were estimated using both the primal and dual specifications. In Table 7.2, the results are summarized.

Table 7.2 Average total factor productivity change and its components

Specification	TFP	Scale	Technical	Efficiency
Primal	-0.96%	1.03%	-1.96%	-0.03%
Dual	-1.62%	2.32%	-1.63%	-2.31%

7.4 Policy implications

The results from chapter 4 provide evidence in support of the existence of a high persistence in technical inefficiency among New Zealand DHBs. As a result, DHBs choose to remain inefficient in the short run and instead aim to reach their long-run efficiency level, which is determined by the level of adjustment costs in the sector. Further, the average short-run level of technical efficiency shows that most DHBs operated close to the long-run equilibrium level of technical efficiency.

As indicated in chapter 4, adjustment costs among New Zealand DHBs may have their roots in inadequate infrastructure (clinical and physical) and lack of modern information technology. The Auditor General's recent report pointed towards deferred maintenance, underinvestment in buildings, and capital equipment as a significant hurdle for DHBs to reduce cost and maximise efficiency (Controller and Auditor-General, 2016a). For example, several DHBs such as the Southern (Ministry of Health, 2017; Southern District Health Board, 2016) and Capital & Coast (Capital & Coast District Health Board, 2017, 2018) suffer from inadequate hospital building and operation theatre capacity and outdated clinical and administrative information systems. There may be other factors such as management practices, weak absorptive capacity, and market structure that may also drive inefficiency persistence.

Numerous DHBs also have significant capacity issues relating to hospital space, with inadequate operating theatre capacity and an ageing information infrastructure contributing to inefficient healthcare delivery practises (Northern Regional Alliance, 2018a, 2018b). Constraints on capacity in relation to demand result in low asset utilisation, which results in wasteful use of hospital space, while ageing information technology results in significant duplication of administrative operations. A well-designed hospital employs fewer staff members, maximises the utilisation of diagnostic and treatment rooms, minimises frequent supply movement, decreases operational costs, and improves the patient experience.

Over the past decade, all three large and urban DHBs - Auckland, Manukau, and Waitemata have underinvested in critical clinical infrastructure and face serious issues relating to inadequate hospital spaces (Northern Regional Alliance, 2018a) drive inefficiencies. There has also been evidence of increasing outsourcing costs that led many DHBs into deficits due to the growing number of elective surgeries performed in private healthcare practices and the lack of surgical theatre capacity at DHB hospitals (Akoorie, 2017; Lewis, 2018).

The policy of capital charge is also known to disincentivise public departments in investing in capital assets and maintain working capital and inventories at efficient levels (State Services Commission, 2010). Recognising the adverse impact of capital charges, more recently, the government has temporarily taken on the responsibility to directly fund the DHBs' capital charge cost to encourage them to invest in hospital buildings and other critical infrastructure (Clark, 2019). Furthermore, authorities believe that funding capital charges in the interim will take some pressure off the existing operational funding that deters capital investment.

From a policy perspective, further research to quantify the contribution of inadequate hospital infrastructure and regulatory policies on the persistence of inefficiency would be very insightful. If a significant relationship is found, then substandard infrastructure and space constraints need to be prioritised. This could include building new state-of-the-art modern and efficient hospitals and promoting incentive-based capital funding policies that complement the DHBs efforts to address both the short-run operational needs and long-run infrastructural investments. Efforts to address long-term inefficiency would require greater government spending under prudent supervision.

The second empirical topic in Chapter 5 measures the persistence of cost inefficiency while controlling for the unobserved and observed heterogeneity at the DHB level. Although the results still show a high degree of inefficiency persistence and corresponding long-run cost efficiency of 0.93 for the sector, the long-run cost efficiency for DHBs providing hospital services to rural areas was lower, at 0.87. This suggests that these DHBs face high adjustment costs compared to those DHBs providing services to urban areas. Policy initiatives to address this may include greater investment in virtual healthcare services, and increased utilisation of mobile surgical units will improve health outcomes and reduce the associated inefficiencies. Although most DHBs performed well relative to their respective long-run equilibrium level of cost performance, Whanganui and Hawke's Bay DHBs operated consistently below their equilibrium level, indicating mismanagement of resources in these DHBs.

With reference to the study in Chapter 6, the results from both primal and dual approaches are consistent and point towards a general decline in the total factor productivity from 2011 to 2018. The primary determinant of the decline in total factor productivity was the technical change component, which was negative every year. In contrast, the scale component positively influenced the TFP every year. The performance-driven 'elective initiative' in 2016 appears to have allowed DHBs to harness existing economies of scale and improve efficiency. Regulatory authorities will need to analyse elective initiative's results to understand how it influences the DHB's decisions and to research what other policy initiatives can be developed, based on that experience, to boost the overall productivity of DHBs.

7.5 Suggestions for future research

This thesis introduced the application of a dynamic stochastic frontier approach into the healthcare literature to estimate the technical and cost efficiency of New Zealand DHBs. Complementing the modelling approach used in Chapters 4 and 5, future research can look into estimating the DHBs specific inefficiency persistence parameters to gain more insights and draw relevant policy implications. More recently, a study by Skevas et al. (2018) on German dairy farms allowed each farm to have its own level of persistence, leading to heterogeneity in each farm's long-run efficiency.

Secondly, since DHBs provide hospital services based on geographical coverage, it will be interesting to see how model parameters and the estimated inefficiencies change when spatial dependence is allowed. The spatial dependence could be allowed in the variance of the estimated function (de Graaff, 2020), the latent equation (Skevas, 2020) or even in the estimation of the inefficiency persistence parameter.

Another extension would be to identify suitable quality measures and apply them within the dynamic model context. One of the earliest quality-based healthcare efficiency studies by Carey (2003) found that improved healthcare quality was associated with increased costs. On the other hand, Deily and McKay (2006) argued that reductions in inefficiency would also reduce mortality rates. Therefore, this study's extension would check whether or not the trade-off between efficiency and quality exists under the dynamic stochastic frontier model.

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Appendices

Appendix A. Major public hospitals and clinics

DHB	Major public hospitals and clinics
Auckland	Auckland City Hospital, Greenlane Clinical Centre, Starship Children's Hospital
Bay of Plenty	Tauranga Hospital and Whakatane Hospital
Canterbury	Christchurch Hospital, Christchurch Women's Hospital, Burwood Hospital, The Princess
Capital and Coast	Wellington Regional Hospital, Wellington Children's Hospital and Kenerpuru Community
Counties Manukau	Middlemore Hospital, Manukau Super Clinic, Botany SuperClinic, Kidz First Children's Hospital,
Hawke's Bay	Hawke's Bay Fallen Soldiers' Memorial Hospital
Hutt Valley	Hutt Valley Hospital
Lakes	Rotorua Hospital and Taupo Hospital
Mid Central	Palmerston North Hospital and Dannevirke Community Hospital
Nelson	Nelson Hospital, Murchison Hospital, Wairau Hospital and Alexandra Hospital
Northland	Whangarei Hospital, Bay of Islands Hospital, Dargaville Hospital and Kaitaia Hospital
South Canterbury	Timaru Hospital
Southern	Dunedin Hospital, Wakari Hospital, Lake District Hospital and Southland Hospital
Tairawhiti	Gisborne Hospital
Taranaki	Taranaki Base Hospital and Hawera Hospital
Waikato	Waikato Hospital, Te Kuiti Hospital, Taumarunui Hospital, Thames Hospital and Tokoroa
Wairarapa	Wairarapa Hospital
Waitemata	North Shore Hospital and Waitakere Hospital
West Coast	Grey Base Hospital
Whanganui	Whanganui Hospital

Appendix B. Previous contribution to healthcare technical, allocative and cost efficiency studies

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Vitaliano and Toren (1994)	USA	Cost efficiency	604 nursing and other health-related facilities. Data relates to the years 1987 and 1990.	SFA	**Outputs**: patient days, admissions and transfers. **Prices:** wages of nursing aids, nurses and property expenses per square feet of a nursing home. An indicator variable for the type of owner and a variable for controlling quality was also used.
Koop et al. (1997)	USA	Cost efficiency	382 non-teaching hospitals from 1987-1991	Bayesian SFA	**Outputs**: number of discharges, inpatient days, beds, outpatient visits and case mix index. **Prices:** wage-price index.
Fried et al. (1999)	USA	Technical efficiency	990 nursing homes. Data relates to the year 1993.	DEA	**Outputs:** inpatient days. **Labour inputs:** registered nurses (FTEs), licensed practical nurses (FTEs), other personnel (FTEs). **Other input:** non-payroll expenses.
Maniadakis and Thanassoulis (2000)	Scotland	Technical, allocative and scale efficiency	75 acute hospitals over the period 1992 to 1996.	DEA	**Outputs:** accident and emergency attendances, case-mix adjusted outpatient attendances, day cases and inpatient discharges. **Labour inputs:** FTEs of doctors, nurses and other personnel. **Capital inputs:** hospital beds and the cubic metres of the hospital buildings

