PRODUCTION AND EFFICIENCY: THE CASE OF THE AUSTRALIAN RUGBY LEAGUE

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Abstract

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What matters in the "production" of a game of rugby league? This analysis finds that several game-specific inputs (such as successful goal-kicking percentage, inherent team strength, and momentum of results) in the generation of a game outcome are statistically significantly different from zero at the 10% level or lower. This study also looks closely at measures of productive efficiency, including stochastic frontier modelling and data envelopment analysis (DEA). Panel data from the 1995, 1996 and 1998 National Rugby League (NRL) regular seasons are used to formulate average production functions and stochastic production frontier models and their respective measures of efficiency. It is found that many Sydney-based teams performed relatively more efficiently when compared to non-Sydney teams in 1998. There also appears to be evidence of a "weaker teams bringing the stronger teams down to their level" effect due to differences in point-scoring efficiency and game outcome efficiency in 1998.

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Chapter 1

INTRODUCTION

"Technical efficiency concerns the physical relationships between inputs and outputs. Many decision-makers are regularly faced with decisions about what combinations of inputs to use or develop in order to attain the most desirable output. Such decisions about the 'best' use of inputs, often aiming at maximum output, are concerned with a quest for technical efficiency."

Gratton and Taylor (1985) p.136.

Rugby League is one of Australia's (and New Zealand's) most popular sports. In recent times, the game has undergone significant structural changes with the emergence of Super League in 1996 (see Chapter Two for details). There is presently a proposal under consideration by the NRL to rationalise the competition from the present 20-team format to a 14-team competition in 2000.

Rationalisation of the NRL is partly based on performance, and the one central objective in the operation of a rugby league club is performance on the field. Good performances on the field attract spectators, improve gate revenue, and attract sponsorship.

The NRL has a criteria document that it will use to rationalise the competition in 2000. Included in this criteria document are categories by which teams can be ranked, such as attendance, financial viability, sponsorship revenues, and on-field performance.

This study is an economic investigation into production and efficiency in the Australian Rugby League (ARL) and National Rugby League (NRL) in Australia.

It will examine the efficiency, in terms of production, of all teams in the ARL/NRL competition(s) through use of individual game data.

Production can be defined in one of two ways: (a) as the points scored by a team, or (b) as the generation of game outcomes. Production efficiency thus is the measurement of how efficiently (or inefficently) a team performs relative to the 'best' (or potential) outcome that can be achieved given the inputs into the production process.

The purpose of this study is to examine in close detail the determinants of team performance on the field and from these to calculate measures of efficiency. Ranking of teams by on-field efficiency measures may add another dimension to the analysis of proposed changes in the competition.

Rugby League is a sport that generates millions of dollars in revenue, and like so many other sports, analysis of the fundamentals of the game can only be beneficial to players, coaches and administrators alike. Analyses can be undertaken to examine the links between each critical area within a football club – from on-field performance to crowd attendance, to sponsorship revenues, and similarly important measures of efficiency.

1.1 Objectives

The objectives for this study are:

1. To determine and quantify the determinants of performance.
2. To measure the relative importance of these determinants.
3. To analyse production efficiency, and
4. To determine implications for individual team management, as well as overall League administration.

Using individual game data, several regression models will be estimated, and results presented. Different ways of modelling such data will be examined, and the most suitable model(s) will be determined.

There are a number of different models that can be estimated (see Chapter 2 for details) and as a result a variety of different results to examine. One area of debate is how one can tell which is the 'best' model. To make this choice, we need criteria. One criterion is to compare results with actual outcomes to see which models are the most accurate estimators of performance. Another way is to observe the predictive power of respective models. These criteria are discussed in further detail in Chapters 4 and 5.

The third objective encompasses the major work involved in this thesis – the analysis of production and calculation of efficiency estimates. A number of alternative approaches will be examined in order to develop a comprehensive treatment of efficiency. These are discussed in Chapter 2.

This research will use publicly available information and seeks to determine how this information can help in explaining the outcomes of matches in rugby league. In Chapter 3 we develop a model to explain the outcome of rugby league games. The results of this model are presented in Chapter 4. Both the determinants of performance and the extent to which they impact on game outcomes are of interest in this study. As identified in Borland and Lye (1992), the more unpredictable a game is, the greater is the positive impact on attendance. With attendance being a major factor in the NRL's criteria for excluding teams from the 2000 competition, the identification of contributing factors to performance is of particular importance to various club officials and League management.

In the development and application of a cohesive and logical model, this study will incorporate a number of characteristics derived from other studies in this area and will model the "production" process in the game of Rugby League as well as generating measures of efficiency.

1.2 Background: Rugby League

This section presents a brief background to the sport of Rugby League, its inception in Australia, the present situation, and plans for the future.

1.2.1 The Origins Of Rugby League

On the 29th of August 1895, the sport of rugby league was conceived. In Huddersfield, Yorkshire, 21 rugby union teams from the north of England elected to resign from the Rugby Football Union (RFU) and form their own Northern Rugby Union, with its own constitution. The major objective was to compensate players for loss of earnings incurred when playing rugby, or in other words, to pay players for playing the game. This step was the advent of professionalism. The London-based RFU objected to this, but the lure of compensation for playing proved too attractive for players in the industrial north of England.

The Northern Rugby Union revolutionised the rules of the game of rugby to make it more attractive for paying spectators. Included among these initial radical moves were the removal of the lineout, and the rationalisation of the scoring system to make try-scoring the more attractive option (over goal-kicking). In 1906, the number of players per side was reduced to thirteeen, with the two flank-forward positions being sacrificed in a bid to make the game more open. The final piece of the plan was the restructuring of the ruck and maul situation after a tackle was made and replacing this with the 'play-the-ball', a two man 'scrum'. The game of rugby league had become visibly separate from rugby union.

1.2.2 Rugby League In Australia

"Born of struggle and discontent in Sydney's suburbs, league has always been seen as the "people's game" and the "working man's game". Loyalties to the game, its pioneers, its fundamental ethics (of an egalitarian game available to

all people from all classes of society) have always been deep-rooted – and especially so in the old, traditional Sydney clubs" (Heads 1995, p.6)

Rugby League was born in Australia in January 1908. In August 1907, three pioneering Northern Union (as it was then known) matches were played at the Agricultural Ground (Sydney Showground) between an Australian team and the New Zealand All Golds. Like in England, rugby union was very much the local rugby game. These three matches sparked a movement in the suburbs of Sydney to form individual clubs and to establish a 'breakaway' Northern Union competition. In 1908, the Glebe, Newtown, South Sydney, Eastern Suburbs, North Sydney, Balmain, Western Suburbs, Newcastle and Cumberland clubs participated in the inaugural New South Wales Rugby League Premiership.

From these humble beginnings, the New South Wales Rugby League (NSWRL) Premiership – now the Australian Rugby League (ARL) – Premiership has continued over the past ninety years, with a number of clubs entering and exiting the competition during this time. Of the original nine clubs in 1908, five remain: South Sydney, North Sydney, Eastern Suburbs (presently Sydney City), Western Suburbs and Balmain.

The key decades in recent history were the 1980s and the 1990s. In 1982, Illawarra and Canberra joined the 11-team competition. In 1988, in what was considered at the time to be the League's most ambitious move, teams from Brisbane, the Gold Coast and Newcastle were invited to enter the competition, making for a 16-team premiership. This move coupled with aggressive marketing and a successful sponsorship arrangement with Winfield created enormous interest, as well as generating huge international exposure.

In 1995, the Australian Rugby League embarked on its most significant move and accepted entries in the ARL premiership from Auckland, North Queensland, South Queensland and Perth (Western Reds), which enlarged the competition to 20 teams.

1.2.3 The Clubs

The following is the list of clubs and the years of participation in the NSWRL/ARL premiership:

TABLE 1.1: Participating Clubs in the NSWRL Premiership 1908-1998

Present Clubs	Year Entered
Adelaide[α]	1998
Auckland	1995
Balmain	1908
Brisbane	1988
Canberra	1982
Canterbury-Bankstown	1935
Cronulla-Sutherland	1967
Gold Coast	1988
Illawarra	1982
Manly-Warringah	1947
Melbourne	1998
Newcastle[β]	1988
North Queensland	1995
North Sydney	1908
Parramatta	1947
Penrith	1967
St George	1921
South Sydney	1908
Sydney City (Eastern Suburbs)	1908
Western Suburbs	1908

Defunct Clubs	Year Entered	Last Season
Annandale	1910	1920
Cumberland	1908	1908
Glebe	1908	1929
Newcastle	1908	1909
Newtown	1908	1983
South Queensland	1995	1997
University	1920	1937
Western Reds (Perth)[χ]	1995	1996

Source: The Australian Rugby League Yearbook 1997

[α] Adelaide was a Super League expansion club in 1997 – it's first (and last) NRL season was 1998.
[β] A team representing the Newcastle and Hunter district competed in the NSWRL premiership in 1908 and 1909, and withdrew in 1910 to form their own competition.
[χ] The Western Reds participated in Super League in 1997 before becoming defunct. Their last ARL premiership year was 1996.

The research in this study will include game outcomes involving all twenty teams involved in the 1998 premiership, as well as the now-defunct clubs South

Queensland and the Western Reds, who participated in the ARL competition in 1995 and 1996.

1.2.4 Super League

"These sorts of intangibles [loyalties] *were always going to present high hurdles to be jumped for any corporate raider eyeing the flash new '90s game of Rugby League as a potential target"* (Heads 1995, p.6)

In 1995, as a result of increased commercialisation and the success of the Australian Rugby League, a rival organisation emerged – Super League. The emergence of Super League had dramatic implications for the game of Rugby League. In 1995, legal action barred Super League from starting a competition in 1996. Numerous 'loyal' ARL clubs elected to break ties with the establishment and go with the 'rebel' competition in a move reminiscent of the founding of Rugby League in Australia. This caused numerous standoffs and heated arguments between the two factions, which ultimately resulted in the cancellation of six first-round matches of the 1996 ARL season, after Super League-aligned clubs refused to play. Later that year, the ARL decided against including Super League-aligned players in the Australian national side.[1]

In 1997, Super League was legally cleared to run a competition. Two competitions were run side by side for the first time – the ARL's Optus Cup with eleven teams, and Super League's Telstra Cup with ten teams. Through the events of 1997, damage was done to the game that is still visible today. Spectators, disillusioned by the divide in 'their game', left Rugby League in droves. As a result, both sides could see that two competitions were just not working. In December 1997 a peace deal was negotiated which would see a return to a combined twenty-team competition run by a combination of the ARL and Super League administration. This was the birth of the National Rugby

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[1] In 1995, Super League-aligned players were not selected for ARL State of Origin representative teams, or the national side. In 1996, Super League players were eligible for selection in State of Origin, but were passed over for selection in the national side.

League (NRL), the game's governing body today. In 1998, the new NRL competition kicked off, hoping to heal the pain that the game of Rugby League had suffered over the previous three years.

1.2.5 The NRL – Plans For The Future

One key component of the peace deal brokered in late 1997-early 1998 was the controversial 'criteria document', released in mid-May 1998. This document is designed to reduce the number of teams in the NRL competition from twenty to fourteen by the year 2000. A number of stringent conditions have to be met in areas including playing venues, sponsorship, gate receipts, crowd figures for both home and away matches, and other income sources.[2]

Already, numerous clubs have publicly voiced opinions on the realistic (and increasingly necessary) possibility of merging with other clubs to ensure survival in a rationalised competition. South Sydney, Balmain, Illawarra, St. George, Cronulla, Gold Coast, Penrith, Parramatta, Western Suburbs, Canterbury, Sydney City and Adelaide have all acknowledged that mergers will be inevitable in order to guarantee survival post-2000. Indeed, at the time of writing, six of these clubs had voluntarily (or involuntarily) taken steps for this process, with Illawarra and St George merging, Adelaide and the Gold Coast not fielding teams in the 1999 premiership, and Balmain and Western Suburbs merging in mid-1999.

1.3 Summary

Taking into consideration the criteria required for survival beyond 2000, the underlying implication for all teams, either directly or indirectly, is that "winning matters". A winning team generates greater crowd support that in turn increases gate receipts and aids in financial viability. Winning teams become more marketable which has the effect of increasing sponsorship revenues. Winning is the rock on which foundations for survival in an elite competition can be built.

Measures of efficiency can be used to rank teams in terms of their winning ability and actual performance. In the following chapters, production and efficiency measures will be formulated, estimated and discussed in detail.

1.4 Thesis Outline

In Chapter 2, literature surrounding this topic is discussed. Methodology is outlined and explained in Chapter 3. Results of empirical analyses of determinants of production and construction of efficiency measures as well as discussion of these results are presented in Chapter 4. Chapter 5 outlines the stochastic frontier procedure adopted to model production, and the results are presented and discussed. The results of efficiency are reported and discussed in Chapter 6 and the study is concluded in Chapter 7.

[2] From report "Merger moves heat up" at *http://www.tvone.co.nz/sports/stories/21May1023.html*

Chapter 2

LITERATURE REVIEW

2.1 The Measurement Of Efficiency

This section discusses the measurement of efficiency, from the simplistic approach of residual calculation and subsequent measures of efficiency to more complex and varied measures. In section 2.4.1 parametric approaches are outlined and discussed. Section 2.4.2 details non-parametric approaches, specifically data envelopment analysis (DEA). Finally, section 2.4.3 looks at three applications that use different methods of measuring efficiency and these are discussed with an eye to the analysis of this study.

Barrow and Wagstaff (1989) discussed efficiency measurement. Their review of techniques came about due to "dissatisfaction with the current performance indicators – and indeed with their precursors", which has led "several researchers to try and improve on them using statistical and other quantitative techniques" (p.72). A number of techniques were discussed, including non-frontier approaches to efficiency measurement such as ordinary least squares (OLS) estimation of Cobb-Douglas production functions. Barrow and Wagstaff quote a number of studies that use non-frontier methods, including Feldstein (1967) and Levitt and Joyce (1987). However, despite the non-frontier approaches being grounded in economic theory, and the clarity of inefficiency measurement, some problems remained. Notably, no information was provided as to the level of efficiency, and the non-frontier measures implicitly assumed that "all cross-sample variation in the error term of the estimating equation is due to variation in efficiency" (p.81). This is a highly unrealistic assumption, when one considers that random influences as well as statistical 'noise' often affect a residual.

The weaknesses in the measurement of efficiency from non-frontier approaches as identified above have led to the emergence over time of frontier approaches to efficiency measurement. Barrow and Wagstaff (1989) note that there are differences in the interpretation of the frontier concept. Interpretations included the construction of an "absolute" frontier (that is, what can be produced if the available technology was used to full advantage), and the construction of a "best-practice" frontier through using data for all firms in the sample. Perhaps the most important distinction between such frontier approaches is whether the method under scrutiny is 'parametric or non-parametric' (p.82). Parametric approaches require a specific functional form for the equation, whereas non-parametric approaches do not (they use 'non-special form' equations). As a consequence, parametric estimation tends to be statistical in nature, while non-parametric approaches tend to be non-statistical.