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Giokas (2001)	Greece	Technical efficiency	91 hospitals (72 general and 19 teaching hospitals) for the year 1992.	DEA & SFA	**Outputs:** inpatient days, outpatient visits and ancillary services. **Labour input:** total staff earnings. **Other input:** expenditure on operating services and supplies.
Rosko (2001)	USA	Cost efficiency	1631 urban hospitals for the period 1990–1996.	SFA	**Outputs:** outpatient visits and case-mix adjusted inpatient discharges. **Labour prices:** average annual salary per FTE employee. **Capital price:** depreciation and interest expenses per bed.
Athanassopoulos and Gounaris (2001)	Greece	Technical and allocative efficiency	98 public hospitals in the year 1992.	DEA	**Outputs:** medical patients, surgical patients, medical examinations and laboratory tests. **Labour inputs:** a count of medical, administrative and nursing personnel. Other inputs: operating and pharmaceutical costs, medical supply and other supply costs. **Prices:** only the labour price: average annual costs per hospital employee.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Steinmann and Zweifel (2003)	Switzerland	Technical efficiency	89 Swiss hospitals covering the years 1993–1996	DEA	**Outputs:** inpatients days. **Labour inputs:** expenditure on academic, nursing and administrative staff. **Other input:** non-labour expenditure.
Brown (2003)	USA	Technical efficiency	613 hospitals relating to years 1992-1996	SFA	**Outputs:** Case-mix discharges**. Labour inputs:** The FTEs of employees. **Capital input:** total beds and total expenses minus labour expenses are proxies for capital equipment**.** Indicator variables for year specific effects, profit and public hospitals were used.
Chang et al. (2004)	Taiwan	Technical efficiency	1996: 43 regional hospitals and 440 district hospitals. In 1997, the 44 regional hospitals and 429 district hospitals.	DEA	**Outputs:** patient days, outpatient visits and surgeries. **Labour inputs:** the number of physicians, nurses and ancillary service personnel. **Capital input:** number of beds.
Blank and Valdmanis (2005)	The Netherlands	Cost efficiency	71 homes for the disabled. Data for the year 1998	DEA	**Outputs:** number of patient days. **Inputs:** number of general personnel, nursing and medical personnel, auxiliary personnel and weighted material supplies costs. **Input prices:** the regional price index was used.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Pilyavsky et al. (2006)	Ukraine	Technical efficiency	61 community hospitals	DEA-bootstrap	**Outputs:** number of medical admissions and surgical admissions. **Labour inputs:** number of physicians and nurses. **Capital inputs:** number of hospital beds.
Aletras et al. (2007)	Greece	Technical and scale efficiency	51 general hospitals for the years 2000 and 2003.	DEA	**Outputs: c**ase-mix adjusted inpatient cases, outpatient visits and surgical operations. **Labour inputs:** FTEs of medical and other staff. **Capital input:** staffed hospital beds.
Linna et al. (2006)	Norway & Finland	Cost efficiency	47 Finnish and 51 Norwegian public hospitals in 1999 were studied.	DEA	**Outputs: w**eighted discharges, bed days, daycare and outpatient visits. **Prices:** wage expenditure per FTE employee and an input price index for operating costs.
Herr (2008)	Germany	Technical & cost efficiency	1556–1635 general hospitals each year for 2000 and 2003.	SFA	**Output: w**eighted hospital cases**. Labour inputs:** FTE counts of doctors, nurses, and other staff. **Capital input:** number of beds. **Labour input prices:** cost for each labour group divided by respective FTEs. **Capital price:** costs for all medical requirements (pharmaceutical drugs, medical instruments, transplants, etc.) divided by the number of installed beds.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Pilyavsky and Staat (2008)	Ukraine	Technical efficiency	193 community hospitals and polyclinics for the years 1997–2001.	Order-m estimator (related to FDH/DEA)	**Hospital Outputs:** admissions and surgical procedures. **Polyclinics Outputs:** admissions, surgical procedures, laboratory tests and X-rays. **Hospital inputs:** a count of nurses, physicians and beds. **Polyclinics Inputs:** a count of nurses and physicians.
Mutter et al. (2008)	USA	Cost efficiency	1,290 urban hospitals in 20 states operating in 2001.	SFA	**Outputs:** inpatient admissions, outpatient visits and patient days in nonacute care units. **Labour price:** average salary and benefits per FTE employee. **Capital price**: depreciation and interest expenses per bed. **Quality variable:** teaching and the excess in-hospital mortality rate index.
Friesner et al. (2008)	USA	Technical, allocative & scale efficiency	80 hospitals and 1076 observations, balanced longitudinal data for period 1998–2001.	DEA	**Outputs:** case-mix outpatient visits, inpatient days. **Inputs:** hospital beds, square feet of hospital, and paid labour hours. **Labour price:** average real wage paid by the hospital. **Intermediate input price:** supply expenses divided by the number of licensed beds and the producer price index. **Capital price:** the sum of interest and depreciation expenses divided by the square footage of the hospital and the producer price index.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Shimshak et al. (2009)	USA	Technical efficiency	38 rest homes for year 2003.	DEA	**Outputs:** number of residents, separated by who needs bathing, dressing, transferring, toileting and eating. **Inputs:** FTEs of nurses, nursing aids, ancillary and administrative staff.
Ancarani et al. (2009)	Italy	Technical efficiency	48 hospital wards for the year 2004.	DEA	**Outputs:** ambulatory visits, discharges and day surgeries. **Inputs:** number of physicians, non-medical personnel, number of beds, shifts of surgery rooms and maintenance costs of medical equipment.
Herr et al. (2011)	Germany	Cost, technical & profit efficiency	541 hospitals between period 2002 and 2006. Unbalanced longitudinal.	SFA	**Outputs:** weighted hospital cases. **Inputs:** FTEs of doctors, nurses and other staff. **Labour input prices:** salary of doctors, nurses and other staff divided FTEs. **Other input prices:** administration costs per bed and material cost per bed. **Capital input:** installed beds.
Ng (2011)	China	Scale and technical efficiency	Data for 2004–08 on 463 hospitals (balanced longitudinal).	DEA	**Outputs:** outpatients and inpatient cases. **Inputs:** number of doctors, nurses, pharmacists and other staff. **Capital input:** number of beds.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Medin et al. (2011)	Norway, Finland, Denmark and Sweden.	Cost efficiency	70 university hospitals in the Nordic countries over 3 years (2002–2004). Unbalanced longitudinal data.	DEA-bootstrap	**Outputs:** case-mix medical daycare and inpatient discharges, surgical daycare and inpatient discharges, and clinical teaching activities. **Inputs:** operating costs, costs for physicians and nurses. **Input prices:** wage index of respective countries. The authors also used quality indicators.
Hu et al. (2012)	China	Technical efficiency	30 province-level hospital data for years 2002–2008.	DEA	**Outputs:** number of outpatient and emergency room visits and the total number of inpatient days. Undesirable output - patient mortality. **Labour inputs:** number of doctors, medical technicians (nurse and physicians), other personnel (mainly administrative staff). **Capital inputs:** hospital beds
Nedelea and Fannin (2013)	USA	Cost efficiency	Unbalanced longitudinal data for a set of Critical Access Hospitals in the period 1999–2006.	DEA-bootstrap	**Outputs:** outpatient visits, admissions, post-admission days, emergency room visits, outpatient surgeries, and total births**. Labour input:** FTEs of personnel. **Capital input:** staffed and licensed beds. **Labour prices:** the price of labour (payroll expenses + employee benefits) divided by total FTEs. **Capital price:** depreciation expenses plus interest expenses divided by the number of beds in each facility. A quality proxy variable was used in the second stage truncated regression.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Ferrier and Trivitt (2013)	USA	Technical efficiency	1,074 general acute-care hospitals operating in 2005.	DEA	**Outputs: c**ase-mix measure of **i**npatient days, emergency room visits, outpatient visits, outpatient surgeries and inpatient surgeries. **Inputs:** FTEs of registered nurses, licensed practical nurses, medical residents and other labour. Various measures of quality were also used.
Barros et al. (2013)	Portugal	Cost efficiency	51 hospitals relating to year 1997-2008 (balanced longitudinal data).	Latent class SFA	**Outputs: n**umber of discharged patients, external consultations and emergency visits. **Input prices: r**atio of wages to the number of employees and the regional price index. Capital input proxied by the number of beds.
Cozad and Wichmann (2013)	USA	Technical efficiency	48 State level balanced longitudinal data from 2000 to 2007.	DEA-bootstrap	**Outputs: s**urvival rates, health status, and population share without disabilities. **Labour input:** number of general practitioners and registered nurses. **Capital input:** number of hospital beds.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Kinfu (2013)	South Africa	Technical efficiency	52 districts in South Africa for the year 2001	SFA	**Outputs:** under-five mortality and coverage of birth care. **Inputs:** per-capita public expenditures on health, health insurance coverage, the proportion of the population with access to safe drinking water, sanitation and waste disposal, the density of hospital beds and the number of health workers.
Yang and Zeng (2014)	China	Technical efficiency	46 are public hospitals for period 2006-2010 (balanced longitudinal).	DEA	**Outputs:** number of outpatient visits and inpatients. **Labour inputs:** number of doctors, nurses, administrative staff and other staff. **Capital input:** number of beds.
Alonso et al. (2015)	Spain	Technical efficiency	25 public hospitals, in the year 2009.	DEA-bootstrap	**Output:** desirable outputs: Case-mix adjusted number of discharges and the number of outpatient visits. Undesirable outputs: In-hospital mortality rate and the ratio between patient readmissions and discharges. **Labour inputs:** FTEs of physicians and nursing staff. **Capital input:** number of beds.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Mateus et al. (2015)	England, Portugal, Spain and Slovenia.	Technical efficiency	Portugal - 102 hospitals. England - 163 hospitals. Spain - 287 hospitals. Slovenia - 19 hospitals	SFA	**Outputs:** weighted hospital discharges. **Labour inputs:** headcounts of physicians, nurses and other employees. **Capital input:** number of beds.
Gok and Altındağ (2015)	Turkey	Technical efficiency	251 hospitals for the period 2011-2008 (balanced longitudinal data).	DEA	**Outputs:** bed utilization rate, bed turnover rate, total surgical operations, number of births, total outpatient visits, average facility inpatient days, and number of discharges. **Labour inputs:** number of specialized physicians and non-specialized physicians. **Capital inputs:** number of hospital beds.
Mitropoulos et al. (2015)	Greece	Technical efficiency	117 general public hospitals for the year 2009.	DEA	**Outputs:** numbers of inpatient admissions and aggregated scheduled and emergency outpatient visits. **Labour inputs:** number of doctors as an aggregation of all specialties of doctors in the hospital, number of other personnel as an aggregation of nurses, administrative and support staff in the hospital. **Capital input:** number of hospital beds.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Cordero et al. (2015)	Spain	Technical efficiency	132 primary care providers in the year 2010.	DEA	**Outputs:** hospitalisation rates. **Inputs**: number of GPs, nurses and number of prescriptions.
Ancarani et al. (2016)	UAE	Technical efficiency	48 wards of three main hospitals in Dubai for the year 2013.	DEA	**Outputs:** inpatient surgery discharges, inpatient non-surgery discharges and outpatients**. Labour inputs:** number of doctors and nurses. **Capital input:** number of beds.
Widmer (2015)	Switzerland	Cost efficiency	333 hospitals for period 2004-2009.	Bayesian SFA	**Outputs:** number of case-mix adjusted inpatient cases and revenue from outpatient's treatment**. Labour prices:** labour expenditure divided by FTEs. **Other input prices:** price of other inputs such as energy, material, and purchased services, computed by dividing total costs by the number of admissions.
Chowdhury and Zelenyuk (2016)	Canada	Technical efficiency	113 acute-care hospitals in Ontario for the years 2003 and 2006	DEA-bootstrap	**Outputs:** ambulatory visits and case-mix weighted inpatient days. **Labour inputs:** FTEs of nurses and administrative workers. **Other inputs:** Medical supplies costs and equipment costs. **Capital input:** number of staffed beds**.**

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Cetin and Bahce (2016)	OECD countries	Technical efficiency	26 OECD countries in the year 2016.	DEA	**Outputs:** life expectancy and infant mortality rates. **Inputs:** number of doctors, beds and health expenditure per capita.
Al-Amin et al. (2016)	USA	Cost efficiency	1108 hospitals that reported HCAPHS data in both August 2008 and July 2009	SFA	**Outputs: r**atio of emergency department visits to total outpatient visits, the ratio of outpatient surgeries to total outpatient visits, the proportion of total hospital beds classified as acute care, and the ratio of births to total admissions. **Labour input prices:** the price of labour was approximated by the area average annual salary per full-time-equivalent employee. **Capital price:** depreciation and interest expenses per bed.
Chen et al. (2016)	China	Cost efficiency	31 provincial-level hospital data from 2002-2011.	Bayesian SFA	**Outputs:** number of surgeries and total revenue. **Input prices:** salary expenditure by the staff of the hospitals. **Capital price:** total depreciation by total assets
Jiang et al. (2017)	China	Technical efficiency	1105 hospitals across 31 provinces for period 2008-2012.	DEA	**Outputs:** outpatient & emergency visits and inpatient days. **Labour inputs:** number of physicians, nurses, medical technicians. **Capital input:** number of open beds.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
DePuccio and Ozcan (2017)	USA	Technical efficiency	2212 general medical-surgical hospitals in the year 2012.	DEA	**Outputs:** medicare case mix-adjusted inpatient admissions, outpatient visits, and ED visits. **Labour inputs:** hospital service-mix, non-physician FTEs. **Other input:** non-labour operating expenses. **Capital input:** number of staffed and set-up beds.
Colombi et al. (2017)	Italy	Technical efficiency	133 acute hospitals during the period 2008-2013.	SFA	**Outputs:** hospital annual acute discharges corrected by treatment cost. **Labour inputs:** annual working hours of physicians, nurses and other workers. **Capital input:** total beds for acute discharges.
Stefko et al. (2018)	Slovak Republic	Technical efficiency	8 regions during the period 2008-2015	DEA	**Outputs:** use of beds and average nursing time. **Labour inputs:** number of medical staff. **Other input**: quantity of medical equipment, magnetic resonance and computed tomography. **Capital input:** number of beds.
Sultan and Crispim (2018)	Palestine	Technical efficiency	11 public hospitals from 2010 to 2015.	DEA	**Outputs:** total number of annual care days, annual outpatient visits and cases served without admission. **Inputs:** FTEs of nurses, technicians, and other employees in para-medical departments and the administrative staff. **Capital input:** number of hospital beds.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Ferreira and Marques (2019)	Portugal	Technical efficiency	7 hospitals and 20 hospital centres, operating between 2013 and 2016.	DEA	**Outputs:** number of inpatient discharges, emergency cases, first medical appointments, follow-up medical appointments, outpatient surgeries, conventional surgeries, urgent surgeries and number of births. **Labour inputs:** FTEs of doctors, nurses, hospital days. Also, the use of various expenditures as inputs.
Giménez et al. (2019)	Mexico	Technical efficiency	606 public and 182 private hospitals	DEA	**Outputs:** surgical medical procedures, medical consultations, days of stay and hospital discharges. **Labour inputs:** number of doctors in direct contact with the patient and nurses**. Capital inputs:** operating rooms and licensed beds.
Ahmed et al. (2019)	Bangladesh	Technical efficiency	62 District hospitals for the year 2015	DEA	**Outputs:** number of women receiving ANC services, regular deliveries, caesarean-section services, PNC services, outpatient visits and inpatient admissions. **Labour inputs:** number of doctors and nurses. **Capital input:** number of beds.

Study	Country	Efficiency type	Facility type and period	Methodology	Variables
Jiang and Andrews (2020)	New Zealand	Technical efficiency and cost efficiency	20 District health boards for period 2011-2017.	SFA & DEA	**Outputs:** case-weighted inpatient discharges and price-weighted outpatient visits. **Labour inputs:** FTEs of medical and weighted nurses and other staff. **Capital input:** depreciation and capital charges. **Intermediate inputs**: expenditure on clinical supplies. **Labour price:** total expenditure divided by FTEs. **Capital price:** capital charges divided by inpatient discharges. **Intermediate input price:** total expenditure divided by inpatient discharges.
Andrews (2020a)	New Zealand	Technical efficiency	20 District health boards for the period 2011-2017.	DEA-bootstrap	**Outputs:** case-weighted inpatient discharges and price-weighted outpatient visits. **Labour inputs:** FTEs of medical, nurses, allied, support and management staff. **Capital input:** capital assets value. **Intermediate inputs**: clinical supply expenditure.
Andrews (2020b)	New Zealand	Technical efficiency	20 District health boards for period 2011-2018.	DEA-bootstrap	**Outputs:** case-weighted inpatient discharges and price-weighted outpatient visits. **Labour inputs:** FTEs of medical and weighted nurses & other staff. **Capital input:** capital assets value. **Intermediate input**: clinical supply expenditure.

Appendix C. Previous contribution to healthcare TFP studies

Study	Country	Facility type and period	Methodology	Variables	Findings
Färe et al. (1992)	Sweden	42 Swedish group pharmacies for period 1980-1989	Malmquist index	**Outputs:** number of drug deliveries, prescription drugs, medical appliances and over the counter goods. **Labour inputs:** number of hours of pharmacists, technical staff, other building and equipment services staff. **Capital input:** depreciation amount.	Average TFP increased in seven periods and decreased in two periods. On average, progress in TFP during the latter part of the 1980s was due to the positive shifts in the frontier.
Burgess and Wilson (1995)	USA	137 nonpsychiatric hospitals for the period 1985-1988.	DEA-Malmquist index	**Outputs:** number of acute care inpatient days, case-mix weighted acute care inpatient discharges, long-term care inpatient days, outpatient visits; ambulatory surgical procedures and inpatient surgical procedures. **Labour inputs:** FTEs of nurses, other clinical labour, nonclinical labour, and long-term care labour staff. **Capital input:** number of acute-care beds and long-term hospital beds.	On average, there was technical regress which dominated changes in inefficiency in determining changes in TFP.

Study	Country	Facility type and period	Methodology	Variables	Findings
Färe et al. (1995)	Sweden	257 pharmacies in cities and suburban areas for the period 1990-1991.	Malmquist index	**Outputs:** number of prescriptions, drug deliveries, prescription drugs, medical appliances and over the counter goods. **Labour inputs:** number of hours of pharmacists, technical staff, building and equipment services staff. **Capital input:** depreciation amount.	The results suggest that the incorporation of quality makes a difference in measured productivity change.
Tambour (1997)	Sweden	20 ophthalmology departments in various hospitals from 1988 to 1993.	DEA-bootstrap Malmquist index	**Outputs:** number of performed operations for cataract, glaucoma, squint diseases and number of physician visits. **Labour inputs:** FTEs of specialists and other physicians. **Capital input:** number of beds.	The positive changes in TFP are mainly due to positive changes in production technology rather than an overall positive change in relative (technical) efficiency or scale efficiency.
Linna (1998)	Finland	43 acute hospitals in period 1988-1994.	Malmquist index	**Outputs:** DRG weighted inpatient episodes, number of outpatients, emergency visits, residents, research outputs and nursing students. **Labour price:** personnel price index.	Results showed a 3–5% annual average increase in TFP, half of which was due to an improvement in cost efficiency and the other half due to technological change

Study	Country	Facility type and period	Methodology	Variables	Findings
Dismuke and Sena (1999)	Portugal	58 hospitals during the years 1992-1994.	SFA and DEA-Malmquist index	**Outputs:** DRG weighted desirable and undesirable discharges. **Inputs:** authors concentrate on diagnostic technology utilisation on three technological inputs: the computerised axial tomography scanner, the electrocardiogram and the echocardiogram in the production of discharges.	Improvement of technical efficiency has not been accompanied by an equivalent improvement in the quality of output in district hospitals. The parametric frontiers show technical progress in most outputs, except echocardiograms which experienced technical regress.
Giuffrida (1999)	United Kingdom	90 English Family Health Service Authorities over the period 1991–1995.	DEA-Malmquist index	**Outputs:** the total number of people registered with a general practitioner broken down by various demographics. Also, a measure of intermediate outputs, such as pre-determined targets for children, was also included. **Labour inputs:** number of general practitioner and practice nurses.	The improvement in TFP was very small. The rise was due to pure progress in technical efficiency and positive changes in scale efficiency, although the technology shows no noticeable change. Analysis indicates very a limited scope for productivity growth in this sector.

Study	Country	Facility type and period	Methodology	Variables	Findings
Maniadakis et al. (1999)	United Kingdom	72 acute Scottish hospitals for the period 1992–1996.	DEA-Malmquist index	**Outputs:** number of accident and emergency attendances, case-mix adjusted outpatient attendances, day cases and inpatient discharges. **Labour inputs:** number of doctors, nurses, other personnel. **Capital input:** number of beds.	The improvement in TFP was dominated by technical change rather than hospital relative efficiency changes.
Maniadakis and Thanassoulis (2000)	United Kingdom	75 Scottish hospitals for the period 1992–1996.	DEA-Malmquist index	**Outputs:** number of accident and emergency attendances, case-mix adjusted outpatient attendances, day cases and inpatient discharges. **Labour inputs:** number of doctors, nurses, other personnel. **Capital input:** number of beds.	The improvement in TFP is due to overall progress in efficiency, which, in turn, is primarily attributed to an increase in allocative efficiency. Technical progress resulted in a small reduction in the number of inputs used, but also a higher cost of production due to the worsening of the match between input mixes and relative input prices.

Study	Country	Facility type and period	Methodology	Variables	Findings
Sommersguter-Reichmann (2000)	Austria	22 Austrian hospitals for period 1994 and 1998.	DEA-Malmquist index	**Outputs:** the total number of patients treated in the outpatients and the number of credit points reported by each hospital, multiplied by a steering factor. Labour i**nputs:** FTEs of labour. **Intermediate input:** expenses for external medical services. **Capital input:** number of beds.	TFP decreased from 1994 to 1995, while it increased from 1995 to 1996. The results showed a positive shift in technology between 1996 and 1998, without any technical efficiency improvement.
Jiménez et al. (2003)	United Kingdom	39 English county council hospitals for period 1992 to 1995.	DEA-Malmquist index	**Outputs:** number of people who receive residential care at day centres; the number of hours of domiciliary care delivered; the number of meals delivered to people at home; and the magnitude of the user charges raised from those in care. **Inputs:** gross cost of all services for older people.	The TFP shows a steady increase, from 0.7% in year 2 to 2.3% in year 5. There was minimal improvement in any of the components in 1993/94. Subsequently, a dip of 3.5% in technological progress in 1994/95 was offset by a 13.3% rise in the following year. Conversely, both pure and scale efficiencies fell back in the final year.

Study	Country	Facility type and period	Methodology	Variables	Findings
González and Gascón (2004)	Spain	80 pharmaceutical labs for the period 1994 to 2000.	DEA-Malmquist index	**Outputs:** net sales. **Labour input:** labour costs. **Capital input:** fixed assets depreciation (capital). **Intermediate input:** other costs.	The results indicate that improvements in technical efficiency and changing technology explain most of the observed TFP growth. However, the contribution of technological improvements to productivity growth is minimal.
Gannon (2008)	Ireland	Set of hospitals from 1995 to 1998.	DEA-Malmquist index	**Outputs:** number of case-mix adjusted inpatients, outpatients and day cases. **Labour inputs:** FTEs of people employed in each hospital. **Capital input:** number of beds in each hospital.	Results show that, on average, both technical and efficiency changes contribute to a higher TFP in larger hospitals but lead to lower productivity levels in smaller hospitals. However, the contribution of these productivity components varies over time, and technical improvements play a more critical role in increasing the productivity of larger hospitals.