2.1.1 Efficiency – The Parametric Approach

The use of production frontier models is becoming increasingly widespread, as the idea of a frontier is consistent with the economic theory of optimising behaviour. Deviations from a frontier also have clear interpretation as measures of the efficiency with which economic units meet their objective – profit maximisation. The relative efficiency of units can have important policy implications for management of those units seen as "less efficient".

The introduction of the 'stochastic' production function was proposed by Zellner, Kmenta and Dreze (1966), who modified the traditional Cobb-Douglas production function, originally based on deterministic profit maximisation. The Cobb-Douglas model was transformed by assuming that profits are stochastic, that is, entrepreneurs are conscious of the inherent stochastic nature of production in a firm's profit-maximising ventures. This can be done by introducing random disturbance terms into the model. An important point made in their conclusion to justify the use of the Zellner *et al.* model was that "...Current specifying assumptions for production models may very well be found seriously deficient in terms of such an analysis [taking into account temporal aggregation of data]" (p.795).

Timmer (1971) used a probabilistic frontier production function to measure efficiency, through the use of linear programming techniques. A Cobb-Douglas production function was fitted for US agriculture from 1960 to 1967, using what the author notes as the "average farm" in each state in each year as the unit of observation. The measured technical inefficiency was defined "relative to the probabilistic frontier function", and the extent of such inefficiency was calculated for each state. Essentially, the procedure involved estimation of production functions with a single error term, within which a component was assumed to account for systematic inefficiency. Three measures of efficiency were calculated. Firstly, OLS residuals were reported and ranked. Secondly, restrictions were imposed on the Cobb-Douglas production frontier function so that predicted output could not exceed actual output. Linear programming techniques were then applied to the Cobb-Douglas production frontier, using the calculated residuals. The third measure of efficiency introduced in the paper is the intercept term calculated from the average production functions.

Afriat (1972) heeded the warning given by Zellner *et al.* (1966), noting that workable functions such as Cobb-Douglas, CES and such types are scarce in reality. These types of production function were found to be "too restrictive in their properties, which include homogeneity, complete additive separability, constant elasticity of substitution, and so on" (p.568). Another limitation of the parametric technique is that the approach is not "readily adapted" to the possibility of joint production. Linear programming methods were promoted as the better measurement tool, to "escape from several objections that bear on the parametric production function technique" (p.569). However, it was noted that linear programming was not necessarily the better tool when stochastic measurement was involved.

Aigner, Lovell and Schmidt (1977) wrote one of the seminal articles on the formulation of the stochastic frontier model. In this model the error term was decomposed into two components, with one component being a random disturbance (negative), and the other component a symmetric disturbance distributed as truncations of the normal distribution (non-negative values). The negative random disturbance reflects the fact that each firm's output must lie on or below its frontier. The stochastic frontier model specification was compared directly with the three specifications outlined in Timmer (1971). The stochastic frontier model was found to give similar results to Timmer's production function/frontier, using cross-sectional data. The tests of the estimated model using real-world data indicated "relatively small one-sided components of the disturbance" (Aigner *et al.* 1977, p.35). This implied that there were high levels of efficiency relative to the stochastic frontier.

Bauer (1990) reviewed work in the field of econometric estimation of frontiers. He noted that there were some advantages in choosing a stochastic frontier over the traditional deterministic frontier. The use of the stochastic frontier allows for the possibility of statistical noise affecting the frontier – things that are outside the firm's control. The stochastic frontier can also be considered as "allowing for some types of specification error and for omitted variables uncorrelated with the included regressors" (p.40). Bauer noted that while this method had its advantages, the use of the deterministic frontier was less complex. The deterministic approach directly yields estimates of individual firm efficiency as the estimation residuals. Bauer quoted an anonymous referee as saying "Stronger assumptions generate stronger results, but they strain one's conscience more" (p.41). This is the inherent difficulty associated with the two approaches to measurement. The appropriate structure can be decided upon after careful analysis of the data and the nature of the industry under review. Appropriate statistical tests are not always available to assist in this process.

2.1.1.1 Stochastic Production Frontier Modelling

The stochastic frontier model provides a sophisticated way of overcoming the problems associated with deterministic production function measures of efficiency, which allows the measurement of inefficiency from the residual. Where initial estimates of efficiency assumed that the error term was not affected in any way by statistical 'noise' and thus represented inefficiency, the stochastic frontier model decomposes the error term into two parts. One part captures the effects of random shocks and noise, while the other part is a one-sided term reflecting inefficiency, which in a production context is non-positive.

A recent seminal work on the construction of the stochastic frontier production model is Battese and Coelli (1992). They present a stochastic frontier production model for panel data in an empirical context using agricultural data for paddy farmers in a village in India. Technical efficiency is defined as the ratio of a farm's mean production to the corresponding mean production if the farm utilised its levels of inputs most efficiently. The maximum-likelihood estimates of the parameters of the model and the predictors of technical efficiency for farms were calculated with the use of the computer program FRONTIER (see Coelli 1996). The frontier function was estimated for various basic models, and statistical tests were conducted as to the suitability of the models. Efficiency is examined from the selected model, which included calculated time-varying technical inefficiencies. Battese and Coelli found that the application of a stochastic production frontier model to their data was appropriate. Through the use of statistical tests it was found that individual farm technical inefficiencies were time-varying. However, the inclusion of a 'year of observation' variable to represent technical progress rendered the stochastic specification no better than the traditional "average-response" model where firm technical inefficiencies are zero, or in other words, are assumed not to exist. Such a finding implies that "...given the state of technology ... technical inefficiency is not an issue of significance provided technical change is provided for in the empirical analysis" (p.162).

An application of this methodology in a sporting context by Hofler and Payne (1996) is detailed in Section 2.2.

2.1.2 Efficiency – The Non-Parametric Approach

Non-parametric approaches measure efficiency using linear programming methods. The foundation paper in this area of research is by Farrell (1957) who measured production efficiency using non-regression techniques. Charnes, Cooper and Rhodes (1978) developed measures of efficiency from the work of Farrell (1957) with particular reference to "possible use in evaluating public programs" (p.429). The measurement of efficiency was derived from the analysis of a collection of decision-making units with common inputs and outputs. The methodology of Charnes *et al.*, known in the literature as data envelopment analysis (DEA), is detailed further in Section 2.1.2.1. A limitation outlined by Charnes *et al.* may be the lack of data availability at the level of the individual decision-making unit. The intention of such an efficiency measure (DEA) is to "...evaluate the accomplishments, or resource conservation possibilities, for every decision-making unit with the resources assigned to it" (p.443). To illustrate the concept, Charnes *et al.* use a golfing analogy - where the DEA measure is a "...measure of 'distance' rather than 'direction' with respect to what has been (and might be) accomplished" (p.443).

Fare, Grosskopf, Logan and Lovell (1985) extended Farrell's work by relaxing assumptions on the structure of production technology by developing and adopting linear programming techniques in an application to electric utilities. The principal measure of efficiency calculated was technical efficiency, which was defined as the maximum amount by which output can be increased and still remain "producible" by inputs.

The above papers were the foundations of the development of the linear programming technique known as Data Envelopment Analysis (DEA). Norman and Stoker (1991) describe the DEA technique as "a very powerful tool for evaluating the performance of comparable organisational units, whether they are in the public or private sector" (p.xvii).

2.1.2.1 Data Envelopment Analysis

Trick (1996) provides an excellent summary and introduction to the procedure of DEA. Strengths of DEA include the ability to handle multiple input and multiple output models, the absence of an assumption of a specific functional form relating inputs to outputs, the ability to compare decision-making units (DMUs) against a combination of peer DMUs, and the added advantage that inputs and outputs can be measured in very different units. However, it is worth noting that there are some limitations with this method, which include computationally intensive problem-solving methods for large problems[3], and being a non-parametric technique, an inability to conduct statistical hypothesis tests. DEA is proven to be good at estimating relative efficiency, that is, how well a DMU is performing relative to its peers, but it cannot indicate how well a DMU is performing compared to a theoretical maximum. As for actual measurement, efficiency is measured as the ratio of inputs to outputs, and is constrained to be no more than 1. It is also noted that as the number of inputs and outputs increases, more DMUs tend to get an efficiency rating of 1 as they become too specialised to be evaluated with respect to other DMUs. As is the case in any study, inputs and outputs have to be correctly specified in order for the analysis to produce feasible results.

An important point that Bauer (1990) makes is that with any frontier estimation procedure, problems exist with choosing an appropriate functional form of the frontier as well as the appropriate model of inefficiency. We can either impose a model structure determined *a priori*, or we can implement a flexible model so as to test possible restrictions that may be present. The DEA approach has no such statistical testing facility but has the advantage of not requiring a specific functional form for the analysis. Seiford and Thrall (1990) noted that the non-

[3] As DEA assigns an individual linear program for each DMU, solving large-scale problems can be a "computationally-intensive" process.

parametric method measures efficiency as the efficiency of a decision-making unit (DMU) relative to all other DMU's with the simple restriction imposed that all DMU's operate either on or below the "efficient" frontier.

Where the deterministic production function/frontier is concerned with central, or average, tendencies, the DEA approach is concerned with actual frontier estimation. Seiford and Thrall (1990) explain that "...instead of trying to fit a regression plane through the *center* of the data, one 'floats' a piecewise linear surface to rest *on top* of the observations" (p.8). As a linear programming technique, DEA can identify the possibilities of increasing, decreasing or constant returns to scale through slight modification of the constraints to the linear program. The DEA procedure initiated by Charnes, Cooper and Rhodes (1978) assumes constant returns to scale. With the linear programming aspect, the use of DEA brings added benefits (as listed in Seiford and Thrall, 1990) of ease of computation, dual variables and clear interpretations of results and implications. However, as is the case with any estimation technique, problems can and do arise. DEA assumes that there is at least a moderate relationship between input(s) and output(s) in an analysis. Thus it may be more sensitive to data errors if this relationship is not evident. With DEA being a procedure that "relies on extremal points", Seiford and Thrall (1990) note that variable selection, model specification and data errors are all critically important factors in an analysis, and that caution should be used when formulating such models.

Recent applications of the DEA technique include Chang and Kao (1992), who used DEA to analyse the relative efficiency of public versus private municipal bus firms in Taiwan. Cloutier and Rowley (1993) used DEA to analyse the distribution of productive efficiency across dairy farms in Quebec, Canada. Premachandra (1996) used a generalised form of data envelopment analysis (DEA) to analyse technical efficiencies of decision-making units of similar nature, meaning DMUs faced with similar constraints and output decisions. The advantages of using this method are that it is a simple method, and output produced contains "informative statistical measures pertaining to the distribution of the technical efficiencies which can be used for comparison purposes" (p.15).

DEA was also used to estimate potential cost savings in sewerage provision (Thanassoulis, 1997).

The overriding theme of the aforementioned studies is the relative simplicity and the powerful nature of the non-statistical data envelopment analysis technique. Whether used in public or private sector analyses, DEA presents an interesting alternative measure to the parametric method.

Bjurek, Hjalmarsson and Forsund (1990) analysed productive efficiency in local social insurance offices of the Swedish social insurance system using three different approaches: (1) a Cobb-Douglas deterministic frontier production function, (2) a quadratic deterministic frontier production function, and (3) a deterministic non-parametric frontier using Data Envelopment Analysis. Three different types of DEA were estimated – constant returns to scale (CRS - the standard DEA approach), variable returns to scale (VRS), and non-increasing returns to scale (NIRS). Barrow and Wagstaff (1989) made the claim that more than one measure of efficiency has to be considered in order to make policy advice, given that there may be differences in efficiency estimates between approaches. This comparison study concluded that the differences between the estimation approaches were "surprisingly small". The main differences lie between the more flexible approaches (quadratic, VRS DEA and NIRS DEA) that generate higher values of efficiency than the more structured Cobb-Douglas and CRS DEA models. Bjurek *et al.* (1990) attributed this not only to differing scale properties, but also to differing transformation properties.

Prior (1996) used DEA to examine economies of scope in Spanish hospitals. The DEA model was outlined and manipulated to produce measures of scope. The results obtained from this study confirmed the presence of technical inefficiencies and potential economies of scope. The author described this technique as one "...that allows us to capture potential economies of scope, avoiding the level of technical efficiency and scale economies of each unit" (p.1300). The results were also in accordance with previous research in this particular area.

Another study using DEA is Papahristodoulou (1997). This study used DEA to evaluate the efficiency of a selection of personal cars. Essentially, the basic DEA model was used, with both constant and variable returns to scale efficiencies calculated for each of the 121 vehicles in the study. The analysis was constructed using (i) economic variables (for example: price of the car, taxes and insurance per year, fuel costs etc.) and (ii) technical variables (for example: wheelbase in millimetres, dimensions in cubic metres, net weight in kg, towing capacity in kg. etc.). The author examined both cost efficiency and performance efficiency using this data, and found results consistent with theory – that lower efficiency measures were found under constant returns to scale than under variable returns to scale. The study then sought to rank efficient cars using additional criteria – safety scores and defective parts. It was found that safety and defective parts were not related to efficiency – and so a car buyer could choose from efficient cars in terms of performance and cost. DEA was found useful in terms of incorporating different types and specifications of variables into the analysis. However the author does note that "if it were possible to weight the included characteristics and add all the remaining ones, the study would be improved significantly" (p.1500).

As an envelopment analysis, DEA is concerned with identification of the frontier of a group of decision-making units in the sample. The purpose of a DEA approach is to provide results that "provide insight into the operations of the organisation" (Norman and Stoker, 1991 p.179). Results presented in a DEA analysis will give the researcher rankings of producers: from those producers which have relative efficiency scores of 1.0 – producers we can label as relatively efficient producers – to producers with lower relative scores of efficiency. Therefore we would have a list of the "best" producers at the top and the "worst" producers at the bottom.

Norman and Stoker split such an efficiency listing into four main groups: (p.179)

(a) Robustly efficient units: These are likely to remain efficient "unless there were major shifts in their fortunes".
(b) Marginally efficient units: These units are likely to drop below 1.0 if there was even a small drop in the value of an output variable (or a small increase in the value of an input variable).
(c) Marginally inefficient units: These will have an efficiency rating of lower than 1.0 (between 1.0 and 0.9 as suggested by Norman and Stoker), and may be able to increase their efficiency score to 1.0.
(d) Distinctly inefficient units: With an efficiency score lower than that of the marginally inefficient unit, these units face some difficulty in transforming themselves into an efficient unit in the short term. Norman and Stoker suggested those units with efficiency scores lower than 0.75 would remain inefficient until there was significant change in the unit's state of affairs, governing factors, environment etc.

Those units found to have scores in the group (a) as defined above can be regarded as the units that best utilise their inputs given the circumstances in which they have to operate. Those in group (d) are not operating to a similar effect, and if this analysis has been correctly performed, one would have to ask questions about the management of such units.