Study	Country	Facility type and period	Methodology	Variables	Findings
Pilyavsky and Staat (2008)	Ukraine	193 Community hospitals for the years 1997-2001.	DEA-Malmquist index	**Outputs:** number of admissions and surgical procedures. **Labour inputs:** FTEs of people employed in each hospital. **Capital input:** number of beds in each hospital.	The overall average TFP did not change throughout the observation period. However, substantial deviations from unity can be observed depending on the period and the region.
Morikawa (2010)	Japan	239 secondary medical areas for the period 1998-2007.	Fixed-effects regression	**Outputs:** number of inpatient days and outpatient visits. **Labour inputs:** FTEs of the physicians and the ratio of physicians to the total number of other staff. **Capital input:** number of beds multiplied by the utilization rate.	TFP increases by more than 10% when the size of the hospital doubles.
Ng (2011)	China	463 hospitals from Guangdong province for period 2004-2008.	DEA-Malmquist index	**Outputs:** number of inpatient and outpatient cases. **Labour inputs:** number of doctors, nurses, pharmacists and other staff. **Capital input:** number of hospital beds.	TFP grew between 2004 and 2008, mainly driven by technological progress. However, technical efficiency deteriorated in the period under study.

Study	Country	Facility type and period	Methodology	Variables	Findings
Blank and Eggink (2014)	The Netherlands	Aggregated hospital data over the period 1972-2010 which yielded 39 observations.	Time series regression	**Outputs:** number of surgeries and total revenue. **Input prices:** price of personnel per FTE, price of material supplies is proxied by the consumer price index. **Capital price:** total capital costs divided by depreciation and investment.	The results indicate that the average productivity of the hospital sector in different periods varies and that these differences are related to the structure of regulation in those periods. Further, the authors argue that competition reform failed in improving hospital sector productivity.
Kittelsen et al. (2015)	Denmark, Finland, Norway and Sweden	Public acute somatic hospitals for the period 2005-2007.	DEA-Malmquist index	**Outputs:** number of outpatient visits, DRG weighted inpatients and day patients. **Inputs:** real operating costs.	The results show small differences in scale and technical efficiency between countries but significant differences in production possibilities (frontier position). The country-specific Finnish frontier is the key source of the Finnish productivity advantage.

Study	Country	Facility type and period	Methodology	Variables	Findings
Karmann and Roesel (2017)	Germany	Hospitals from 16 federal states for the period 1993–2013	Frontier based Malmquist approach and Non-frontier Tornqvist approach	**Outputs:** the number of discharges, a quality index, and the quality-adjusted number of discharges (outcome). **Labour inputs:** FTEs of physicians, nurses, and other staff. **Intermediate inputs:** deflated costs of energy, materials, and service expenses. **Capital input:** proxied by the amount of deflated capital stocks.	The authors find that quality improvements rather than increases in quantity volumes generate TFP growth in hospital care. Also, reducing the length of stay is a proper way to enhance hospital TFP.

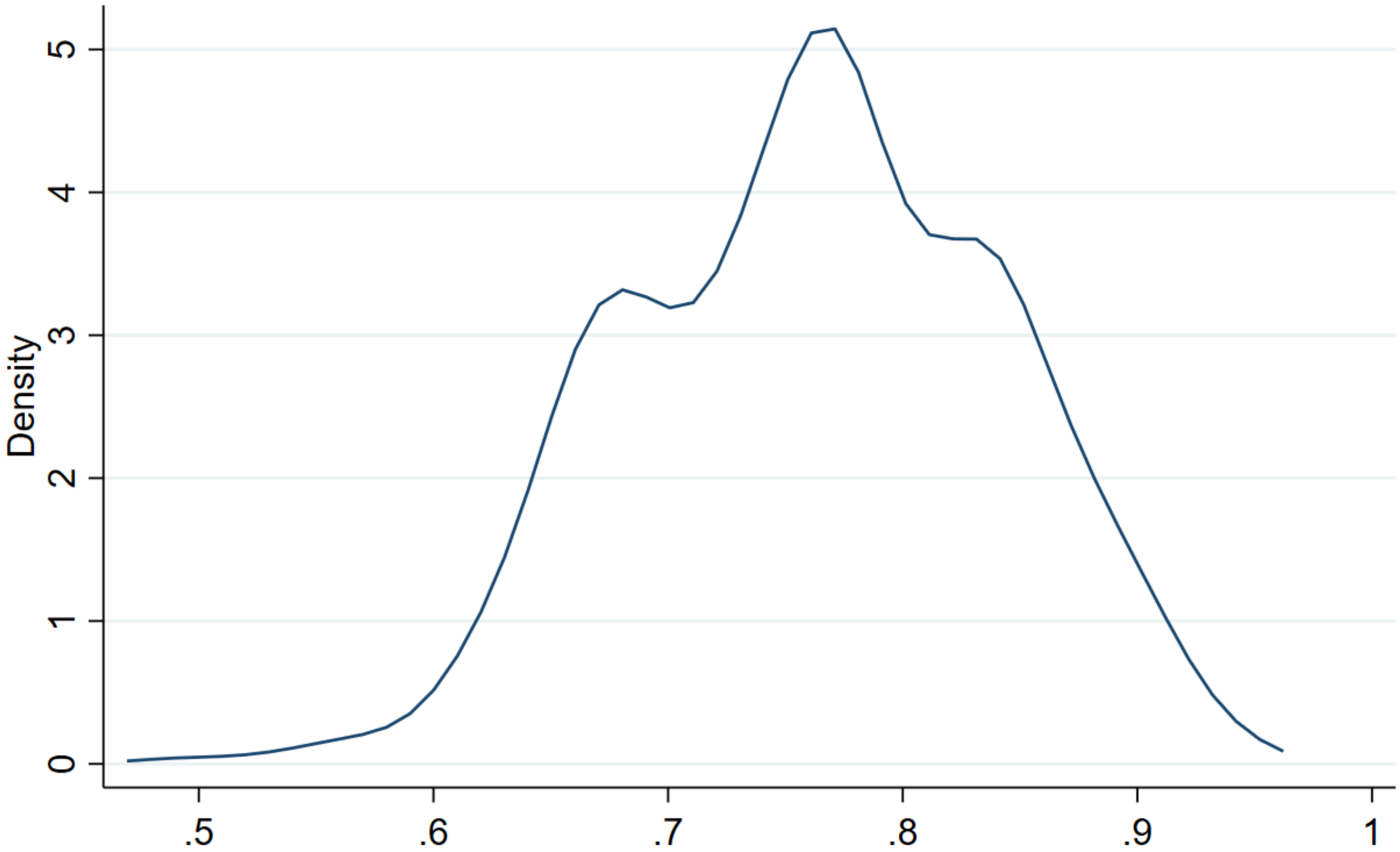
Appendix D. Variable definitions

Variable	Description†
Labour input	
Medical staff	All internal staff employed primarily as physicians or surgeons (but excluding medical staff employed solely in a management role).
Other staff	This includes the weighted FTE measure of nursing, allied, management and support staff.
Capital and other inputs	
Capital asset values	The monetary value of all capital assets, which includes buildings, equipment (clinical and non-clinical), information technology, and motor vehicles.
Outsourced labour and clinical costs	Labour costs and expenditure on the provision of entire diagnostic or other treatments to the DHB as an outsourced service (i.e., more than just the pure labour).
Clinical supplies costs	Cost of materials or supplies used or consumed, either directly or indirectly, in the treatment of patients. Examples include treatment disposables, pharmaceuticals, etc.
Outputs	
Case-weighted inpatients	Refers to the patients who are admitted to a healthcare facility for treatment. This also includes patients admitted as emergency department cases.
Price-weighted outpatient visits	Refers to the patients who receive a preadmission assessment or a diagnostic treatment at a healthcare facility who are not admitted. Outpatients generally leave the facility within three hours from the start of the consultation.

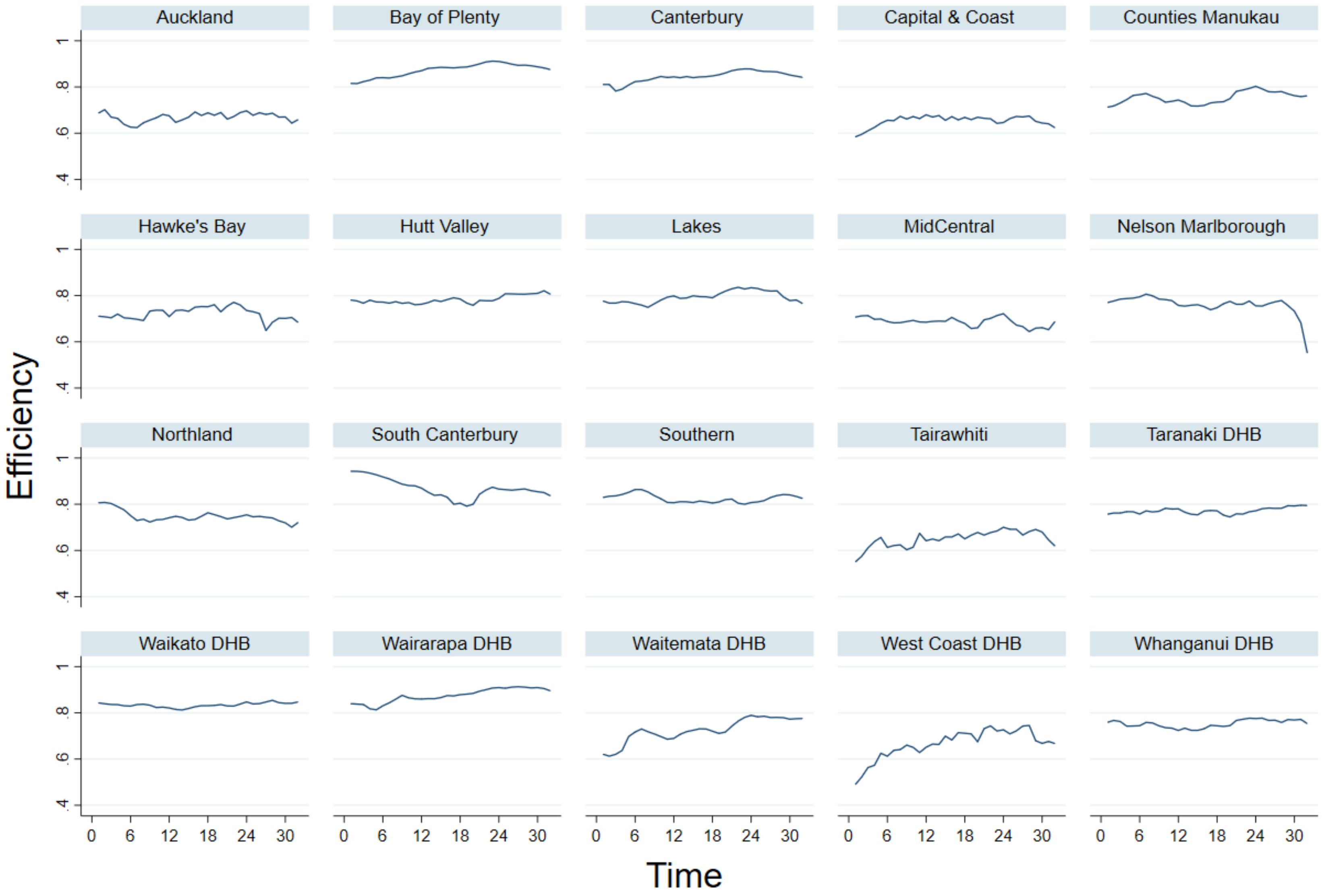
Appendix E. Mean efficiency performance by year

DHB	2011	2012	2013	2014	2015	2016	2017	2018	**Mean**
Auckland	0.68	0.63	0.67	0.67	0.68	0.68	0.68	0.66	0.67
Bay of Plenty	0.82	0.84	0.86	0.88	0.89	0.91	0.90	0.88	0.87
Canterbury	0.80	0.82	0.84	0.84	0.85	0.88	0.87	0.85	0.84
Capital & Coast	0.60	0.66	0.67	0.67	0.66	0.65	0.67	0.64	0.65
Counties Manukau	0.73	0.77	0.74	0.72	0.74	0.79	0.78	0.76	0.75
Hawke’s Bay	0.71	0.70	0.73	0.74	0.75	0.76	0.70	0.70	0.72
Hutt Valley	0.78	0.77	0.76	0.78	0.78	0.78	0.81	0.81	0.78
Lakes	0.77	0.76	0.78	0.79	0.80	0.83	0.82	0.78	0.79
Mid Central	0.71	0.69	0.69	0.69	0.67	0.71	0.67	0.67	0.69
Nelson Marlborough	0.78	0.80	0.78	0.76	0.76	0.76	0.77	0.68	0.76
Northland	0.80	0.75	0.73	0.74	0.75	0.74	0.74	0.72	0.75
South Canterbury	0.94	0.91	0.88	0.84	0.80	0.86	0.86	0.85	0.87
Southern	0.84	0.86	0.82	0.81	0.81	0.81	0.82	0.84	0.83
Tairawhiti	0.59	0.63	0.63	0.65	0.67	0.68	0.68	0.66	0.65
Taranaki	0.76	0.77	0.78	0.76	0.76	0.76	0.78	0.79	0.77
Waikato	0.84	0.83	0.83	0.82	0.83	0.84	0.84	0.84	0.83
Wairarapa	0.83	0.84	0.87	0.87	0.88	0.90	0.91	0.90	0.87
Waitemata	0.62	0.72	0.70	0.72	0.72	0.77	0.78	0.78	0.73
West Coast	0.54	0.63	0.65	0.68	0.70	0.73	0.73	0.67	0.67
Whanganui	0.76	0.75	0.73	0.73	0.74	0.77	0.77	0.77	0.75
Grand Mean	**0.74**	**0.76**	**0.76**	**0.76**	**0.76**	**0.78**	**0.78**	**0.76**	**0.76**

Appendix F. Kernel density plot of technical efficiency scores



Appendix G. Technical efficiency scores overtime by DHB



Appendix H. Estimated parameters from the dynamic stochastic frontier (DSF)

Variable	Posterior Mean	Standard Deviation	90%credible interval
log_med_ price	0.13	0.03	[0.09, 0.18]
log_other_ price	0.49	0.06	[0.38, 0.59]
log_clinical_ price	0.26	0.11	[0.08, 0.44]
log_capital_ price	0.11	0.05	[0.02,0.20]
log_inpatients	0.69	0.03	[0.64,0.74]
log_outpatients	0.30	0.03	[0.26, 0.35]
log_med_price^2	0.15	0.21	[-0.19, 0.49]
log_med_ price × *log_other_ price*	-0.51	0.37	[-1.12, 0.10]
log_med_ price × *log_clinical_ price*	0.85	0.74	[-0.37, 2.07]
log_med_ price × *log_capital_ price*	-0.06	0.19	[-0.37, 0.26]
log_med_ price × *log_inpatients*	0.06	0.11	[-0.13, 0.24]
log_med_ price × *log_outpatients*	0.04	0.14	[-0.20, 0.27]
log_other_ price^2	0.26	0.95	[-1.29, 1.81]
log_other_ price × *log_clinical_ price*	1.08	2.13	[-2.42, 4.58]
log_other_ price × *log_capital_ price*	-0.68	0.42	[-1.37, 0.00]
log_other_ price × *log_inpatients*	-0.34	0.20	[-0.68, 0.00]
log_other_ price × *log_outpatients*	0.18	0.27	[-0.26, 0.63]
log_clinical_ price^2	-5.83	5.58	[-15.02, 3.35]
log_clinical_ price × *log_capital_ price*	-1.97	0.64	[-3.02, -0.91]
log_clinical_ price × *log_inpatients*	-0.29	0.42	[-0.98, 0.41]
log_clinical_ price × *log_outpatients*	0.40	0.54	[-0.49, 1.29]
log_capital_ price^2	0.69	0.41	[0.01, 1.36]
log_capital_ price × *log_inpatients*	0.30	0.11	[0.11, 0.48]
log_capital_ price × *log_outpatients*	-0.38	0.15	[-0.62, -0.14]
log_inpatients × *log_outpatients*	-0.69	0.12	[-0.88, -0.49]
log_inpatients^2	0.69	0.10	[0.53, 0.86]
log_outpatients^2	0.80	0.14	[0.56, 1.04]
quarter 1	-0.05	4.3×10^{-3}	[-0.06, -0.04]
quarter 2	-0.01	4.0×10^{-3}	[-0.02, -4.6×10^{-3}]

quarter 3	0.02	4.4×10^{-3}	[0.01, 0.03]
trend	3.0×10^{-3}	9.2×10^{-4}	[1.5×10^{-3}, 4.6×10^{-3}]
trend^2	-1.5×10^{-4}	6.2×10^{-5}	[2.5×10^{-4}, 4.5×10^{-5}]
small	-	-	-
medium	-	-	-
rural	-	-	-
constant	3.76	0.04	[3.68, 3.83]
Dynamic parameters			
constant	0.01	0.00	[0.00, 0.02]
small	-	-	-
medium	-	-	-
rural	-	-	-
log_beds			
$\boldsymbol{\rho}$	98.78 %	4.4×10^{-3}	[97.95 %, 99.33 %]
Precision parameters			
$\boldsymbol{\tau}$	1510.38	156.87	[1270.60, 1784.24]
$\boldsymbol{\phi}$	225.85	58.11	[142.41, 334.75]
Standard deviations			
$\boldsymbol{\sigma_v}$	0.03	1.3×10^{-3}	[0.02, 0.03]
$\boldsymbol{\sigma_s}$	0.07	8.6×10^{-3}	[0.05, 0.08]
Log marginal likelihood	880.01		

Appendix I. Estimated parameters from the dynamic stochastic frontier with DHB specific indicators (DSF_IND)

Variable	Posterior Mean	Standard Deviation	90%credible interval
log_med_ price	0.18	0.02	[0.15, 0.21]
log_other_ price	0.38	0.04	[0.32, 0.45]
log_clinical_ price	0.16	0.07	[0.05, 0.27]
log_capital_ price	0.08	0.03	[0.04,0.14]
log_inpatients	0.25	0.02	[0.21,0.29]
log_outpatients	0.09	0.02	[0.06, 0.12]
$log\_med\_price^2$	0.26	0.16	[7.4×10^{-3}, 0.52]
log_med_ price × *log_other_ price*	-0.37	0.25	[-0.77, 0.04]
log_med_ price × *log_clinical_ price*	0.56	0.48	[-0.23, 1.34]
log_med_ price × *log_capital_ price*	-0.24	0.13	[-0.46, -0.02]
log_med_ price × *log_inpatients*	0.12	0.07	[2.2×10^{-3}, 0.24]
log_med_ price × *log_outpatients*	-0.07	0.09	[-0.22, 0.07]
$log\_other\_price^2$	0.50	0.64	[-0.56, 1.54]
log_other_ price × *log_clinical_ price*	-0.48	1.38	[-2.76, 1.79]
log_other_ price × *log_capital_ price*	-0.02	0.27	[-0.47, 0.42]
log_other_ price × *log_inpatients*	-0.37	0.13	[-0.59, -0.15]
log_other_ price × *log_outpatients*	0.43	0.17	[0.14, 0.72]
$log\_clinical\_price^2$	-1.60	3.51	[-7.42, 4.15]
log_clinical_ price × *log_capital_ price*	-3.13	0.41	[-3.82, -2.46]
log_clinical_ price × *log_inpatients*	0.10	0.28	[-0.36, 0.56]
log_clinical_ price × *log_outpatients*	0.09	0.36	[-0.50, 0.69]
$log\_capital\_price^2$	0.47	0.26	[0.04, 0.89]
log_capital_ price × *log_inpatients*	0.08	0.08	[-0.05, 0.20]
log_capital_ price × *log_outpatients*	-0.15	0.09	[-0.30, 3.3×10^{-3}]
log_inpatients × *log_outpatients*	-0.24	0.09	[-0.38, -0.09]
$log\_inpatients^2$	0.24	0.07	[0.12, 0.36]
$log\_outpatients^2$	0.26	0.11	[0.08, 0.43]
quarter 1	-0.02	2.8×10^{-3}	[-0.03, -0.02]
quarter 2	-0.01	2.5×10^{-3}	[-0.01, -4.3×10^{-3}]

quarter 3	-0.01	2.8×10^{-3}	[-0.02, -5.6×10^{-3}]
trend	4.0×10^{-3}	5.3×10^{-4}	[3.2×10^{-3}, 4.9×10^{-3}]
trend²	-7.4×10^{-5}	3.8×10^{-5}	[1.4×10^{-4}, 9.2×10^{-6}]
small	-1.52	0.07	[-1.64, -1.41]
medium	-0.84	0.04	[-0.91, -0.78]
rural	-0.32	0.03	[-0.37, -0.27]
constant	4.73	0.03	[4.67, 4.77]
Dynamic parameters			
constant	0.75	0.01	[0.44, 1.12]
small	-0.22	0.06	[-0.33, -0.13]
medium	-0.12	0.04	[-0.19, -0.07]
rural	-0.03	0.01	[-0.05, -0.01]
log_beds	-0.09	0.03	[-0.14, -0.06]
$\boldsymbol{\rho}$	96.51 %	9.8×10^{-3}	[94.74 %, 97.95 %]
Precision parameters			
$\boldsymbol{\tau}$	5442.52	708.71	[4359.28, 6677.72]
$\boldsymbol{\phi}$	165.08	23.90	[129.69, 207.21]
Standard deviations			
$\boldsymbol{\sigma_v}$	0.01	8.8×10^{-4}	[0.01, 0.02]
$\boldsymbol{\sigma_s}$	0.08	0.01	[0.07, 0.09]
Log marginal likelihood	1110.00		

Appendix J. Estimated parameters from the random-effects dynamic stochastic frontier with DHB specific indicators (REDSF)