A major query that often arises is whether or not a DEA measure of efficiency is consistent with efficiency measures from other different approaches. Specifically, DEA is, according to Norman and Stoker, "probably the only analytical tool in use that attempts to assess performance 'in the round'"(p.180). In other words, DEA assesses performance as an outcome of overall consequences, by comparison with other performances.
The deterministic regression analysis derives a relationship between a single (or more than one) output (input) and a group of input (output) factors. The analysis identifies producers which perform better than or worse than the average. This is the fundamental difference between the deterministic

regression approach and the DEA approach – regression evaluates efficiency from the average outcome, whereas DEA evaluates efficiency from the best outcome. Thus direct comparison cannot be made between the two approaches, but DEA can be used in conjunction with traditional measures of performance to provide a better overall picture of the situation from a management perspective.

DEA is similar in nature to stochastic frontier modelling in that a frontier of best possible output or performance is constructed in both approaches. Thus we would expect the two approaches to produce similar results. Indeed, Seiford and Thrall (1990) note that the result of recent developments in both parametric and non-parametric approaches “should be increased integration and improvement of both approaches” (p.29).

The vast majority of DEA applications reported in the literature present analyses of firms and industries using elementary DEA models, with appropriate data. This data was initially always **non-zero** and **non-negative**. In the current study, we deal with variables that frequently take positive, zero or negative values according to the specification of the data. This is a significant problem in that it reduces the applicability of DEA. Advice was sought from the DEA mailing list. Recommendations included using ‘inverse values’ (e.g. divide the ‘undesirable’ output by 100) or subtracting the negative values from large positive numbers. In both of these cases, the relative output/input mix is changed, and this can create problems.[4]

Larry Seiford pointed out in his e-mail that the difficulty in this case is that “negative inputs (since as ordered numbers they move in the "wrong" direction) are treated by the model as outputs and vice versa”.[5] Couple this with many negative output values (also moving in the wrong direction) and this is a case where DEA is not applicable in its original format.

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[4] (Emmanuel Thanassolis 1998, e-mail 17 November)

[5] (Larry Seiford 1998, e-mail 16 November)

Pastor (1996) discussed the issue of translation in DEA – with particular attention to the invariance of DEA after translation takes place. Pastor (1996) then used an example – in which an input is negative in three individual observations (out of 42 separate observations), and outputs take positive values. The 'new' approach was found to work, although the application did not include the possibility of outputs taking zero or negative values. The only way to eliminate the negativity aspect is to translate the data – but this disrupts the output/input mix. The composition of the output/input mix in the current study is particularly important for interpretation purposes, and any alteration of this mix makes analysis and interpretation difficult. Thus DEA is not an appropriate measure in this particular case. This is not to say that DEA is unusable in an analysis of sport production with negative data – with the right specification of data, DEA has been proven to be a powerful tool of efficiency measurement.

2.2 Efficiency Applications To Professional Sport

The work on production efficiency is a growing area, and the application of production efficiency to professional sport is a small section of this effort. Here we discuss four papers estimating the efficiency of professional sports using different estimation procedures.

Zak *et al.* (1979), one of the pioneering works in this field, estimated a Cobb-Douglas production frontier for the National Basketball Association (NBA) for the 1976-77 season. Potential output (in non-technical terms, the potential number of points that a team is capable of scoring) was estimated, as well as the efficiency with which inputs were combined through the employment of the Richmond technique of estimating production efficiency[6]. This measure estimates efficiency as a simple function of the gamma distribution parameter (the variance of the regression). In terms of overall findings, "the interaction of team potential and efficiency used to evaluate performance and rank teams

[6] See Richmond (1974) for details.

results in a ranking identical with one based on actual win/loss records" (p.391). It was found that of the input variables involved in the generation of a game outcome, both of the shooting percentage variables (free throws and field goals) were significantly different from zero at the 5% significance level. In other words, they were significant inputs in production, as were the measures of opposition mistakes (turnovers) and fouls. These variables have parallel measures in rugby league and similar measures will be used in the current study.

The use of production functions in professional sport has been a small but extremely interesting area in economic literature in years gone by. Bairam *et al.* (1990) followed the methodology used by Schofield (1988) to analyse the relationship between team success and appropriate performance inputs into the generation of success in professional cricket. Schofield used English county cricket as the basis for analysis, whereas Bairam *et al.* used data from New Zealand and Australia to estimate production functions along similar lines to Schofield's analysis. The model used in the Bairam *et al.* (1990) analysis is the constant elasticity of substitution (CES) model, estimated using a maximum likelihood procedure. From the results, comments were made as to the ideal strategy in the two countries in terms of playing to succeed, as well as challenging conventional wisdom. An important point that is noted is that "...cricket is a complex game; it's tactical and strategic nuances cannot adequately be captured in a single production function" (p.879). Similar things can be said about rugby league. Of particular relevance to this thesis is the comment that "[the complexity of the game], together with the changing environmental context of the game (especially important in comparative studies), underlines the danger of specifying production functions with *a priori* assumptions about the functional form" (p.879). Thus one must tread carefully when estimating a production function, according to Bairam *et al.* (1990).

Carmichael and Thomas (1995) formulated a production function for English rugby league football using performance-influencing as well as performance-related variables as input data at a seasonal level (using aggregate data from seasons). Efficiency is calculated based on computed residuals from the estimated production function – actual percentage of wins minus the estimated percentage of wins. The outcome of using such data is described by the authors as partially successful. The implication of this finding is that different combinations of the various inputs with the same amount of players will result in a different output level, output in this case referred to as the overall success of a team over a season. Another important point noted was that team success was not only a function of how well the team plays, but also of how well the opposition plays.

The approach to be taken in this thesis is fundamentally different from that of Carmichael and Thomas (hereafter CM), in that CM present their model as one of overall season performance with contributing variables such as number of tries, number of goals, number of professionals and average age of the squad. The current study, detailed in the next chapter, presents a model of individual game outcomes, so the focus is quite different. However the CM study has suggested a number of potential explanatory variables.

Hofler and Payne (1996) estimated a stochastic production frontier model for teams in the National Football League (NFL). This study used the methodology of the stochastic frontier model developed by Aigner, Lovell and Schmidt (1977) and extended by Battese and Coelli (1992) in a cross-sectional data context. 'Production' is defined as the team's scoring, and the frontier is the maximum attainable scoring that a team can achieve, given the input variables measured. Thus 'efficiency' is defined in this case as how close a team can perform to its potential. A homogeneous Cobb-Douglas production model was estimated for offensive performance in the NFL. With high estimates of efficiency, the paper concluded that NFL teams are excellent at exploiting their talent. Hofler and Payne's approach in terms of estimating production frontiers will be adopted in the current study.

2.3 Introduction To The Economics Of Sport

Sport in the modern economy is big business. Consumers all around the world pay to view sport and are interested analysts of sporting outcomes. Economic analysis of sporting contests and behaviour is a natural progression of this worldwide interest. Areas that have provoked interest in the sporting field include individual incentives in sports performance (Lehn 1982, McCormick and Tollison 1984), team production processes (Zak *et al.* 1979, Hofler and Payne 1996), structure of competition (Laband 1990) and the efficient markets hypothesis (in betting markets particularly – see Zuber *et al.* 1985, Gandar *et al.* 1988, Russo *et al.* 1989, Dare and MacDonald (1996) and Gandar *et al.* 1998). The efficient markets hypothesis is not in the scope of this study, and thus the literature in this area is not reviewed. The analyses of professional sports and their implications are presented in this section.

Sporting behaviour mirrors consumer and business behaviour in many ways. The available data on sport and sporting contests are plentiful and comprehensive. Thus, analysis of sport is an economic 'gymnasium' in which many economic hypotheses can be tested and analysed.

There are a variety of sports that have been analysed in some form, particularly North American sports such as American football (Hofler and Payne 1996), ice hockey (Jones *et al.* 1993), basketball (Clement and McCormick 1989, McCormick and Tollison 1984, Zak *et al.* 1979) and baseball (Kahane and Shmanske 1997). These sports attract significant attention from researchers due to the availability and high level of data specificity. Other sports that have been analysed include horse racing (Higgins and Tollison 1990), soccer (Hart *et al.* 1975, Walker 1986, Cairns 1987, Szymanski and Smith 1997), cricket (Schofield 1988), as well as rugby league (Davies *et al.* 1995, Carmichael and Thomas 1995, Burkitt and Cameron 1992).

2.3.1 Other Analyses of Professional Team Sports

The economics of professional team sports is an offshoot of the broad spectrum of sport and recreational economics. The basic assumption made is that a professional team sport is a commercial activity. This explains why economic analyses have primarily been concerned with how sports clubs can maximise profits and achieve commercial objectives.

The four main areas of research in the economics of professional team sports are:

1. Demand for professional team sports. When we consider demand, we mean attendance at sporting events – people who pay to watch sport – not participation in sport (Walker 1986, Davies *et al.* 1995).
2. Supply of professional team sports. This is where the team or club is viewed as a firm. In supply-side analysis, we concern ourselves with the behaviour of the team as a production process (Zak *et al.* 1979, Carmichael and Thomas 1995, Hofler and Payne 1996). This particular area is discussed in further detail in a later sub-section.
3. The so-called 'failure' of the market in professional team sports. Uncertainty of outcome is the primary characteristic of sporting competitions, and this generates conflicting roles within a sporting competition. On one hand, we have the competition's governing body, which wishes to keep the uncertainty of outcome by aiming to achieve rough equality of playing strengths of competing sides. On the other hand, we have individual clubs seeking to maximise revenues by whatever means possible. In doing so however, market forces can create a cycle where winning teams with success have rising attendance, rising revenue, more money to spend on recruitment, and then continued success and so on. Other teams may fall into a cycle whereby poor performances generate lower attendance and lower revenues. The selling of top players to free up resources for additional recruitment often results in the purchase of lower quality players, who may not fix the problem of poor form, and there are

repeated poor performances, and the cycle continues. One could well argue that this is just the regular working of the market and not 'failure' as such. Literature in this area discusses ways of eliminating this problem (Thomas 1997).

4. Policy. This area is tied in with the point above, as it is concerned with the implementation of policy dealing with, among other things, the uncertainty of outcome objective.

2.3.2 Previous Analyses Of Professional Sport With Relevance To Rugby League

Analyses of professional team sports consider a number of important determinants and make a number of important observations, many of them with relevant implications to the sport of Rugby League in Australia.

In terms of demand analyses, Hart, *et al.* (1975) take a quantitative approach to the analysis of attendance at English soccer matches. They construct and estimate a simple log-linear demand model for attendance at four English first division (as it was then known – now known as Premier League) clubs. Three seasons of data were pooled for each time series, and parameters were estimated for each of the clubs separately. In terms of data used, the independent variables were grouped into three main areas: (i) those of an economic nature, (ii) those of a demographic or geographic nature, and (iii) those relating to the attractiveness of a match and its rival attractions, as well as including a trend factor. All three groups of independent variables were found to have varying degrees of explanatory success, notably the demographic factors. The same model was also estimated using Seemingly Unrelated Least Squares (SUR), with results being similar to those obtained by OLS. It was found, in general, that "while there is clearly a large irrational element in the psychology of football support, [this paper has] shown that a quantitative approach to the problem can account for a significant proportion of the short-term variation in attendances" (p.27).

To test the link between on-field performance and crowd attendance, Walker (1986) extends the work done by Hart *et al.* (1975) and looks closely at demand determinants of professional soccer in Britain. Using similar methodology, it was found that the link between on-field performance and attendance was strong. The results, in general, were similar to those found by Hart *et al.* (1975). An important relationship found was that teams in larger centres achieved higher league standings. Because home league position is a significant determinant of attendance in general, this suggests the possibility of 'success breeding success' for large city teams.

In a strong claim, Davies *et al.* (1995) noted that previous empirical work was misleading, as no account had been taken of possible faulty regression and time-series properties associated with the data used. Another problem was the fact that the direction of causality between the variables was presumed rather than demonstrated. Their study, through use of a vector autoregressive (VAR) time-series approach, examined rugby league in Britain and presented evidence that attendance drives success, and not vice-versa. This implies that teams should place more importance on their spectators than has previously been the case.

Laband (1990) analysed how competition structure influenced performance in two professional sports, tennis and golf. The study applied the structure-conduct-performance model used in industrial organisation to tennis and golf. The study concludes that the structure of competition "may be largely responsible for determining the short-run and long-run performance of athletes in each respective sport" (p.148). The study also concluded that "dominance of the sport of tennis by the top players can be explained by the match-play structure of competition and the practice of seeding the top players against weaker players" (p.148). In the case of rugby league, the structure of the competition is determined by where a team finishes on the competition table in the previous year, unlike the seeding system used in tennis. Thus, to use the same logic as in the Laband (1990) study, with a lack of a seeding system, there is more likelihood of different winners in the competition from year to year.

Lehn (1982) conducted an empirical study of information asymmetries in baseball's free agent market. The study hypothesised that the clubs that the players played for prior to the player becoming a free agent have more information than other clubs wishing to recruit the player, and thus that information asymmetries exist. The necessary empirical result needed for this to be true was that the expected performance of free agents would be lower than the expected performance of players who do not become free-agents. Contract and performance data were collected for a sample of major league baseball players (p.344). The empirical test was carried out on two groups of players: players that utilised their free-agent status (i.e. signed for new teams), and players that signed with the clubs they were previously playing for. The study identified two types of information: information concerning the player's motivation, and information about the player's health. The study concluded that "there are theoretical grounds for believing that information regarding the expected performance of free-agent players is distributed asymmetrically between clubs which have employed the players and other clubs" (p.364). The study presented evidence that "post contract increase in disability is significantly higher among free agent pitchers who sign multi-year contracts than it is among eligible pitchers who have not become free agents" (p.364). While the results were not conclusive, "... they do suggest that over time clubs have become less enthusiastic about participating in the free agent market" (p.364).

Such information asymmetries may exist in many professional sports, including rugby league. The implication that can be drawn from the Lehn (1982) study is that clubs dealing with potential free agents from their own team are more informed about the player's future performance than clubs who are seeking to recruit from other teams. For teams looking to recruit from other clubs, the lesson is to offer short-term contracts that can enable clubs to act more quickly than those clubs signing free agents to long-term contracts if there is increased player disability.

Closely linked with this area of analysis is a study by Kahane and Shmanske (1997) on the effect of team roster turnover (the changing from year-to-year of a club's playing roster) and attendance. Kahane and Shmanske (1997) linked team behaviour (in terms of roster activity) to attendance – i.e. what do the fans like? The study estimated a regression model of attendance, using attendance as the dependent variable and independent variables that include price, income, population, team quality, league, year and stadium effects, as well as a variable for roster turnover. The study found that attendance "is influenced in the expected direction by price, quality and demographic variables, and by the extent of roster turnover" (p.430). The findings were that "the loss of one average player or 4% of the roster will cost the team between $420 000 and $540 000 in lost revenue" (p.430). The policy implications of such a result are clear – that team management should take into account the potential changes in revenue that may result from the changing of personnel on the team roster. The identity of the replacement player was not dealt with in the study. Effects would be different if the replacement player was an established superstar or an untried rookie. This possibility was not dealt with in the study.