Variable	Posterior Mean	Standard Deviation	90%credible interval
log_med_ price	0.17	0.02	[0.15, 0.20]
log_other_ price	0.40	0.04	[0.34, 0.46]
log_clinical_ price	0.19	0.06	[0.09, 0.29]
log_capital_ price	0.06	0.03	[0.01,0.11]
log_inpatients	0.17	0.03	[0.12,0.21]
log_outpatients	0.07	0.02	[0.05, 0.10]
log_med_price^2	0.29	0.14	[0.05, 0.52]
log_med_ price × *log_other_ price*	-0.41	0.22	[-0.77, -0.06]
log_med_ price × *log_clinical_ price*	0.59	0.45	[-0.16, 1.34]
log_med_ price × *log_capital_ price*	-0.21	0.12	[-0.40, -0.01]
log_med_ price × *log_inpatients*	0.10	0.06	[2.4×10^{-3}, 0.21]
log_med_ price × *log_outpatients*	-0.04	0.08	[-0.18, 0.10]
log_other_ price^2	0.41	0.55	[-0.51, 1.31]
log_other_ price × *log_clinical_ price*	0.52	1.16	[-1.40, 2.44]
log_other_ price × *log_capital_ price*	-0.05	0.27	[-0.49, 0.40]
log_other_ price × *log_inpatients*	-0.40	0.12	[-0.59, -0.20]
log_other_ price × *log_outpatients*	0.46	0.16	[0.19, 0.73]
log_clinical_ price^2	-3.82	3.09	[-8.93, 1.25]
log_clinical_ price × *log_capital_ price*	-2.93	0.41	[-3.60, -2.26]
log_clinical_ price × *log_inpatients*	-0.02	0.24	[-0.41, 0.37]
log_clinical_ price × *log_outpatients*	0.29	0.31	[-0.22, 0.81]
log_capital_ price^2	0.27	0.24	[-0.12, 0.66]
log_capital_ price × *log_inpatients*	0.05	0.07	[-0.05, 0.16]
log_capital_ price × *log_outpatients*	-0.13	0.09	[-0.28, 0.01]
log_inpatients × *log_outpatients*	-0.24	0.08	[-0.37, -0.11]
log_inpatients^2	0.23	0.07	[0.12, 0.34]
log_outpatients^2	0.28	0.10	[0.11, 0.44]
quarter 1	-0.02	2.8×10^{-3}	[-0.02, -0.02]
quarter 2	-0.01	2.4×10^{-3}	[-0.01, -4.1×10^{-3}]

quarter 3	-0.01	2.8×10^{-3}	$[-0.02, -9.9 \times 10^{-3}]$
trend	4.5×10^{-3}	4.4×10^{-4}	$[3.8\times 10^{-3}, 5.2\times 10^{-3}]$
trend^2	-1.0×10^{-4}	3.3×10^{-5}	$[1.6 \times 10^{-4}, 4.9 \times 10^{-6}]$
small	-1.69	0.15	[-1.93, -1.43]
medium	-0.83	0.11	[-1.00, -0.65]
rural	-0.23	0.09	[-0.39, -0.07]
constant	4.95	0.08	[4.82, 5.08]
Dynamic parameters			
constant	0.96	0.42	[0.36, 1.72]
small	-	-	-
medium	-	-	-
rural	-	-	-
log_beds			
$\boldsymbol{\rho}$	96.38 %	0.02	[93.46 %, 98.43 %]
Precision parameters			
$\boldsymbol{\tau}$	5245.60	640.325	[4294.42, 6377.16]
$\boldsymbol{\phi}$	23.01	9.68	[11.22, 41.53]
Ω	1.84	0.63	[0.96, 2.99]
Standard deviations			
$\boldsymbol{\sigma_v}$	0.01	8.3×10^{-4}	[0.01, 0.03]
$\boldsymbol{\sigma_s}$	0.22	0.04	[0.15, 0.30]
$\boldsymbol{\sigma_\alpha}$	0.77	0.14	[0.57, 1.02]
Log marginal likelihood	1175.30		

Appendix K. Estimated parameters from the random-effects dynamic stochastic frontier (REDSF_IND)

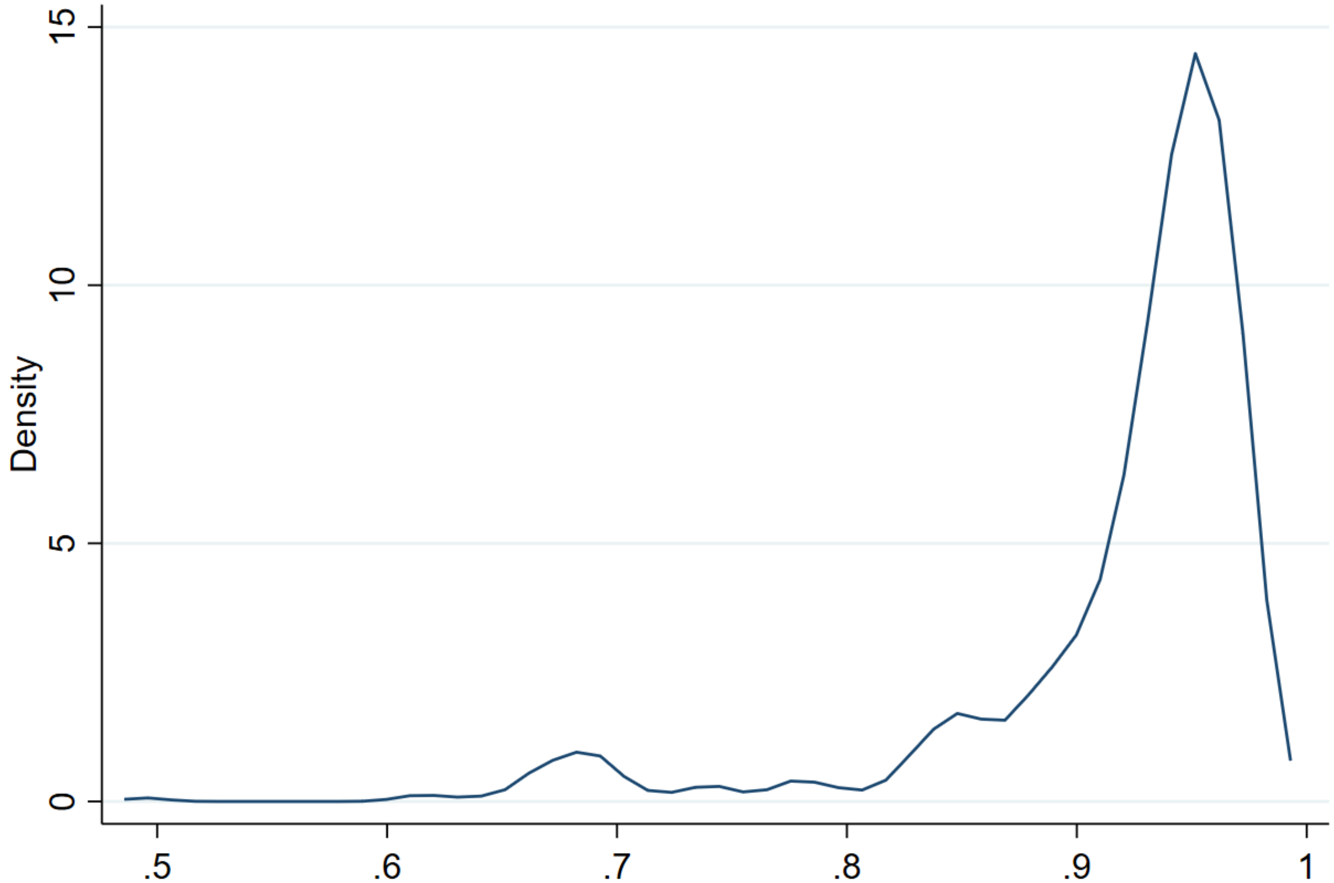
Variable	Posterior Mean	Standard Deviation	90% credible interval
log_med_ price	0.18	0.02	[0.15, 0.21]
log_other_ price	0.41	0.04	[0.35, 0.47]
log_clinical_ price	0.20	0.06	[0.10, 0.30]
log_capital_ price	0.07	0.03	[0.02,0.12]
log_inpatients	0.17	0.03	[0.12,0.21]
log_outpatients	0.08	0.02	[0.05, 0.11]
log_med_price^2	0.27	0.14	[0.03, 0.50]
log_med_ price × *log_other_ price*	-0.47	0.21	[-0.81, -0.12]
log_med_ price × *log_clinical_ price*	0.67	0.45	[-0.08, 1.41]
log_med_ price × *log_capital_ price*	-0.22	0.12	[-0.42, -0.02]
log_med_ price × *log_inpatients*	0.10	0.06	[8.7×10^{-3}, 0.20]
log_med_ price × *log_outpatients*	-0.03	0.09	[-0.17, 0.11]
log_other_ price^2	0.50	0.55	[-0.40, 1.39]
log_other_ price × *log_clinical_ price*	0.77	1.16	[-1.14, 2.69]
log_other_ price × *log_capital_ price*	0.04	0.27	[-0.41, 0.48]
log_other_ price × *log_inpatients*	-0.41	0.12	[-0.61, -0.21]
log_other_ price × *log_outpatients*	0.44	0.17	[0.16, 0.72]
log_clinical_ price^2	-4.57	3.06	[-9.63, 0.45]
log_clinical_ price × *log_capital_ price*	-2.79	0.40	[-3.46, -2.14]
log_clinical_ price × *log_inpatients*	-0.06	0.24	[-0.45, 0.33]
log_clinical_ price × *log_outpatients*	0.32	0.31	[-0.19, 0.84]
log_capital_ price^2	0.30	0.24	[-0.09, 0.69]
log_capital_ price × *log_inpatients*	0.05	0.07	[-0.05, 0.17]
log_capital_ price × *log_outpatients*	-0.14	0.09	[-0.30, 0.01]
log_inpatients × *log_outpatients*	-0.26	0.08	[-0.39, -0.13]
log_inpatients^2	0.25	0.07	[0.14, 0.36]
log_outpatients^2	0.31	0.10	[0.14, 0.48]
quarter 1	-0.02	2.8×10^{-3}	[-0.01, -0.01]
quarter 2	-8.0×10^{-3}	2.4×10^{-3}	[-0.01, -4.1×10^{-3}]

quarter 3	-0.01	2.8×10^{-3}	[-1.89, -9.5×10^{-3}]
trend	4.4×10^{-3}	4.5×10^{-4}	[3.7×10^{-3}, 5.2×10^{-3}]
trend²	-1.1×10^{-4}	3.5×10^{-5}	[1.7×10^{-4}, 5.6×10^{-5}]
small	-	-	-
medium	-	-	-
rural	-	-	-
constant	4.10	0.17	[3.82, 4.38]
Dynamic parameters			
constant	0.96	0.42	[0.36, 1.72]
small	-0.26	0.12	[-0.47, -0.09]
medium	-0.12	0.06	[-0.22, -0.03]
rural	-0.07	0.03	[-0.12, -0.02]
log_beds	-0.10	0.05	[-0.19, -0.02]
$\boldsymbol{\rho}$	92.00 %	0.03	[86.57 %, 95.59 %]
Precision parameters			
$\boldsymbol{\tau}$	5599.01	724.17	[4524.14, 6879.97]
$\boldsymbol{\phi}$	23.24	8.22	[12.25, 38.57]
Ω	33.89	12.45	[16.55, 56.76]
Standard deviations			
$\boldsymbol{\sigma_v}$	0.01	8.5×10^{-4}	[0.01, 0.02]
$\boldsymbol{\sigma_s}$	0.22	0.04	[0.16, 0.29]
$\boldsymbol{\sigma_\alpha}$	0.18	0.04	[0.13, 0.25]
Log marginal likelihood	1153.16		

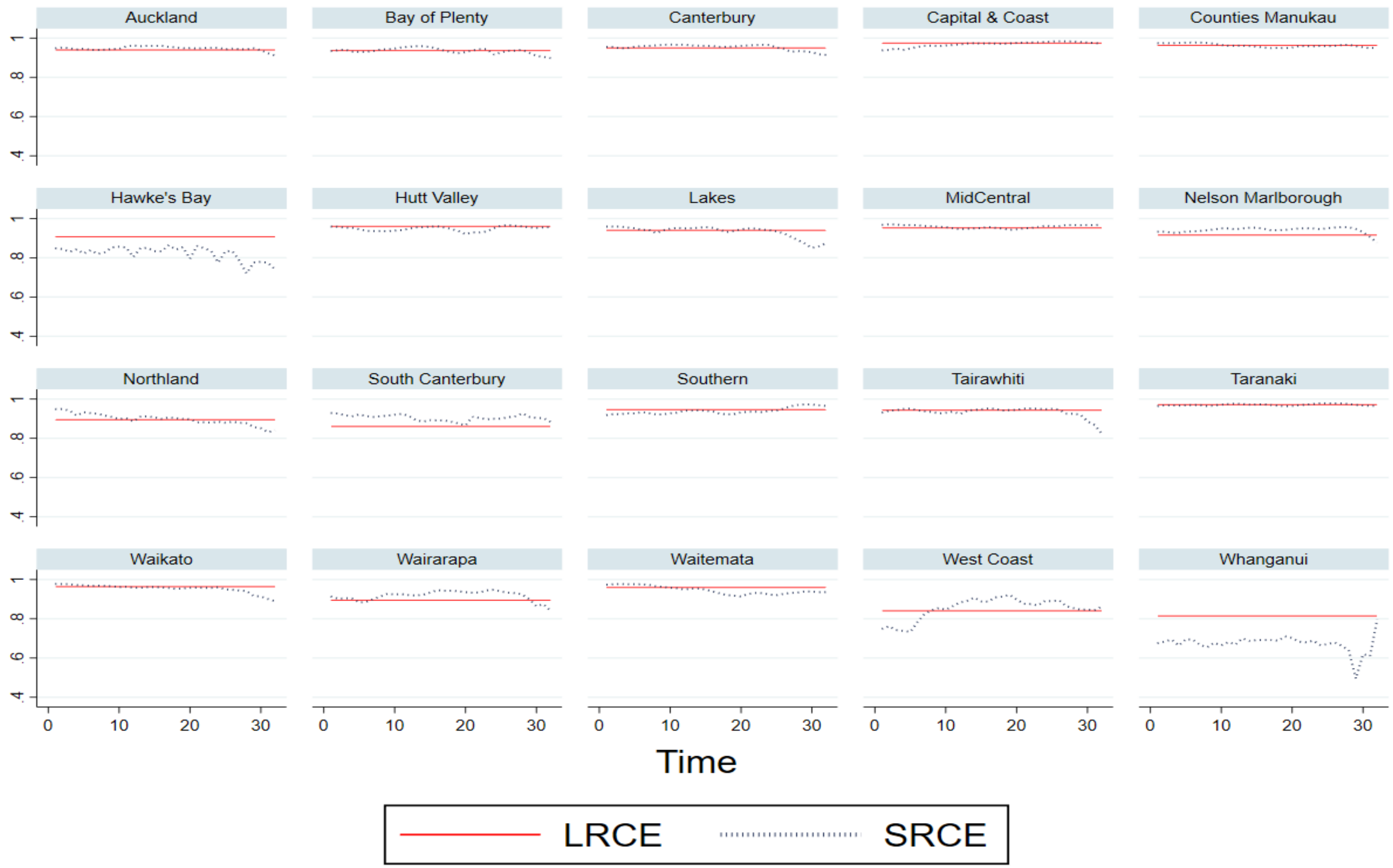
Appendix L. Mean yearly short-run cost efficiency scores

DHB	2011	2012	2013	2014	2015	2016	2017	2018	Mean
Auckland	0.95	0.94	0.95	0.96	0.95	0.95	0.94	0.93	0.95
Bay of Plenty	0.94	0.93	0.95	0.96	0.93	0.94	0.93	0.91	0.94
Canterbury	0.95	0.96	0.97	0.96	0.96	0.96	0.94	0.92	0.95
Capital & Coast	0.94	0.96	0.96	0.97	0.97	0.98	0.98	0.98	0.97
Counties Manukau	0.97	0.98	0.96	0.96	0.95	0.96	0.96	0.95	0.96
Hawke’s Bay	0.84	0.83	0.84	0.84	0.84	0.83	0.79	0.77	0.82
Hutt Valley	0.96	0.94	0.94	0.96	0.94	0.94	0.96	0.95	0.95
Lakes	0.96	0.94	0.95	0.95	0.94	0.95	0.91	0.86	0.93
Mid Central	0.97	0.96	0.95	0.95	0.95	0.96	0.96	0.97	0.96
Nelson Marlborough	0.93	0.94	0.95	0.95	0.94	0.95	0.95	0.92	0.94
Northland	0.94	0.93	0.90	0.91	0.90	0.88	0.88	0.85	0.90
South Canterbury	0.92	0.91	0.92	0.89	0.88	0.90	0.91	0.90	0.90
Southern	0.92	0.93	0.93	0.94	0.93	0.94	0.96	0.97	0.94
Tairawhiti	0.94	0.94	0.93	0.95	0.95	0.95	0.94	0.88	0.93
Taranaki	0.97	0.97	0.97	0.97	0.97	0.97	0.98	0.97	0.97
Waikato	0.98	0.97	0.96	0.96	0.96	0.96	0.95	0.91	0.95
Wairarapa	0.91	0.90	0.92	0.93	0.94	0.94	0.93	0.87	0.92
Waitemata	0.98	0.97	0.96	0.95	0.92	0.93	0.93	0.94	0.95
West Coast	0.75	0.80	0.86	0.89	0.91	0.88	0.88	0.85	0.85
Whanganui	0.68	0.68	0.67	0.69	0.70	0.68	0.66	0.63	0.67
Grand Mean	0.92	0.92	0.92	0.93	0.92	0.92	0.92	0.90	0.92

Appendix M. Kernel density plot of short-run cost efficiency scores



Appendix N. Time series plot of long-and short-run cost efficiency scores by DHB



Appendix O. Estimated parameters from the IDF with half-normal inefficiency distribution

Variable	Posterior Mean	Standard Deviation	90% credible interval
log_inpatients	-0.33	0.03	[-0.40, -0.26]
log_outpatients	-0.14	0.02	[-0.18, -0.11]
log_other_staff	0.12	0.02	[0.08, 0.16]
log_clinical_cost	0.18	0.02	[0.14,0.22]
log_out_cost	0.04	0.01	[0.02,0.05]
log_capital	0.03	0.01	[0.01, 0.05]
log_other_staff ^{2}	0.06	0.08	[-0.09, 0.23]
log_clinical_cost ^{2}	0.17	0.10	[-0.03, 0.37]
log_out_cost ^{2}	0.03	0.02	[-0.02, 0.07]
log_capital ^{2}	0.25	0.04	[0.17, 0.34]
log_inpatients ^{2}	-0.20	0.10	[-0.40, -0.05]
log_outpatients ^{2}	-0.21	0.13	[-0.47, 0.05]
log_other_staff × *log_clinical_cost*	0.03	0.08	[-0.13, 0.19]
log_other_staff × *log_out_cost*	-0.15	0.03	[-0.21, -0.10]
log_other_staff × *log_capital*	0.07	0.05	[-0.03, 0.16]
log_other_staff × *log_inpatients*	-0.04	0.08	[-0.19, 0.12]
log_other_staff × *log_outpatients*	-0.07	0.13	[-0.25, 0.11]
log_clinical_cost × *log_out_cost*	0.03	0.03	[-0.03, 0.10]
log_clinical_cost × *log_capital*	0.03	0.05	[-0.08, 0.13]
log_clinical_cost × *log_inpatients*	0.00	0.08	[-0.15, 0.15]
log_clinical_cost × *log_outpatients*	0.00	0.09	[-0.18, 0.18]
log_out_cost × *log_capital*	-0.07	0.02	[-0.10, -0.04]
log_out_cost × *log_inpatients*	-0.07	0.03	[-0.12, -0.02]
log_out_cost × *log_outpatients*	0.07	0.04	[-0.02, 0.14]
log_capital × *log_inpatients*	0.12	0.05	0.01, 0.22]
log_capital × *log_outpatients*	-0.07	0.07	[-0.18, 0.05]
log_inpatients × *log_outpatients*	0.22	0.11	[-0.01, 0.43]
trend	-5.0×10^{-3}	2.0×10^{-4}	[-5.5×10^{-3}, -4.6×10^{-3}]
trend ^{2}	0.00	0.00	[0.00, 0.00]

trend × *log_inpatients*	3.0×10^{-3}	1.1×10^{-3}	$[1\times 10^{-3}, 5.1 \times 10^{-3}]$
trend × *log_outpatients*	-6.5×10^{-3}	1.2×10^{-3}	$[-9.0\times 10^{-3}, -4.2 \times 10^{-3}]$
trend × *log_other_staff*	3.1×10^{-3}	1.1×10^{-3}	$[-5.4\times 10^{-3}, -9.0 \times 10^{-4}]$
trend × *log_clinical_cost*	-7.0×10^{-3}	1.2×10^{-3}	$[-9.3\times 10^{-3}, -4.6 \times 10^{-3}]$
trend × *log_out_cost*	0.00	5.0×10^{-4}	$[-9.0\times 10^{-4}, 9.0 \times 10^{-4}]$
trend × *log_capital*	1.8×10^{-3}	7.0×10^{-4}	$[3.0\times 10^{-4}, 3.3 \times 10^{-3}]$
quarter 1	0.03	4.0×10^{-3}	[0.02, 0.04]
quarter 2	0.01	3.6×10^{-3}	$[2.8\times 10^{-3}, 0.02]$
quarter 3	-7.3×10^{-3}	4.2×10^{-3}	$[-0.02, 1.3 \times 10^{-3}]$
constant	1.8×10^{-3}	0.14	[-0.28, 0.26]
Precision parameters			
$\boldsymbol{\tau_v}$	1978.15	249.96	[1607.48, 2422.45]
$\boldsymbol{\tau_u}$	45.09	4.43	[38.42, 52.87]
$\boldsymbol{\tau_\alpha}$	2.97	1.04	[1.51, 4.87]
Standard deviations			
$\boldsymbol{\sigma_v}$	0.02	1.4×10^{-3}	[0.02, 0.02]
$\boldsymbol{\sigma_u}$	0.12	2.2×10^{-3}	[0.09, 0.15]
$\boldsymbol{\sigma_\alpha}$	0.61	0.11	[0.45, 0.81]
Log marginal likelihood	929.76		

Appendix P. Estimated parameters from the cost function with half-normal inefficiency distribution