Jones *et al.* (1993) examined the effect of violence on attendance in the National Hockey League. The study tested two hypotheses: firstly, the hypothesis that fans were attracted to the sport by violence (i.e. violence and hockey attendance are positively related); and secondly, the hypothesis that extreme degrees of hockey violence were more popular with American fans than Canadian fans. The study built an empirical model of team behaviour consisting of two equations, with attendance and price as the dependent variables, and independent variables that included measures of degrees of violence as well as location, uncertainty of outcome and team-specific variables. The model was estimated using the seemingly unrelated regression (SUR) technique, and the results were particularly interesting. Firstly, the variables representing uncertainty of outcome[7] were found to be "... seldom significant and, more often than not, have the wrong sign" (p.73). This finding was consistent with previous analyses and points to the possibility that either (a) outcome is unimportant when analysing attendance, or (b) outcome has been measured inappropriately. Results for the violence variables indicated that violence was positively related to attendance for all teams, and that there was a clear "blood sport" mentality towards hockey by American fans, whereas this mentality was not found for Canadian fans. US fans were found to like the more extreme forms of violence, whereas the Canadian fans liked the minor forms of violence.

These findings made for interesting policy advice – that if the National Hockey League wanted to correct this situation, US fans would have to be "weaned away from hockey violence" or some form of government intervention would need to be sanctioned (p.74). The former proposal required the League to "eliminate what has been successfully sold in the US for many years, violence" (p.74). The view of the NHL was summarised as generally condoning violence if it meant that clubs were successful in (a) performance, and/or (b) attracting crowds.

Higgins and Tollison (1990) looked at the behaviour of players in a game or runners in a race and sought to explain it using economic theory. The study looked specifically at runners in races, and sought to solve the economic problem of how runners can minimise running times subject to constraints. The study uses the theory of contests to derive the equilibrium distribution of running times in a race. The winning time model derived was tested empirically using data from Olympic Games track events and the Kentucky Derby. The model estimated was a regression model that had the running time of the contestant as the dependent variable, and included independent variables capturing the

[7] Two dummy variables were used: (i) a dummy variable representing high uncertainty of outcome – the variable took the value of 1 if both of the two teams were ranked in the top 3 teams in the league, and zero otherwise – and (ii) a dummy variable representing low uncertainty of outcome – the variable took the value of 1 if one of the teams was ranked in the top 3 teams in the league and the other team was ranked in the bottom 3 teams of the league, and zero otherwise. See Jones *et al.* (1993) for further specifics.

type of event, a time trend, individual incentives (i.e. the importance of the event to the individual), and various technology changes such as the use of a curved track. The models were viewed as successful by the authors, who note that "theory makes certain predictions about the impact of the number of competitors, the value of winning, technology, and so forth on the average running time in a race; and we find these predictions supported in a test using data from the sprint events in the modern Olympic Games" (p.33).

Economic theory is found to have high explanatory power when examining the behaviour of contestants in athletic events, and this finding fits in nicely with the idea behind the present study. Higgins and Tollison (1990) were able to apply economic theory to individual contestants with success. The present study will attempt to build economic models that explain the behaviour of teams in competition with each other.

Policy studies were identified above as an important subset of the economics of professional sport, and many previous studies have important policy implications for rugby league in Australia. Cairns (1987) looked at the effect of the introduction of a Premier League in Scottish football, and found that manipulation of league structure can change the nature of the product. It was found that after restructuring of the competition format had taken place, there were inequitable benefit allocations. Szymanski and Smith (1997) analysed the English soccer 'industry' by marrying together the analysis of supply and demand conditions, using accounting data as well as League performance data. It was found that "...most firms made losses, their plants were antiquated and grossly under-utilised and heavy investment was required both to meet government mandated safety standards and to improve the quality of the product sufficiently to compete on modern markets" (p.150). The failure of market forces in restructuring such industries was attributed to the failure of the market for corporate control – in other words, moving to corporate control of teams didn't result in successful restructuring of these industries. The market for corporate control is an important feature in the National Rugby League, and will continue to be important, particularly when restructuring takes place in 2000.

Burkitt and Cameron (1992) present an econometric analysis of attendance of rugby league matches in Britain over the period 1966-1990. In 1973, the Rugby Football League (RFL) moved from a one-tier league to a two-tier league structure in 1973. The authors found that, despite there being a major effect on attendance, "...the benefits of restructuring were distributed inequitably to the marked advantage of first division clubs. The desirability of such an outcome is highly contentious" (p.271).

With the proposed restructuring of the Australian competition to take place in 2000, the implication of such evidence suggests that there should be thorough and accurate planning both at the League and individual club level. Davies *et al.* (1995) in their analysis of British rugby league found that it was not evident that the addition of 'potentially successful' new clubs, or reshaping the competition format, necessarily generated additional support.

Another study with particular relevance to Australian sport is Borland and Lye's (1992) study on the determinants of attendance at Australian Rules football. While Australian Rules football and rugby league are quite different sports, they both share popularity in their respective states (Australian Rules in Victoria and Western Australia, Rugby League in New South Wales and Queensland). A factor that Borland and Lye identified as having a positive relationship with attendance is the degree of the uncertainty of outcome phenomena. Borland and Lye considered two parts to this phenomenon – the degree of predictability of the match outcome and the degree of uncertainty surrounding whether or not the teams participating in the match would win enough games to be finals contenders at the 'business end' of the season.

An interesting study with direct relevance to rugby league is Thomas (1997). Like many previous studies, this one examined changes in the organisation and structure of competition. The case study was rugby league in Britain after the introduction of Super League[8]. The ideal scenario that Super League and the English Rugby Football League (RFL) envisaged "...involves strong, competitive, well-administered, well-supported and financially viable clubs operating in "leagues of an appropriate size to provide sufficient matches over the length of a playing season..." (p.21). However, things do not appear to have developed in the anticipated manner after the introduction of the new governing body, with the RFL stating that there was "...a lack of genuine competitiveness between professional clubs, so producing too many matches in which the result is predictable" (p.21).

Theory identifies 'uncertainty of outcome' as one of the most important conditions of a contest, particularly a sporting contest as noted by Borland and Lye (1992), 'uncertainty of outcome' was an important determinant of attendance. Without careful implementation and monitoring of any policy alternative, such as the restructuring of the National Rugby League in 2000, a situation not unlike the British scenario described above could well happen in Australia.

2.4 Summary

As we have seen, there are a number of sports that have been analysed for a variety of reasons. These sports include sport played by individuals (i.e. golf, athletics, tennis) and sport played by a team (American football, baseball, basketball, ice hockey, rugby, rugby league and soccer). Traditional analyses in sport have been concerned with attendance of sporting contests, dealing with issues such as how the attendance of sports leagues changes after the reorganisation of competition, the role of violence (in ice hockey) in game attendance and the effect of changing team rosters (in baseball) on attendance. Other analyses have focused on production processes implicit within sport, analysing issues that include coaching decisions in team sports, team

[8] With the introduction of the Super League competitions in 1997 in both Australia and England, Super League (in conjunction with the RFL) became the governing body of the English game.

production processes and the efficiency of team production processes. With a wide variety of issues analysed there a variety of different economic techniques and methods used in these analyses. The most common methodology is to apply regression techniques to quantitative areas such as demand analyses and production processes in sport. Policy implications vary from study to study. Perhaps the predominant implication is that the success of the player/team matters a great deal to the player's/team's financial future (through attracting support), the success of the league, and the success of sport in general as an attractive commercial product. There is not universal agreement on the usefulness of the uncertainty of outcome phenomenon in sport. In general, uncertainty of outcome is considered an important determinant of attendance. Borland (1992) found this to be the case in Australian Rules football. However, Jones *et al.* (1993) pointed out that this is not the case in North American ice hockey. The issue is not resolved and requires careful measurement before one can draw policy conclusions.

The literature on 'production' and efficiency measurement in sport is growing. With the importance of sport in modern society, and the increased commercialisation of sport, economic analysis has an important role to play in identifying important areas for policy analysis. Rugby league in Australia, in particular, is about to go through substantial change. Analysis of production and efficiency may have the potential to provide important policy advice.

The construction of production functions and stochastic production frontier models in this study may enable thorough and comprehensive analysis of production and efficiency at an individual team level as well as an overall League level.

Chapter 3

METHODOLOGY

3.0 Introduction

In this section, the methodology of the study is detailed. The selection and justification of the models used in this analysis is given, then the variables used in the analysis are explained in detail. The sources of data are discussed and finally the manipulation of data is explained.

3.1 Selection Of Model

In order to measure the production process in rugby league, and analyse the contribution of game- and team-specific variables in this process, we develop a linear non-frontier deterministic production function model, which is similar to that modelled by Carmichael and Thomas (1995). This model is used for an exploratory analysis of the process of generating a game outcome. This model will be used to analyse the production processes in the game of rugby league.

3.2 The Difference in Points Scored (DPS) Model

The first model to be used in this analysis is the linear Difference in Points Scored (DPS) model, which is specified as:

$$DPS = \beta_0 + \sum \beta_i X_i + e_i \qquad \text{(where } i = 1,2,....\text{N)} \qquad (3.1)$$

where DPS is measured as the difference in points scored $PS^H - PS^V$ (points scored by the home team minus the points scored by the visiting team). X_i are game- or team-specific performance variables in game i (these variables are discussed in Section 3.3). These variables (except where they are dummy variables) are measured as $X_i^H - X_i^V$, with superscripts H and V denoting home and visitor respectively. The β's are coefficients to be estimated, with β_0 the constant coefficient and β_i the coefficient on the respective input variable i. The error term in this specification is assumed to capture the full extent of team inefficiency.

The choice of difference variables rather than the more widely-used ratio specification of variables is because the results of rugby league games are not suitable for using ratio measures. Zak *et al.* (1979) used ratios in their study of the NBA, justified by the argument that a 110-104 game is a closer game than a 96-90 game, despite there being the same absolute difference between the two scores. In rugby league, score differences tend to vary a lot more than in basketball. It is not uncommon (in fact it does happen in the data set used for this study) for there to be games in which one team fails to score any points. Thus the use of ratios is not feasible. The next best alternative to measure the outcome of the rugby league contest is taking the differences in points scored.

The reason for selecting this model is primarily due to its ease of interpretation. With the various input variables measured in a variety of different ways, this model can give clear and easily understood explanations as to the contribution of a game- or team-specific input into the process of producing a game outcome. The results of this model are presented in Chapter 4.

3.3 Stochastic Frontier Modelling

For the second stage of this analysis, this study adopts the specification of Battese and Coelli (1992) who outlined a stochastic frontier production function for (unbalanced) panel data with firm effects that can vary systematically over time. The model is:

$$Y_{it} = x_{it}\beta + (V_{it} - U_{it}) \qquad i = 1,...,N, t = 1,...,T \qquad (3.2)$$

where Y_{it} is the log of the production of the i-th firm in the t-th time period, x_{it} is a vector of input quantities of the i-th firm in the t-th time period and β is a vector of unknown parameters. The error term is comprised of two separate parts – V_{it} are random variables assumed to be identically and independently distributed (iid) $N(0,\sigma^2_V)$, and independent from U_{it}. The U_i (defined as $(U_i \exp(-\eta(t - T)))$) are non-negative random variables which are assumed to account for technical inefficiency in production and are assumed to be iid as truncations at zero of the $N(0,\sigma^2_U)$ distribution. η is a parameter to be estimated, which determines whether inefficiencies are time-varying or time invariant. The panel of data used in such an analysis is not required to be complete, that is it can be unbalanced. The model also applies the methodology of Battese and Corra (1977) which replaces σ^2_V and σ^2_U with $\sigma^2=\sigma^2_V+\sigma^2_U$ and $\gamma=\sigma^2_U/(\sigma^2_V+\sigma^2_U)$. The parameter γ must have a value between 0 and 1 for use in an iterative maximisation process.

Production, for this model, is defined in two ways: either (a) the difference in points scored (as in section 3.2), or (b) the number of points a team scored in a game (a team production model). We model each of the two different production processes as functions of team-specific variables, with the team production model including the **number of points scored by the opposition** as an additional explanatory variable. We do this to incorporate the contest (the game aspect) in the model. Each specification of model is used to calculate a stochastic frontier production model for each of the measures of production. The results are used to examine the production efficiency of individual teams as both home teams or visiting teams in separate analyses, for each of the three years under observation.

We generate these frontiers and subsequent estimates of efficiency through the use of the computer software program FRONTIER Version 4.1, obtained from Dr. Tim Coelli, the program's author. The review of the program's estimation procedure below is based upon Coelli's (1996) paper detailing the program and it's capabilities.

The procedure performed by FRONTIER is a three-stage process to obtain maximum likelihood estimates of the coefficients of a stochastic frontier production function. These three steps are as follows:[9]

Firstly, the ordinary least squares (OLS) estimates of the coefficients are found. These estimates, with the exception of the constant, are unbiased.

Secondly, a two-phase grid search of γ is done, with the OLS estimates set as the parameter values, and along with the intercept term and the variance parameters, are adjusted by a corrected ordinary least squares formula. The other parameters (η,μ,δ) are set to zero in the grid search.

Thirdly, the values obtained from step 2 are subsequently used as starting values in an iterative procedure (in this case the Davidon-Fletcher-Powell Quasi-Newton method) to return the final maximum likelihood estimates of the parameters.

The grid search as noted in the second step is conducted across the parameter space of γ. Values of γ are evaluated anywhere between 0.1 and 0.9.

The iterative maximisation procedure is conducted through taking first-order partial derivatives of the log-likelihood functions obtained from the initial OLS estimation. The procedure takes the parameter values obtained from the grid search as starting values, and updates the parameter estimates by the Davidon-Fletcher-Powell method until either of two things happen:

a) Convergence is reached. Convergence is set in FRONTIER such that if the proportional change in the likelihood function and each of the parameters is less than 0.00001, then the iterative procedure completes, or
b) The maximum number of iterations is exceeded without convergence.

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[9] See Coelli (1996) for model specifics.

To obtain maximum likelihood estimates of the model parameters, FRONTIER calculates a prediction of individual firm technical efficiencies from the estimated stochastic production frontier.

Restrictions can be placed on this model, with varying effects. In order to estimate a time-invariant model, we can simply set η equal to zero. There are also a number of choices that have to be made with regards to the suitability of different model types. We can select the appropriate representation of the data using likelihood ratio tests.

3.3.1 The Measurement of Efficiency in the Stochastic Frontier Model

Before defining efficiency in the technical sense, it is useful to illustrate the measurement of efficiency in general terms.