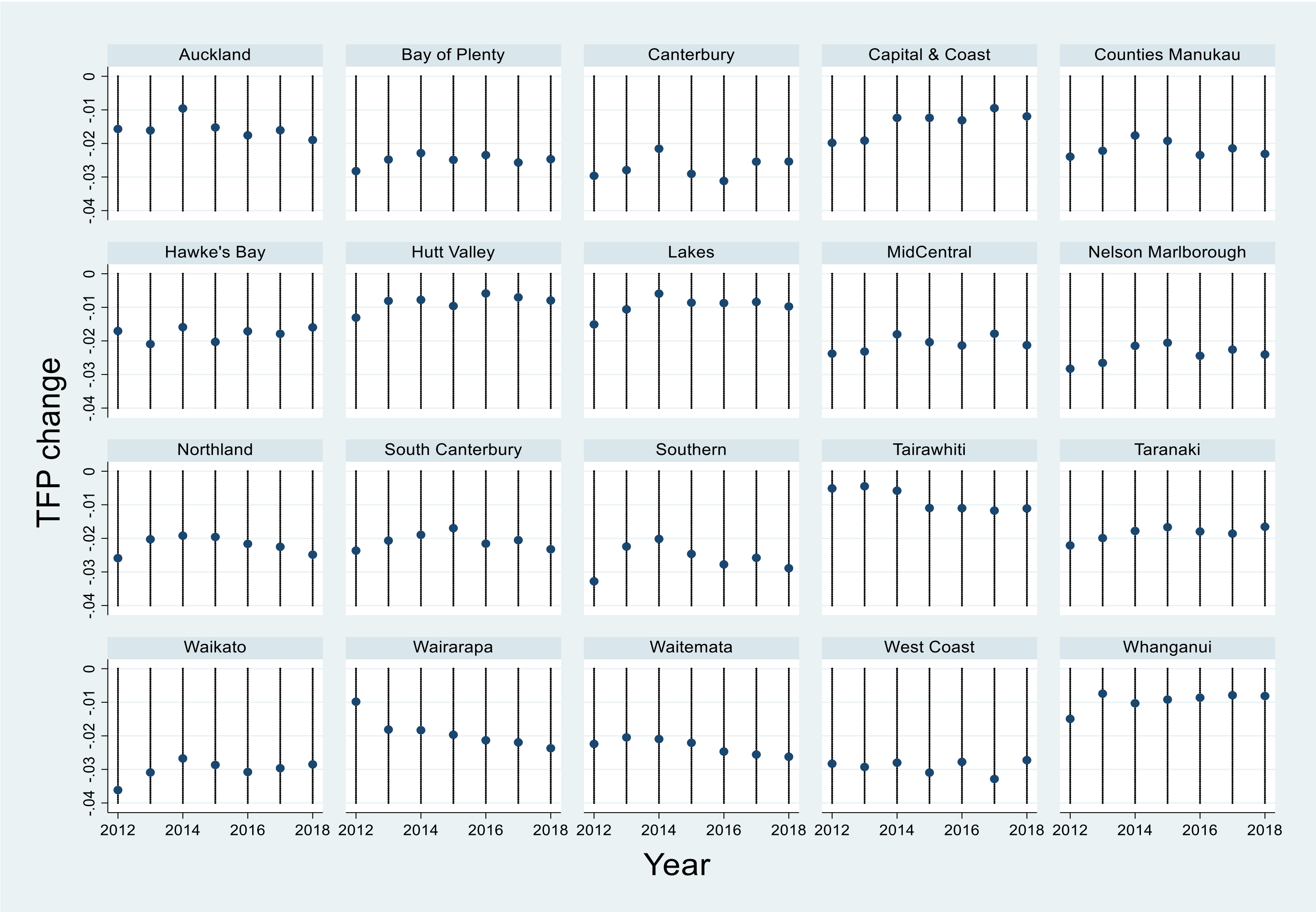
Variable	Posterior Mean	Standard Deviation	90%credible interval
log_inpatients	0.33	0.03	[0.27,0.38]
log_outpatients	0.13	0.02	[0.10, 0.16]
log_med_ price	0.12	0.02	[0.08, 0.17]
log_other_ price	0.45	0.05	[0.35, 0.54]
log_clinical_ price	0.19	0.08	[0.02, 0.35]
log_capital_ price	0.03	0.01	[0.01,0.06]
log_med_price^2	-0.03	0.16	[-0.35, 0.29]
log_med_ price × *log_other_ price*	-0.28	0.29	[-0.87, 0.30]
log_med_ price × *log_clinical_ price*	-0.09	0.48	[-1.03, 0.83]
log_med_ price × *log_capital_ price*	-0.08	0.07	[-0.21, 0.05]
log_med_ price × *log_inpatients*	0.16	0.08	[1.0×10^{-3}, 0.31]
log_med_ price × *log_outpatients*	-0.22	0.10	[-0.42, -0.03]
log_other_ price^2	-0.09	0.59	[-1.25, 1.06]
log_other_ price × *log_clinical_ price*	-0.21	0.88	[-1.94, 1.53]
log_other_ price × *log_capital_ price*	0.13	0.14	[-0.16, 0.41]
log_other_ price × *log_inpatients*	-0.49	0.17	[-0.81, -0.17]
log_other_ price × *log_outpatients*	0.60	0.23	[0.16, 1.04]
log_clinical_ price^2	-0.43	0.98	[-2.34, 1.49]
log_clinical_ price × *log_capital_ price*	0.81	0.32	[0.18, 1.41]
log_clinical_ price × *log_inpatients*	0.01	0.28	[-0.53, 0.57]
log_clinical_ price × *log_outpatients*	-0.18	0.37	[-0.92, 0.53]
log_capital_ price^2	-0.11	0.05	[-0.22, -0.01]
log_capital_ price × *log_inpatients*	-0.02	0.04	[-0.11, 0.05]
log_capital_ price × *log_outpatients*	0.04	0.05	[-0.07, 0.14]
log_inpatients × *log_outpatients*	-0.21	0.09	[-0.38, -0.03]
log_inpatients^2	0.16	0.07	[3.8×10^{-3}, 0.30]
log_outpatients^2	0.20	0.11	[-0.03, 0.41]
trend	4.3×10^{-3}	3.0×10^{-4}	[3.7×10^{-3}, 4.8×10^{-3}]
trend^2	-1.0×10^{-4}	0.00	[-2×10^{-4}, 0.00]

trend × *log_inpatients*	-5.0×10^{-4}	8.0×10^{-4}	[2.2×10^{-3}, 1.1×10^{-3}]
trend × *log_outpatients*	2.5×10^{-3}	1.1×10^{-3}	[4.0×10^{-4}, 4.6×10^{-3}]
trend × *log_other_staff*	3.0×10^{-3}	4.7×10^{-3}	[-6.3×10^{-3}, 0.01]
trend × *log_clinical_cost*	0.07	0.01	[0.05, 0.09]
trend × *log_med_cost*	2.0×10^{-3}	1.5×10^{-3}	[-9.0×10^{-4}, 5.2×10^{-3}]
trend × *log_capital*	4.0×10^{-4}	1.0×10^{-3}	[-1.6×10^{-3}, 2.4×10^{-3}]
quarter 1	-0.03	3.9×10^{-3}	-0.04, -0.02]
quarter 2	-0.01	3.5×10^{-3}	[-0.02, -5.9×10^{-3}]
quarter 3	-6.6×10^{-3}	4.0×10^{-3}	[-0.01, 1.1×10^{-3}]
constant	4.13	0.12	[3.87, 4.37]
Precision parameters			
$\boldsymbol{\tau_v}$	7755.95	1565.99	[5517.62, 10584.40]
$\boldsymbol{\tau_u}$	232.03	231.69	[207.77, 257.39]
$\boldsymbol{\tau_\alpha}$	4.34	1.57	[2.18, 7.22]
Standard deviations			
$\boldsymbol{\sigma_v}$	0.01	1.1×10^{-3}	[9.7×10^{-3}, 1.34]
$\boldsymbol{\sigma_u}$	0.07	2.1×10^{-3}	[0.06, 0.07]
$\boldsymbol{\sigma_\alpha}$	0.50	0.09	[0.37, 0.68]
Log marginal likelihood	889.822		

Appendix Q. Mean of all the components of TFP

DHB	Scale change		Technical change		Efficiency change		TFP change	
	IDF	Cost	IDF	Cost	IDF	Cost	IDF	Cost
Auckland	1.01%	1.48%	-1.56%	-2.51%	-0.03%	-0.07%	-0.58%	-1.10%
Bay of Plenty	1.65%	1.77%	-2.49%	-2.13%	0.05%	-0.21%	-0.79%	-0.57%
Canterbury	1.19%	1.54%	-2.72%	-1.63%	0.18%	-0.02%	-1.34%	-0.11%
Capital & Coast	1.10%	1.24%	-1.40%	-1.95%	-0.03%	0.55%	-0.33%	-0.17%
Counties Manukau	1.06%	1.07%	-2.16%	-2.70%	0.01%	-0.39%	-1.09%	-2.03%
Hawke's Bay	1.13%	1.00%	-1.79%	-1.34%	-0.20%	-0.88%	-0.87%	-1.21%
Hutt Valley	1.02%	1.16%	-0.85%	-1.57%	0.03%	0.06%	0.20%	-0.35%
Lakes	1.43%	1.40%	-0.96%	-1.07%	-0.25%	-0.87%	0.22%	-0.54%
Mid Central	0.48%	0.46%	-2.08%	-2.07%	-0.12%	-0.17%	-1.72%	-1.78%
Nelson Marlborough	-0.47%	-0.16%	-2.40%	-1.96%	-0.23%	-0.55%	-3.09%	-2.67%
Northland	1.36%	1.46%	-2.20%	-1.89%	-0.18%	-1.00%	-1.01%	-1.43%
South Canterbury	-0.10%	-0.08%	-2.08%	-1.45%	-0.05%	-0.35%	-2.22%	-1.87%
Southern	1.10%	1.47%	-2.61%	-2.42%	0.05%	0.62%	-1.46%	-0.33%
Tairawhiti	0.67%	0.56%	-0.86%	-0.83%	0.20%	-1.00%	0.00%	-1.27%
Taranaki	1.06%	1.11%	-1.85%	-2.03%	-0.09%	0.41%	-0.88%	-0.52%
Waikato	1.55%	1.70%	-3.02%	-2.49%	0.01%	-0.79%	-1.46%	-1.58%
Wairarapa	1.83%	1.57%	-1.90%	-0.84%	0.00%	-0.60%	-0.07%	0.13%
Waitemata	3.06%	4.19%	-2.32%	-2.55%	-0.03%	0.00%	0.70%	1.64%
West Coast	0.48%	0.37%	-2.92%	-0.30%	0.23%	1.51%	-2.21%	1.58%
Whanganui	-0.10%	-0.05%	-0.95%	-0.90%	-0.23%	-1.11%	-1.28%	-2.06%
Grand Mean	1.03%	1.16%	-1.96%	-1.73%	-0.03%	-0.24%	-0.96%	-0.73%

Appendix R. Time series plot of technical change overtime from IDF



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