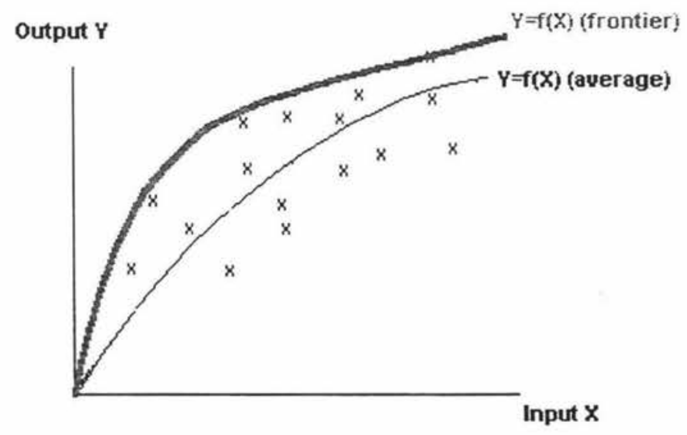

Figure 3.1: Two Approaches to Measuring Efficiency – A Diagrammatic Representation

In Figure 6.1 above, the two approaches in this study are graphically illustrated. The data points are seen as scattered around the average, or pseudo-frontier, production function Y=f(X) (average) that can be estimated from the data. The frontier approach (as adopted in both DEA and in stochastic frontier modelling) is an envelope approach – where the extreme points are enveloped by a function Y=f(X) (frontier) that estimates the frontier.

Turning now to the technical definition, the measure of efficiency in the stochastic frontier model is defined as: (Coelli 1996 p.8)

$$EFF_i = \frac{E(Y_i^*/U_i, X_i)}{E(Y_i^*/U_i = 0, X_i)} \tag{3.3}$$

Y_i^* is the actual production of the i-th firm, which will be equal to *exp*(Y_i) when the dependent variable is in logs. EFF_i in this case takes a value between zero and one. This calculation of efficiency depends on the value of U_i being predicted. Coelli notes that this prediction is achieved by "deriving expressions for the conditional expectation of these functions of the U_i, conditional on the observed value of ($V_i - U_i$)" (p.8). If U_i is predicted, then the efficiency measure is defined as the production of the firm given the non-negative random variable and the input variables, divided by the production of the firm given the input variables and assuming the non-negative random variable is zero.

Remembering that the U_i are the non-negative random variables that account for technical inefficiency, the measure of efficiency can be rewritten as:

$$EFF_i = \exp(-U_i) \tag{6.2}$$

In simple terms, the (in)efficiency measure describes how closely the team is scoring to it's potential.

3.3.2 Additional Model Parameters

From the estimation of the stochastic production frontier models using FRONTIER v.4.1, there are additional model parameters that have been detailed previously. Of interest are the gamma (γ), mu (μ) and eta (η) parameters. The gamma (γ) parameter is the variance-ratio parameter, and is important in determining whether a stochastic production frontier is a 'superior' measure to the simple average production function. Specifically, the average production function has a gamma value of zero (meaning that there is no technical inefficiency (U_i) – that firms are operating to full capacity). The other extreme is where the value of gamma is one, the full-frontier model, where the random variables V_i are not present in the model.

In order to determine whether a stochastic frontier production function is necessary, we can refer directly to the value of gamma and check whether it is significantly different from zero.

The mu parameter (μ) tells us what distribution the inefficiency effects have – a half-normal distribution or truncated normal distribution. Again, a check of the significance of this parameter gives an indication of what distribution is appropriate.

The eta (η) parameter is the parameter that determines whether the inefficiencies are time-varying or time invariant. An eta parameter value that is significantly different from zero indicates time-varying efficiencies, a value not significantly different from zero indicates time invariant efficiencies.

The appropriate mix of these parameters can be tested using likelihood ratio tests from the maximum-likelihood estimates and OLS estimates provided.

3.4 Variables

This section explains the variables used in this analysis.

The dependent variable, or the output, in the DPS model is the **game outcome**. The game outcome in this study is measured as a difference parameter – as described in Section 3.3. The exact specifications for each model will be clarified in the appropriate chapters.

There are a number of input variables relevant to the production process of producing a game outcome.

Goalkicking percentage is a variable that represents the influence of a team's goal-kicker, and is measured by successful shots as a ratio of total shots at goal. The contribution of a goal-kicker is expected to be positive, one reason being that in close games, a greater goal-kicking percentage often proves the difference. The role of goal-kickers has long been an area of debate in rugby league. Ever since the introduction of successful New Zealand goal-kicking rugby union converts Daryl Halligan and Matthew Ridge into Australian rugby league, goal-kicking has been regarded as having an important role in determining the outcome of a match. However, some coaches believe that concentrating on scoring tries is more important. As mentioned in the previous chapter, Zak *et al.* (1979) included an equivalent measure (shooting percentage in NBA basketball) and found it to be significant.

It is important to understand the role of **scrums** in a rugby league match. Scrums are awarded as a result of mistakes being made by the opposition team in the form of knock-ons, accidental off-side infringements and forward passes. Scrums are also awarded through the ball being put into touch by the opposition team in general play. Thus scrums can serve a dual purpose, and this creates uncertainty about the expected sign on this coefficient. On one hand the scrums variable proxies opposition mistakes, the sign in this case would be positive. In other words, opposition mistakes assist point scoring.[10] Opposition mistakes were found to be important in Zak *et al.* (1979) for NBA basketball. On the other hand, scrums also proxy a type of kicking game, with the expected sign on the coefficient to be negative if a strong opposition kicking game has the effect of restricting scoring options through pinning a team down in its own half.[11]

Penalties awarded are a direct measure of serious opposition indiscretions. A variety of offences can bring about penalties, including illegal tackles, off-side play, deliberate forward passes, and illegal kick-offs. Penalties often result in loss of territory through the opportunity for the non-offending team to kick for touch and gain valuable field position. They also result in sustained pressure on the defence through a restarting of the tackle count, and can also directly result in a penalty goal being converted into points. The sign of the coefficient on penalties awarded to a team is expected to be positive. Again, Zak *et al.* (1979) found that opposition fouls were an important determinant into game outcomes. This variable also includes the effect of the opposition having players spending time in the sin-bin, as well as having players sent off.

Interchange players are those who substitute others from the starting line-up throughout the course of the game. Up to four may be substituted at any one time, although any one may be substituted in any position, provided no more than four 'fresh players' are used throughout a match. The interchange bench is an important component of the game, as the composition of a bench has match-influencing potential. The composition of an interchange bench varies, but the conventional bench is typically comprised of an impact back, and three forwards. This variable can take a maximum value of 4 (the team has used its full quota of interchange players and the opposition has used none) to a minimum value of –4 (the opposite scenario). The sign on this coefficient is expected to be positive, as any extra players placed into the game are done so on the assumption that their presence will improve the game situation – either

[10] Opposition mistakes cannot be measured directly as the data is not available. Scrums represent the closest measure of opposition mistakes currently available for this analysis.

to aid the team in scoring more points, or stopping points from being scored. This variable is not used in the stochastic models, as a value of zero will result in interpretation difficulties.

A dummy variable is included for the **team that scores first** in a game, and is specified as 1 for first scorer, 0 for otherwise. This variable is included to capture the effect of being the first scorer, which may have an important psychological impact in that it forces the opposition team to play "catch-up". The sign on the coefficient is therefore expected to be positive, although it could be argued that it depends on the quality of the team concerned. Some teams score first because they are simply better than their opposition, some teams score first because they play their first half with more intensity than their second half with the intention of building a 'comfort zone' at halftime which may (or may not) be an advantage. This variable is not used in the stochastic frontier models, as its use as a dummy variable would make interpretation difficult.

A dummy variable is used to capture the effect of a team having a **half-time lead**. This variable is specified as 1 for leading at halftime, 0 for the scores being level, and –1 for being behind at halftime. Often a solid first-half performance can result in a lead that can be maintained until full-time, but as for any game, nothing is certain. Some teams put their opposition away in the first half, other teams specialise in second-half comebacks. The sign on this coefficient is expected to be positive for much the same reason as for the team that scores first – that if a team is behind at halftime, there is pressure on that team to catch up to the opposition to have a chance of winning the game. Often the pressure of being behind has the effect of disintegrating a team's game plan, and as a result, jeopardising their chances of winning the game. This variable is not used in the stochastic frontier models for the same reasons as the 'team that scores first' dummy variable.

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[11] Time spent in the opposition half is also an important factor in itself. Again, regretfully, the data is not available for this.

A measure of **immediate momentum** is included to capture the effects of a performance streak – either winning or losing. This variable is measured as the team's most recent run of consecutive results, either wins or losses. For example, if a team has won its last three games, then its immediate momentum variable would be +3. If then the team lost its next game, its immediate momentum variable would then read –1. Again, the sign on this coefficient is expected to be positive, as a winning streak has positive effects on team morale and confidence, just as a losing streak dampens team morale and confidence.

A measure of overall season performance is included to proxy the two teams' relative positions, and to proxy relative team strengths. The **momentum** measure is simply the overall win-loss difference for each team at each point in the season (at the time of each game). The sign on this coefficient is expected to be positive. A team with a greater success ratio would be expected, over the course of a season, to reflect 'true' ability and defeat teams with an inferior win-loss record.

Another dummy variable is included to capture the effect of a **night match** on the game outcome, specified as 1 for night game, 0 for otherwise. Over past seasons, some teams have assumed mantles of 'night-game specialists'. Other teams rarely play under lights, and as a result their form is likely to be affected when they play in unfamiliar conditions. The expected sign on this variable is unknown, as it is not a widely recognised factor of performance. This variable is not used in the stochastic frontier models, again as it is a dummy variable.

An important determinant of performance in studies of sporting contests is the measurement of the relative strengths of the two teams contesting the game. In this study, the measure used to proxy this **strength** effect is the average difference in points scored over the previous season, as measured by:

$$Strength = \frac{TPF_{t-1} - TPA_{t-1}}{n} \tag{3.4}$$

where TPF and TPA are total points scored for and against in the previous year respectively, and n is the number of games played. From year to year the strength of a team changes, either for the better or for the worse, and this is reflected in changing average point differentials. One would expect over the course of a season for this variable to be positive and significant, meaning that the 'stronger' team will defeat the 'weaker' team on most occasions, which seems an intuitively attractive proposition. However, in a single game context, there may very well be forces at work that may not always result in the 'stronger' team beating the 'weaker' team in every game, for example, complacency from stronger teams who show little respect for their weaker opposition's ability. These will be captured in this coefficient when we examine individual teams.

3.5 Data

The data for this study are for the regular seasons, excluding playoff matches, covering the 1995, 1996 and 1998 seasons for all 20 teams in the NRL. Data is not included for 1997 because the competition was divided into two separate competitions. There are actually 22 separate teams in this analysis due to changes in the competition between 1996 and 1998. Of the 20 teams in the 1995-1996 seasons, South Queensland and the Western Reds were replaced in 1998 by Adelaide and Melbourne. The game by game data used in this analysis is collected from *Rugby League Week* and *The Australian Rugby League Yearbook* for the 1995, 1996 and 1998 seasons. Overall, there are 672 individual game observations over 22 teams.[12]

[12] There is a shortage of observations, due to data unavailability for 6 games in the 1996 season (as these games were not played) as well as for two of the final games in the 1998 season.

3.6 Modelling The Data

The modelling of the DPS model is to be done in the following way. Firstly, we examine all game observations for home teams as one large sample, and then break it down into yearly samples, and examine any changes that may have occurred. This analysis does not enable us to observe the difference between home and away games, nor does it enable us to examine individual teams. We use this to explain the importance of each variable in the context of the game outcome.

We then modify the model(s) and the variables to examine efficiency, using an appropriate methodology in this case, the stochastic frontier production function as adopted by Battese and Coelli (1992). Analysis of the resulting stochastic frontier production models and corresponding efficiency estimates will provide the opportunity to make comments on both the validity and the policy implications of the models. The results of this analysis of production efficiency are presented in Chapter 5.

Chapter 4

RESULTS: PRODUCTION

4.1 Yearly Analysis

The DPS model regression estimates are presented below.

The data were combined in separate years to look at possible changes from year to year. Data were pooled across teams, for an aggregate average production function in each year. The data was also checked and corrected for heteroskedasticity and autocorrelation The results of the OLS estimation procedure are presented below in Table 4.1. Table 4.1 contains the production function estimates for the National Rugby League with the difference in points scored (DPS) as the dependent variable and performance variables as independent variables, for the years 1995, 1996 and 1998.

Table 4.1: Production Function Results: Year by Year

Variables	*1995*	*1996*	*1998*
Goal-kicking percentage	3.6201 (1.492)	8.1815*** (3.673)	8.3974*** (3.858)
Scrums	-0.34607 (-1.220)	-0.57311** (-2.184)	0.33126 (1.211)
Penalties	0.22230 (0.7628)	0.11780 (0.4494)	0.41744 (1.448)
Interchange players	1.5012* (1.750)	-0.85380 (-0.5079)	-1.1522 (-0.3620)
First scorer	5.0706** (2.426)	-0.13092 (-0.0624)	-0.76424 (-0.3913)
Lead at halftime	9.8554*** (8.776)	8.6112*** (7.721)	9.6200*** (8.581)
Immediate momentum	-0.10112 (-0.3164)	-0.14270 (-0.5635)	-0.32890 (-1.125)
Momentum	0.71316*** (4.175)	0.39270** (2.091)	0.36254** (2.240)
Night game	-2.3602 (-1.169)	-2.9101 (-1.517)	-1.9601 (-1.068)
Strength	0.28251*** (2.958)	0.36964*** (5.436)	0.47965*** (3.887)
Constant	0.91483 (0.5615)	3.3703** (2.014)	4.2910*** (2.664)
Adjusted R^2	0.5818	0.5505	0.5071
No. games	220	214	238

Note that t-statistics are reported in parentheses below coefficient values.
* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

If we look at each individual variable and its behaviour over the three-year period, we notice some interesting changes taking place.

The goal-kicking percentage coefficient has changed quite substantially from 1995 to 1998. If the home team kicker converts all (100%) of his attempts at goal, and the visiting team's kicker misses all of his attempts, the coefficient estimate is the estimated effect that this scenario has on the game outcome[13]. We can see that in 1995 the effect is almost an unconverted try (3.62 points) but is not significantly different from zero. In 1998, this effect has risen to over 8 points and is statistically significant at the 1% level. This would tend to indicate that an accurate kicker is becoming an important requirement in the modern game of rugby league.

The role scrums have in rugby league has also changed from 1995 to 1998. In 1995, for every scrum that the home team was awarded in excess of the visiting team's total scrums awarded, there was a negative effect of 0.35 points, which was not significant. In 1996, the same negative effect increased in value to 0.57 points, and was found to be statistically different from zero at the 5% level. This would indicate a combination of one of two things: either the presence of an effective kicking game by the visiting team (in terms of restricting the opposition's advancement up the field through kicks finding touch deep in opposition territory), or an inability to capitalise (in terms of scoring points) on the awarding of scrums. The awarding of a scrum results in extra possession as well as the chance to orchestrate a set move from a scrum. In 1998, this effect changed to +0.33 points, however this was not found to be significantly different from zero.

The effect penalties have on the process of scoring points does not appear to have changed a lot over the three year period. In 1995, the effect of one extra penalty awarded to the home team in excess of the visiting team's penalty count resulted in a statistically insignificant gain of 0.22 points. In 1998, this had risen to 0.42 points, but still statistically insignificantly different from zero. This tells us that although the awarding of penalties in favour of the home team does

[13] It is acknowledged that this is an unlikely combination of events, but it helps to illustrate the 'maximum' estimated effect that the accuracy of a goal-kicker has on the game outcome.

not have a significant bearing on the final outcome in terms of points scored, the awarding of penalties does have a positive effect on points scored, which is an intuitively expected result.

Interchange players have provided an interesting result over the three-year period. In 1995, when interchange players were optional[14], it was found that for every extra player used as an interchange player by the home team, it resulted in a 1.5 point advantage to the home team, and it was found to be statistically significantly different from zero at the 10% level. In other words, the bench contributed positively (and significantly) to the outcome of the match through the replacement of tired and/or injured players. In 1996, the regulations regarding interchange players were changed[15]. The effect switched from having a positive effect to a negative effect, of 0.85 points. In 1998, this negative effect had increased to a value in excess of a field goal (but statistically insignificantly different from zero).

One noticeable change across the period 1995 to 1998 is the change in value of the First scorer dummy variable. Remembering that the value of this variable is one if the home team scores first, and zero if the visiting team scores first. In 1995 this effect was estimated to be 5.07 points, and this was found to be statistically significantly different from zero at the 5% level. In other words, to score first in a game had a substantial positive effect on the game outcome in terms of the home team. In 1996, this effect had switched dramatically. No longer significantly different from zero, the effect was found to be negative, -0.13 points to be exact. In 1998, this negative effect had grown fractionally larger, to -0.76 points. This indicates that being the first scorer in a game has moved from being a large and significant contributor to the game outcome to having an insignificant effect. As a result of these findings, one can only

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[14] Interchange players in 1995 were subject to the restriction that a maximum of four interchanges were allowed, injuries included, which had to be taken into account when using interchange players by the team's coaching staff.

[15] In 1996, the laws were changed to permit a maximum of four players to be used as interchange players, with unlimited interchanges being made provided one of these four players were used at each interchange. This allowed for frequent interchanges at any stage of the game, with coaches implementing planned interchanges of certain players after certain periods of time.

assume that teams have concentrated on playing more consistent football over the entire 80 minutes, or that being the first scorer is losing importance in terms of the final outcome of a game.

The behaviour of the Lead at halftime dummy variable from 1995 to 1998 as one of the most important input variables is consistent over the time frame. In 1995, the home team in the lead at halftime in their game effectively had an advantage of 9.86 points, which was found to be statistically significantly different from zero at the 1% level. In 1996, the value had decreased to 8.6 points, whereas in 1998, the value of the coefficient had risen to 9.62 points, and all were significant at the 1% level. This indicates that it effectively takes a visiting team a minimum of two scoring moves to catch up (in terms of the final result) to a home team in the lead at halftime.

Immediate momentum, or our 'streak' measure, provides some interesting results. In 1995, for each extra game that the home team had performed better in than their opposition (for example, the home team had won 3 games in succession, and the opposition had won 2, the immediate momentum variable would read 1 in favour of the home team), the estimated effect of this is –0.1 points. This result is not significantly different from zero. In 1996, this effect decreased to –0.14 points, and in 1998, this decreased to –0.33 points, again, the results are not significantly different from zero.

The estimated effect of Momentum, the variable that measures the difference between two sides in terms of positions on the competition ladder, generates expected results. In 1996, for every game that the home team is 'better'[16] than their opposition (in terms of the overall win-loss difference measures at the respective point of the season), the effect is estimated to be approximately 0.7 points, and this is statistically different from zero at the 1% level. In 1996, the estimate falls to 0.39 points (statistically significant at the 5% level), and in

[16] Remembering that the measurement of this variable is done in an identical fashion to the Immediate Momentum variable, with the difference being that Momentum measures relative performance of a season.

1998, this estimate falls again to 0.36 points (significant at the 5% level). This finding tends to indicate that teams are becoming more even in terms of ability. In 1995, a game advantage is twice the size of that in 1998, which suggests that results are getting closer between teams at opposite ends of the competition table, which augers well for future competition.

Night matches are regular and popular features of the rugby league weekend. In 1995, a home game played under lights effectively cost the home team 2.36 points. In 1996, this cost had risen, costing the home team 2.91 points. In 1998, this cost had fallen, now costing a team 1.96 points. None of these results were found to be significantly different from zero.

Strength, a variable that measures inherent strength within a side (a measure of the previous season's performance), is one of the most statistically significant variables in this model. In 1995, for an additional point that a home team has over their opposition (in terms of relative Strength variables), the home side effectively gains 0.28 points. If the home team has a 10-point advantage, then the estimated effect on a game outcome is 2.8 points to the home side. This result was found to be statistically significantly different from zero at the 1% level. In 1996, this effect rose to 0.37 points. In 1998, it rose again to be worth 0.48 points, again significant at the 1% level. This indicates that the inherent strength of a team, as measured by season performance in the previous year, has had a positive and increasing effect over time. This lends weight to the idea that once a team builds a base of performance (whether through the retention of key players, coaches, training regimes etc), then results will improve.

The constant term, in this case, can be interpreted as the home ground effect, or the home ground 'advantage'. In 1995, the home team's constant was 0.91 points, and it was not significantly different from zero. In 1996, this value had increased dramatically to 3.37 points, and was found to be statistically significantly different from zero at the 5% level. The home ground advantage is clearly in evidence here. In 1998, this value had increased again, both in absolute terms and in it's level of significance. The home ground 'advantage' was equivalent to an unconverted try, or 4.29 points, statistically significantly different from zero at the 1% level. In the space of three seasons (1995-1998), the estimated home ground advantage had increased by 3.38 points, and changed from an insignificant to an extremely significant input into the point-scoring production process.

One important point to note is the level of variation explained by this model in the three seasons, as illustrated by the adjusted R^2 results given below each model. The variables used in this analysis are by no means the complete story of a game – due to the lack of more comprehensive variables this analysis has to make do with the 'next-best' measures. The variables used in this analysis all have some relevance to the outcome of a game, but not to the extent of variables available for many US sports. Available variables for many US sports are more specific and comprehensive than the variables in this study. The other point to note is that we are looking at explaining, as well as identifying variables and the extent of their impact on, the game outcome. With an adjusted R^2 of around 0.5 for the models we have estimated, we can attribute some of the unexplained variation to immeasurable factors, such as luck, the bounce of the ball, the video referee etc. The impact of such factors in a study of this type is particularly difficult to quantify, and no attempt is made to do so. Obviously we cannot attribute all of the unexplained variation to luck and the bounce of the ball – there are a lot more factors contributing to a game outcome that are not included in this study for varying reasons. With these aggregated results, we can say that the variables used in this study, which represent the bulk of freely available information, explain approximately 50% of the variation in points scored in individual game outcomes.

4.2 Efficiency in the DPS Model

We can use the DPS 1998 model to obtain a measure of the relative efficiencies of the 20 NRL teams using 1998 data for home and away games, using the model for 1998 as reported in Table 4.1.[17] We follow the method used by Carmichael and Thomas (1995) and calculate our efficiency measures as follows:

$$DPSEfficiency = \left(\frac{actualDPS - estimatedDPS}{actualDPS} \right) \times 100 \qquad (4.1)$$

A team with an efficiency value of zero can be interpreted as operating with average technical efficiency, while a team with a positive (negative) value can be interpreted as operating with above-average (below-average) efficiency. (Carmichael and Thomas, 1995, p.868).

Table 4.2 lists each team's average game efficiency measure and overall efficiency ranking in 1998 for games as the home team and games as the visiting team. Using each team's data, individual efficiency measures are calculated by computing the expected game outcome with the coefficient values in Table 4.1 and entering this estimate along with the actual game outcome into equation 4.1. The individual efficiency measures for each team were then averaged, with the average measures and the team rankings presented overleaf.

[17] The reason for choosing 1998 will become clearer in Chapters 5 and 6.

Table 4.2: Average Game Efficiency and Rankings: Home and Away[18]

Team	Home Efficiency Measure	Home Ranking	Away Efficiency Measure	Away Ranking
Adelaide (ADE)	-20.32	18	36.47	13
Auckland (AUK)	48.17	11	65.27	7
Balmain (BAL)	-14.09	17	97.97	5
Brisbane (BRI)	71.83	8	36.54	12
Canberra (CAN)	-50.8	20	101.21	3
Cronulla (CRO)	69.47	9	-18.87	15
Canterbury (CTB)	20.39	14	188.13	1
Gold Coast (GC)	148.68	3	-41.7	18
Illawarra (ILL)	-2.71	16	-56.9	20
Manly (MAN)	106.35	6	51.45	11
Melbourne (MEL)	37.98	13	-45.63	19
Newcastle (NEW)	86.28	7	-21.33	16
North Sydney (NOR)	59.18	10	99.06	4
North Queensland (NQ)	111.63	5	62.01	9
Parramatta (PAR)	-46.69	19	-40.67	17
Penrith (PEN)	6.26	15	21.64	14
South Sydney (SOU)	147.07	4	62.09	8
St George (STG	182.03	1	136.06	2
Sydney City (SYC)	46.07	12	90.05	6
Western Suburbs (WES)	156.37	2	61.66	10

[18] Note that the abbreviations reported in parentheses after team names are used in Figure 4.1.

We can use these rankings and compare them with the actual overall placings for each team in the 1998 NRL competition. We can also compute a rank correlation coefficient, as presented below in Table 4.3. The correlation coefficient falls within the range from 1 to –1. If the coefficient equals 1, there is a perfect linear relationship between efficiency ranking and overall 1998 ranking. If the coefficient equals –1, there is a perfect inverse linear relationship. If the coefficient equals zero, there is no correlation between the efficiency ranking and the 1998 performance ranking. We would expect a relationship to exist whereby the more efficient a team is, the better performed it should be.

Table 4.3: Rankings and Rank Coefficients: All Teams

Team	Home Rank	Away Rank	1998 Place
Adelaide	18	13	17
Auckland	11	7	15
Balmain	17	5	13
Brisbane	8	12	1
Canberra	20	3	7
Canterbury	9	15	9
Cronulla	14	1	11
Gold Coast	3	18	19
Illawarra	16	20	12
Manly	6	11	10
Melbourne	13	19	3
Newcastle	7	16	2
North Sydney	10	4	5
North Queensland	5	9	16
Parramatta	19	17	4
Penrith	15	14	14
South Sydney	4	8	18
St George	1	2	8
Sydney City	12	6	6
Western Suburbs	2	10	20
Rank Coefficient	***-0.241***	***-0.045***	

If we compare the rank correlation coefficients in Table 4.3 above, we can see that efficiency as the home team is a better predictor of overall performance (as measured by the 1998 placing in the competition) than efficiency as an away (or visiting) team, with a moderate negative rank coefficient.

This is not an expected result – with home efficiency ranking having an inverse relationship with overall performance ranking. A potential explanation for why efficiency was not a strong predictor of overall performance in 1998 could be the possibility that there is considerable variation in input quality across the NRL. These findings are consistent with Carmichael and Thomas (1995) who found a similar pattern for the English second division in 1990-91 (p.868). They note that efficient use of what may be relatively poor quality inputs cannot ensure a high league position.

If we split Table 4.3 into two – the top 10 teams in terms of overall performance, and the bottom 10 teams in terms of overall performance – we may get a result that is consistent with our expectations – these rank coefficients are presented in Table 4.4.

Table 4.4: Rankings and Rank Coefficients: Top 10 and Bottom 10

Teams (Top 10)	Home Efficiency Rank	Away Efficiency Rank	1998 Place
Brisbane	8	12	1
Newcastle	7	16	2
Melbourne	13	19	3
Parramatta	19	17	4
North Sydney	10	4	5
Sydney City	12	6	6
Canberra	20	3	7
St George	1	2	8
Canterbury	9	15	9
Manly	6	11	10
Correlation with Position	***-0.187***	***-0.41***	
Teams (Bottom 10)	Home Efficiency Rank	Away Efficiency Rank	1998 Place
Cronulla	14	1	11
Illawarra	16	20	12
Balmain	17	5	13
Penrith	15	14	14
Auckland	11	7	15
North Queensland	5	9	16
Adelaide	18	13	17
South Sydney	4	8	18
Gold Coast	3	18	19
Western Suburbs	2	10	20
Correlation with Position	***-0.755***	***0.255***	

We can see that home efficiency is a better predictor of overall performance of the bottom ten teams than for the top ten teams, with a strong negative correlation between home efficiency and the 1998 place. A potential explanation for this could be that lower-ranked teams that played more efficiently with "lower-quality" inputs would finish in a lower place than teams who played less efficiently with higher quality inputs. Unfortunately the measurement of the quality of inputs is difficult to do and has not been analysed in this study.

For visiting teams, efficiency is a better predictor of overall performance for the top ten teams (with a moderate negative correlation) than for the bottom ten teams (with a weaker positive correlation).

Below, we graph the rankings we obtain from the above analysis, i.e. home, visiting and the resulting overall ranking. Note that a high value represents a low rank (i.e. a rank of 18 places the team 18th out of 20 teams), and a low value represents a high rank.

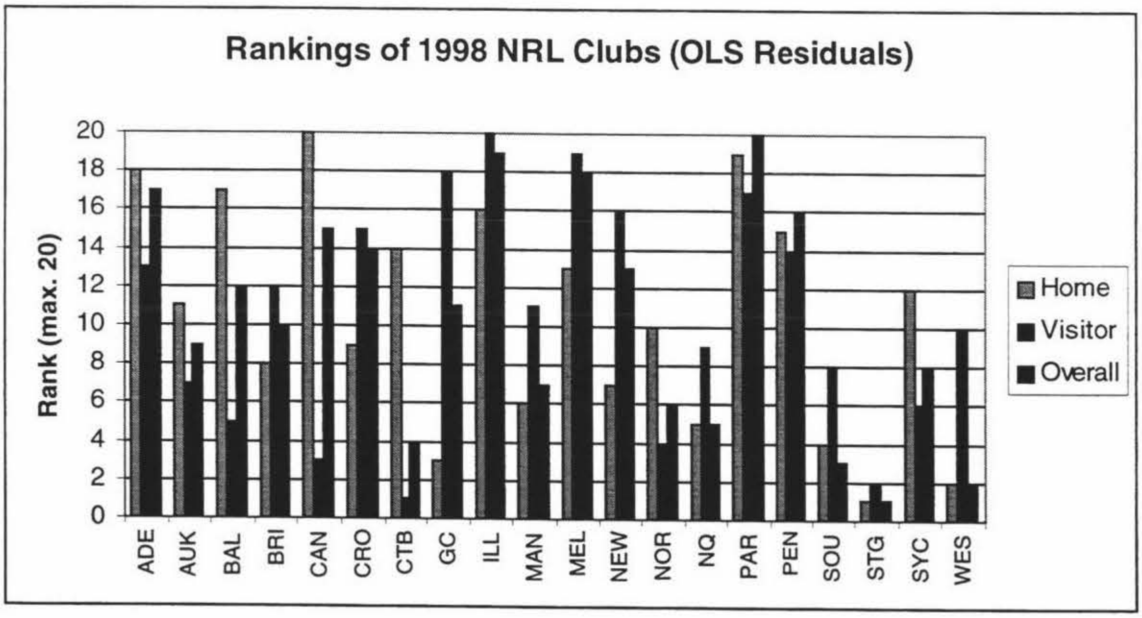

Figure 4.1: DPS Model Home, Visiting and Overall Rankings (1998)[19]

[19] See Table 4.2 for explanation of abbreviations.

The resulting overall rankings are interesting. Of the top eight teams in the 1998 competition in terms of performance (in other words, the teams that made the playoffs), four of those teams, namely Newcastle (ranked 13th), Canberra (15th), Melbourne (18th) and Parramatta (20th) were ranked outside the top ten overall in terms of game performance efficiency. This could indicate that these teams were playing relatively less efficiently than teams such as Western Suburbs (ranked 2nd), South Sydney (3rd), Cronulla (4th), North Queensland (5th) and Auckland (9th), while possibly possessing greater talent and skill. The results suggest that these teams made the playoffs by extracting enough of their superior talent to outperform more efficient (but less talented and skilful) teams. It is also worthwhile mentioning that of the top 10 teams in terms of efficiency, only two of these teams are non-Sydney based teams (Auckland and Brisbane) which is an interesting result given the intention of the NRL to reduce the number of Sydney clubs.

If we look at the overall rankings and compare these to the actual performance measure (i.e. 1998 place in the competition) we get an overall rank coefficient.

Table 4.5: Overall Rankings and Rank Coefficient

Team	Overall Efficiency Ranking	1998 Place
Adelaide	17	17
Auckland	9	15
Balmain	12	13
Brisbane	10	1
Canberra	15	7
Canterbury	14	9
Cronulla	4	11
Gold Coast	11	19
Illawarra	19	12
Manly	7	10
Melbourne	18	3
Newcastle	13	2
North Sydney	6	5
North Queensland	5	16
Parramatta	20	4
Penrith	16	14
South Sydney	3	18
St George	1	8
Sydney City	8	6
Western Suburbs	2	20
Correlation Coefficient	***-0.3895***	

We can see from Table 4.5 that the overall rank correlation coefficient between the overall efficiency rank of 1998 and the places on the competition table in 1998 is a moderate negative coefficient. This result reflects a point made earlier in this section – that there was possibly considerable variation in the quality of inputs across teams in the NRL. Thus if a team played more efficiently with lower quality inputs, (e.g. Western Suburbs), than a team that played less efficiently with higher quality inputs, (e.g. Parramatta), it may not result in a higher position on the competition table.

To help explain these rankings, we can look at the averages of important variables (that is, variables whose coefficients were found to be significantly different from zero in Table 4.1) for each team presented below in Table 4.6.

Table 4.6: Averages of Significant Variables (1998)

Team	DPS	Difference in Goal-kicking percentage	Lead at Halftime	Difference in Momentum	Difference in Strength
Adelaide	-9.25	-0.112	-0.417	-5.833	-6.553
Auckland	2.565	-0.057	0.087	0.739	-0.299
Balmain	-3.417	0.013	0.083	-0.625	-0.871
Brisbane	15.75	-0.039	0.458	5.958	10.36
Canberra	5.625	0.015	0.0	1.875	4.906
Canterbury	2.958	0.394	0.25	-1.208	-1.04
Cronulla	2.125	0.063	0.083	1.75	9.188
Gold Coast	-14.39	-0.1574	-0.565	-7.783	-2.917
Illawarra	-2.696	0.039	0.130	-0.957	1.384
Manly	0.174	-0.044	0.0	-2.696	5.586
Melbourne	7.25	-0.060	0.417	4.833	-1.472
Newcastle	7.542	-0.075	0.25	7.458	7.619
North Sydney	12.33	0.194	0.542	3.25	8.078
North Queensland	-8.125	-0.124	-0.375	-0.375	-8.697
Parramatta	4.625	-0.135	0.292	5.875	1.620
Penrith	-2.292	0.045	-0.292	-3.625	-3.122
South Sydney	-9.208	0.018	-0.5	-7.083	-16.00
St George	-0.167	-0.111	0.125	3.167	-4.36
Sydney City	12.63	0.136	0.333	6.042	4.258
Western Suburbs	-17.96	-0.165	-0.5	-7.542	-4.091

Looking at the different columns, we are able to rank each of these from 1 to 20, and then calculate the correlation coefficient between the rankings of each column with the overall efficiency rankings we obtained from this analysis as presented in Figure 4.1. These correlation coefficients are as follows:

Table 4.7: Correlation Coefficients for Rankings

Variable	Correlation with Efficiency
Difference in Points Scored	-0.191
Difference in Goalkicking Percentage	-0.021
Lead at Halftime	-0.239
Difference in Momentum	-0.125
Difference in Strength	-0.116

As we can see, these results tends to suggest that although these variables are statistically significant in explaining the game outcome in 1998, they aren't as important when it comes to explaining efficiency.

4.3 Summary Of Results

From the above analysis, we have identified some key input variables into the generation of a game outcome at an aggregate level. It provides an interesting insight into what plays a part in a game outcome.

We also calculate efficiency from the residuals of the DPS model, a procedure developed by Carmichael and Thomas (1995). We see that the rankings of the efficiency calculations are interesting for two reasons: (i) that four of the top eight teams by performance ranked outside the top ten in terms of efficiency, and (ii) that of the top ten teams in terms of efficiency, eight of these were Sydney-based teams, with Brisbane and Auckland the only non-Sydney based teams. In terms of overall rankings, it was found that there was a moderately negative rank coefficient between efficiency and performance.

It is important to recognise that in this section we are analysing the generation of a game outcome. A game outcome involves both teams in direct competition, i.e. home minus visitor, or team in concern minus the opposing team. In the next section we will also measure production in a more conventional fashion. As well as measuring the game outcome as team production, we measure team production as the number of points scored by the team in concern as a function of team-specific variables - not as direct home-to-visitor (or vice versa) interaction variables - as well as a function of the points scored by the opposition. This procedure and the results are detailed in Chapter 5.

Chapter 5

RESULTS: MODELLING PRODUCTION USING STOCHASTIC FRONTIER MODELLING

In this section results of production efficiency are presented for the NRL for the following years: 1995, 1996 and 1998. It is hoped that by estimating a stochastic Cobb-Douglas production frontier function with the data, we can obtain estimates of efficiency for teams throughout each of the seasons, for home games or games as the visiting team. Initially, we outline the models estimated, the results of each model are reported and commented on, and the implications of these results are presented. In Chapter 6, likelihood ratio tests are performed to assess the suitability of the stochastic frontier model as a fit of the data and from the appropriate models efficiency estimates are calculated, graphed and commented on.

5.1 Introduction

In order to examine production and efficiency at an individual team level, it is convenient (in terms of analysis and interpretation) to take a traditional approach to the modelling of production. In addition to modelling the actual game outcome as a game-specific variable, it is also appropriate to model individual team production as the points scored by the team in concern, with the points scored by the opposition as an additional input into the production process. Instead of using difference variables as independent variables, we re-specify these variables as team-specific variables to keep with production efficiency analyses in the literature. Thus the analysis follows a traditional production analysis, with the use of a Cobb-Douglas specification for the model, and efficiency measures calculated from this model.

5.2 Methodology

In this section we estimate two two-part models, the two parts being games played (1) as home teams, and (2) as visiting teams. These models are estimated using pooled data for all teams.

5.2.1 Team-Specific Production Models

$$PS_{H,G} = \beta(X_{H,G}, PS_{V,G}) + (V_{H,G} - U_{H,G})^{20} \tag{5.1}$$

where $H, V = 1,\ldots,20$ (teams) and $G = 1,\ldots,12$ (games)

$$PS_{V,G} = \beta(X_{V,G}, PS_{H,G}) + (V_{V,G} - U_{V,G})^{21} \tag{5.2}$$

where $V, H = 1,\ldots,20$ and $G = 1,\ldots,12$

$PS_{H,G}$ is the log of points scored of the H-th home team in the G-th game,
$X_{H,G}$ is the vector of input quantities of the H-th home team in the G-th game, where the inputs are (logged) goal-kicking percentage, scrums, penalties, immediate momentum, momentum and strength.
$PS_{V,G}$ is the log of points scored by the V-th visiting team in the G-th game (in the game under observation),
β is a vector of unknown parameters,
$V_{H,G}$ are random variables assumed to be iid $N(0,\sigma^2)$, and
$U_{H,G}$ are non-negative random variables assumed to account for technical inefficiency (truncations at zero of $N(0,\sigma^2)$).

Model 1 (Equation 5.1) is for games as the home team, and Model 2 (Equation 5.2) is for games played as the visiting team.

[20] Note that $PS_{V,G}$ is the points scored by the visiting team in team *H*'s *G*-th game.

[21] Note that $PS_{H,G}$ is the points scored by the home team in team *V*'s *G*-th game.

5.2.2 Game Outcome Production Models

In these models, we revert back to our initial DPS variable as the game production, while preserving the team-specific inputs into the production process. Thus we make modifications to the above models (5.1) and (5.2) below (note that these models are also estimated using pooled data for all teams):

$$DPS_{H,G} = \beta(X_{H,G}) + (V_{H,G} - U_{H,G}) \tag{5.3}$$

and

$$DPS_{V,G} = \beta(X_{V,G}) + (V_{V,G} - U_{V,G}) \tag{5.4}$$

where the variables and parameters are defined as above, however we use DPS as the dependent variable, and this is specified as the home (or alternatively, visiting) team's score minus the visiting (home) teams score. These specifications differ from the analysis conducted in Chapter 4, as we are viewing the team-specific variables as the inputs, rather than the differences between both teams' team-specific inputs. This enables us to remove to some extent the interaction between teams, and see what impact the actions of one team has on the game outcome. Note for convenience in the following analysis that equation 5.3 is Model 3, and equation 5.4 is Model 4.

5.3 Expected Results

In terms of qualitative results, we would expect that the points scored by the opposing team would have a negative effect on the points scored by the team in concern. That is, it is more difficult to score points if the opposition scores points as well – a contest is in effect. We would expect the signs on goal-kicking percentage, scrums and penalties to be positive, with a more accurate goal-kicker having a positive effect, and scrums and penalties resulting in more possession being awarded to the team in concern. The coefficients on both of the momentum variables should be positive – a team that has either (a) a better result streak, or (b) is placed higher on the competition table, or both, would be expected to score more points than a team in an inferior situation. Strength is also expected to be positive – a team with more inherent strength is expected to score more points than a team with less strength. We would also expect there to be some difference between the coefficients obtained for home teams and to coefficients obtained for visiting teams, due to the result found in Chapter 4 that there seems to be evidence of a 'home-ground advantage' being present.

5.4 Results

These models are estimated using the data for 1995 (220 observations), 1996 (214 observations) and 1998 (238 observations), and the results of the estimation of these models are presented in the tables below.

Table 5.1 : Model 1 (Home) Results (Equation 5.1)

Variable Name	1995	1996	1998
Constant	1.8677***	1.7108***	1.6444***
	(6.907)	(4.037)	(10.43)
Visiting Team's Points Scored	-0.1103**	-0.0380*	-0.1141***
	(-2.032)	(-1.673)	(-2.533)
Goalkicking Percentage	0.6417***	0.3565***	0.2572***
	(11.95)	(14.38)	(7.456)
Scrums	-0.3751**	-0.1494	-0.0678
	(-2.244)	(1.540)	(-0.563)
Penalties	0.1265	-0.2203	-0.0796
	(0.575)	(-1.301)	(-0.584)
Immediate Momentum	0.0172	0.0246	0.0470
	(0.303)	(0.561)	(0.113)
Momentum	-0.0050	-0.0118	0.0246
	(-0.143)	(-0.214)	(1.066)
Strength	-0.0098	0.0949***	0.0311
	(-0.328)	(2.984)	(1.281)
σ^2	0.2989**	0.1642***	1.5819***
	(2.023)	(10.53)	(5.206)
γ	0.2636	0.0018	0.9318***
	(0.653)	(0.007)	(60.57)
μ	-0.5614	0.0072	-2.4282***
	(-0.377)	(0.007)	(-2.816)
η	0.3362	0.1078	-1.0401***
	(0.651)	(0.129)	(-5.815)
LLF	-150.764	-110.476	-92.541

Note that t-statistics are reported in parentheses below coefficient values
* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

There are several noticeable features of the estimates of this model throughout the three periods of estimation. In every year, the Visiting Team's Points Scored coefficient was negative and significant, which is an expected result. Goalkicking percentage is the largest positive coefficient in all three years, and is significantly different from zero at the 1% level of significance. The value is decreasing across the period of analysis, from 0.6417 in 1995 to 0.2572 in 1998. The value of the Scrums coefficient is interesting – given that scrums provide the team that is awarded the scrum the opportunity to restart their tackle count and is thus effectively an extra set of possession – it is negative across all years. However, it is not significantly different from zero (except in 1995 when it is significantly different from zero at the 5% level). Immediate Momentum is found to be positive, although not significantly different from zero. Momentum is found to be positive in 1998, but negative in 1995 and 1996, but not significantly different from zero. Strength was found to be positive and significantly different from zero at the 1% level in 1996, which means that the greater the "inherent strength" of a team, the greater the positive effect on the points scored by the home team.

In terms of the additional model parameters (parameters γ, μ and η), we find that in 1998 the gamma parameter is significantly different from zero and close to one, with a value of 0.9318. The importance of this parameter is in determining whether the model is a stochastic frontier model or a "pseudo-frontier" model (as defined by Battese and Corra (1977)). If the gamma parameter takes a value of zero, then the average production function is the appropriate model for the data. If the gamma parameter is statistically different from zero, then a pseudo-frontier model is appropriate. If gamma equals one, then the stochastic frontier model is appropriate. These parameters are discussed in greater detail when we deal with efficiency in Chapter 6.

If we look at the corresponding model for visiting teams, there are a number of interesting observations that we can note.

Table 5.2 : Model 2 (Visiting) Results (Equation 5.2)

Variable Name	1995	1996	1998
Constant	2.0033***	1.6109***	1.4878***
	(8.994)	(2.728)	(9.350)
Home Team's Points Scored	-0.0925	-0.1199	-0.1485***
	(-1.590)	(1.228)	(-2.377)
Goalkicking Percentage	0.3036***	0.6171***	0.2869***
	(7.551)	(10.44)	(8.237)
Scrums	-0.6647***	-0.0916	-0.0466
	(-3.447)	(0.111)	(-0.516)
Penalties	0.0007	-0.0839	0.0833
	(0.004)	(0.184)	(0.572)
Immediate Momentum	-0.0281	-0.0432	0.0237
	(-0.461)	(0.496)	(0.479)
Momentum	-0.0187	0.0258	0.0220
	(-0.473)	(0.412)	(0.677)
Strength	0.0143	0.0283	-0.0209
	(0.483)	(0.520)	(-0.655)
σ^2	0.2787***	0.3830***	0.8280***
	(6.631)	(7.794)	(4.271)
γ	0.0531	0.0013	0.7822***
	(0.466)	(0.016)	(14.09)
μ	-0.2433	0.0449	-0.1610***
	(-0.445)	(0.269)	(4.259)
η	0.1391	-0.0727	-0.3468***
	(1.664)	(-0.614)	(-2.595)
LLF	-169.600	-200.120	-142.180

Note that t-statistics are reported in parentheses below coefficient values
* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Results for Model 2 are presented above in Table 5.2 – and the results are similar to those obtained for Model 1. The values on the Home Team's Points

Scored coefficients are as expected – but one point we can note with comparison to the results in Table 5.1 is that in 1995 the effect of the home team scoring against the visiting team had a smaller effect than the vice-versa situation (the visiting team scoring against the home team). In 1996 and 1998 this situation had reversed, with the effect of the home team scoring against the visiting team having the greater (negative) effect on points scored than the visiting team scoring against the home team – which lends weight to the theory that teams enjoy an "advantage" (the home ground advantage) when they play at home and teams find it harder to score away from home. Goalkicking percentage is the largest positive coefficient, as for Home teams. Scrums are found to have a negative coefficient value in 1995, which is similar to the findings in Table 5.1. This gives an indication that scrums are not an advantageous form of possession, regardless of where the team played in 1995. One possible explanation for this result is that a scrum enables the team that is not awarded the scrum the opportunity to organise its defensive pattern, and this could result in making it difficult for the team that is awarded the scrum to score points.

Of the additional model parameters, like in Table 5.1, 1998 is the only year that a pseudo-frontier model is the best representation of the data, with a gamma parameter of 0.7822, which is significantly different from zero at the 1% level. Again, these parameters will be discussed in further detail in the section on efficiency.

Note that Models 1 and 2 use the points scored by either the home team or the visiting team as the production (dependent variable) with the team-specific input variables as the inputs into production. We now turn our attention to re-specifying the dependent variable as the difference in points scored (from the point of view of the team in concern, i.e. home or visiting) to see whether this returns better results than the results discussed above. These models are Models 3 and 4, and the results can be seen below in Tables 5.3 and 5.4.

Table 5.3 : Model 3 (Home) Results (Equation 5.3)

Variable Name	1995	1996	1998
Constant	0.1100	0.1990	0.2128
	(0.248)	(0.377)	(0.743)
Goalkicking Percentage	0.7407***	0.4700***	0.3507***
	(8.087)	(4.477)	(5.106)
Scrums	-0.0891	0.2184	0.0150
	(-0.314)	(0.648)	(0.063)
Penalties	0.7308**	0.1628	0.1316
	(2.087)	(0.379)	(0.480)
Immediate Momentum	0.0833	0.0847	0.0385
	(0.889)	(0.790)	(0.490)
Momentum	0.0718	0.0742	0.0838*
	(1.173)	(1.208)	(1.814)
Strength	0.0678	0.2633***	0.0959**
	(1.511)	(3.367)	(2.102)
σ^2	0.6792***	0.8513***	2.1877
	(8.361)	(7.554)	(1.642)
γ	0.0296	0.0120	0.7813***
	(0.326)	(0.104)	(5.058)
μ	0.2837	0.2024	-2.6148
	(1.365)	(0.791)	(-1.248)
η	-0.0413	-0.1233	-1.1989***
	(-0.484)	(-0.936)	(-2.386)
LLF	-267.796	-284.384	-256.232

Note that t-statistics are reported in parentheses below coefficient values
* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

By re-specifying the dependent variable, we can examine the effect of individual team-specific inputs into the generation of a game outcome. In Table 5.3, the results for Model 3 (Home games) are presented. We notice a distinct similarity with Model 1 – that Goalkicking Percentage is positive and significant across all years. However, we note that the importance (in terms of sizes of coefficients) of an accurate goalkicker is greater when we model the game outcome rather than the number of points scored by the home team. Strength is the other coefficient that is significantly different from zero (at the 1% level in 1996 and the 5% level in 1998), and the sign is positive as expected. These results are notable in that despite the fewer number of coefficients significantly different from zero, the values of the coefficients are all as expected (with the exception of the Scrums coefficient in 1995). Thus this model has produced intuitively attractive results.

We can turn now to Model 4, and see whether these results are duplicated for Model 3 in much the same way as Models 1 and 2.

Table 5.4 : Model 4 (Visiting) Results (Equation 5.4)

Variable Name	1995	1996	1998
Constant	0.9809***	0.3632	-0.0324
	(2.424)	(0.591)	(-0.146)
Goalkicking Percentage	0.3301***	0.6720***	0.3712***
	(3.701)	(8.038)	(6.600)
Scrums	-0.7946***	-0.0961	0.1842
	(-2.254)	(-0.133)	(1.237)
Penalties	0.2471	-0.0922	0.1333
	(0.720)	(-0.331)	(0.563)
Immediate Momentum	0.0388	0.0034	0.0550
	(0.378)	(0.019)	(0.686)
Momentum	-0.0235	0.0458	0.0626
	(-0.331)	(0.370)	(1.185)
Strength	0.1627***	0.1336*	0.0643
	(3.170)	(1.778)	(1.299)
σ^2	0.7112***	0.6850***	1.0300
	(9.746)	(5.427)	(1.325)
γ	0.0442*	0.0391	0.5619
	(1.769)	(0.245)	(1.414)
μ	0.3546	0.3275	-1.5216
	(1.371)	(0.337)	(-0.666)
η	0.0166	-0.2126	-0.1424
	(0.422)	(-1.197)	(-1.393)
LLF	-274.735	-260.284	-247.701

Note that t-statistics are reported in parentheses below coefficient values
* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Looking at the results presented in Table 5.4, it is noticeable that Model 4 has some similarities in terms of intuitive results to Model 3. Again, Goalkicking Percentage is positive and significantly different from zero, like in Models 1, 2 and 3. Thus we can come to the conclusion that an accurate goalkicker plays an important part in the game of rugby league, and it can provide an important source of scoring both in absolute terms (one teams scoring) and in relative terms (the game outcome). The value of the Scrums coefficient is negative in 1995 and statistically significant from zero at the 1% level.

In terms of the incidental model parameters, from the significance of the gamma parameter we can see that a pseudo-frontier model is found in 1995, but gamma is not a large value. However, it is significantly different from zero, and that makes it different from the average production function definition (where the gamma parameter is zero and statistically insignificantly different from zero).

5.5 Implications For The Game Of Rugby League

In terms of results from these models, it has been mentioned that the accuracy of a team's goal-kicker is statistically significant, regardless of where a team plays. It is found from Models 5.3 and 5.4 that scrums had a positive (but not significantly different from zero) effect on a game outcome in 1998. The result for Penalties – in terms of the game outcome – implied that penalties had a positive effect for a home team (across the three-year period) and an inconsistent effect for a visiting team (positive in 1995 and 1998, negative in 1996).

In terms of the importance of the momentum variables, having a positive Immediate Momentum (or a positive form streak) is found to have a positive effect in terms of the game outcome in games for both home and visiting teams (although not significantly different from zero). In terms of absolute points scored, home teams enjoy a positive effect from a positive streak of form, whereas the visiting team initially incurred a negative effect in 1995 and 1996, however in 1998 this effect was positive. Thus, the addage of "being in good form" has a positive effect on both the points scored by teams and the game outcome.

Momentum, measuring the teams' season win-loss difference (as a measure of position on the competition table) is found to have an inconsistent effect on the points scored by the home and visiting teams. In 1995, both were negative; in 1996, home momentum was negative, visiting momentum was positive; in 1998 both were positive. In terms of the game outcome, for games as the home team the Momentum coefficient is found to be consistently positive (and significant in 1998 at the 10% level of significance). For games as the visiting team, the findings are similar, with the exception of the coefficient in 1995. These findings confirm that a team in a better position on the competition table has a greater effect on the game outcome than their opposition.

The Strength coefficient, like other variables, does not display a consistent value for point scoring models for home teams or visiting teams. However in terms of the game outcome, the inherent strength of a team has a positive effect both at home and away across the years analysed and is found to be significantly different from zero (for both types of games) for two of the three years. In other words, the stronger the inherent strength of a team, the better the performance in terms of the game outcome.

5.6 Summary of Results

When we consider the results obtained in Chapter 4 and 5, we can note some important points. Firstly, the DPS (OLS) model estimated in Chapter 4 is specified using difference variables for the dependent and independent variables. Thus it captures the contest element between teams. The results we found from Chapter 4 support results found in Models 3 and 4 (stochastic frontiers) in Chapter 5. Models 3 and 4 use the same dependent variable as the model in Chapter 4, but instead of using difference independent variables, Models 3 and 4 use team-specific variables, while omitting the dummy variables. Another difference between the two models is that the DPS model in Chapter 4 did not distinguish between games as the home team and games as the visiting team, whereas Models 3 and 4 represent models of home and visiting team games respectively. The DPS model from Chapter 4 is expressed in raw numbers, whereas Models 3 and 4 from Chapter 5 are expressed in logs. Despite these differences between the models, the same variables are found to be significant (goalkicking percentage and strength), and the results are generally consistent between both models. It was found in Chapter 5 that Models 3 and 4 were not statistically different from the deterministic production function specification, and thus it is appropriate to use the DPS model from Chapter 4 as a basis for analysing efficiency.

Models 1 and 2 of Chapter 5 are specified differently from the model in Chapter 4 and Models 3 and 4 of Chapter 5 in that they use the points scored by the team in concern as the dependent variable rather than the difference in points scored dependent variable. Thus one would expect different results from these models from the results obtained for the DPS model of Chapter 4 and Models 3 and 4 of Chapter 5. Indeed, the results are different, particularly when it was found that the specification of Models 1 and 2 as stochastic frontier models was a more suitable representation of the data than the deterministic average production function for 1998.

The stochastic frontier models Model 1 and Model 2 of Chapter 5 are used to analyse point-scoring efficiency. The results of these approaches are presented in Chapter 6.

Chapter 6

STOCHASTIC FRONTIER RESULTS: EFFICIENCY

In this section, likelihood ratio tests are performed using the models detailed in Chapter 5 to assess the suitability of the stochastic frontier model for an analysis of efficiency in this case. Models that meet specific criteria as a result of these tests are deemed suitable and are used for this analysis. From the suitable models, efficiency estimates are calculated, graphed and commented on.

6.1 Parameter Results

Looking at the results of the additional parameters for stochastic frontier models, we can see that from Tables 6.1, 6.2, 6.3 and 6.4 overleaf, we note that some of the model parameters in 1998 (at least in Models 1, 2 and 3) are significantly different from zero at the 1% level. We therefore choose to use Models 1 to 4 for the 1998 season, and determine the appropriate representation of each model through the use of likelihood ratio tests.

Table 6.1 : Model 1 (Home) Additional Parameter Results[22]

Variable Name	1995	1996	1998
γ	0.2636	0.0018	0.9318***
	(0.653)	(0.007)	(60.57)
μ	-0.5614	0.0072	-2.4282***
	(-0.377)	(0.007)	(-2.816)
η	0.3362	0.1078	-1.0401***
	(0.651)	(0.129)	(-5.815)
LLF	-150.764	-110.476	-92.541

* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 6.2 : Model 2 (Visiting) Additional Parameter Results[23]

Variable Name	1995	1996	1998
γ	0.0531	0.0013	0.7822***
	(0.466)	(0.016)	(14.09)
μ	-0.2433	0.0449	-0.1610***
	(-0.445)	(0.269)	(4.259)
η	0.1391	-0.0727	-0.3468***
	(1.664)	(-0.614)	(-2.595)
LLF	-169.600	-200.120	-142.180

* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

[22] t-statistics are reported in parentheses below coefficient values.

[23] t-statistics are reported in parentheses below coefficient values.

Table 6.3 : Model 3 (Home) Additional Parameter Results[24]

Variable Name	1995	1996	1998
γ	0.0296	0.0120	0.7813***
	(0.326)	(0.104)	(5.058)
μ	0.2837	0.2024	-2.6148
	(1.365)	(0.791)	(-1.248)
η	-0.0413	-0.1233	-1.1989***
	(-0.484)	(-0.936)	(-2.386)
LLF	-267.796	-284.384	-256.232

* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 6.4 : Model 4 (Visiting) Additional Parameter Results[25]

Variable Name	1995	1996	1998
γ	0.0442*	0.0391	0.5619
	(1.769)	(0.245)	(1.414)
μ	0.3546	0.3275	-1.5216
	(1.371)	(0.337)	(-0.666)
η	0.0166	-0.2126	-0.1424
	(0.422)	(-1.197)	(-1.393)
LLF	-274.735	-260.284	-247.701

* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Firstly though, we can make preliminary tests as to whether the models estimated are a better representation of the data than the standard average production function estimated for this data. We can do this using a likelihood ratio test comparing (i) the model with all parameters included (the stochastic frontier model), and (ii) the traditional average production function (where all 'additional' model parameters are zero). The results are listed below in Table

[24] t-statistics are reported in parentheses below coefficient values.

[25] t-statistics are reported in parentheses below coefficient values.

6.1. If the null hypothesis of all 'additional' model parameters being equal to zero is rejected for these models, then we can undertake further tests on the models to check for the validity of each parameter.

Table 6.5 : Likelihood Ratio Tests for All Models

Assumptions	H_0	χ^2 value	$\chi^2_{95\%}$ value	Decision
Model 1 (1995)	$\gamma=\mu=\eta=0$	2.774	7.81	Accept H_0
Model 1 (1996)	$\gamma=\mu=\eta=0$	0.187	7.81	Accept H_0
Model 1 (1998)	$\gamma=\mu=\eta=0$	**47.749**	**7.81**	**Reject H_0**
Model 2 (1995)	$\gamma=\mu=\eta=0$	3.689	7.81	Accept H_0
Model 2 (1996)	$\gamma=\mu=\eta=0$	0.135	7.81	Accept H_0
Model 2 (1998)	$\gamma=\mu=\eta=0$	**16.028**	**7.81**	**Reject H_0**
Model 3 (1995)	$\gamma=\mu=\eta=0$	0.908	7.81	Accept H_0
Model 3 (1996)	$\gamma=\mu=\eta=0$	0.517	7.81	Accept H_0
Model 3 (1998)	$\gamma=\mu=\eta=0$	5.257	7.81	Accept H_0
Model 4 (1995)	$\gamma=\mu=\eta=0$	3.015	7.81	Accept H_0
Model 4 (1996)	$\gamma=\mu=\eta=0$	1.511	7.81	Accept H_0
Model 4 (1998)	$\gamma=\mu=\eta=0$	3.162	7.81	Accept H_0

We can see from the above table that the only models for which H_0 is rejected (that the stochastic frontier model is a better representation of the data than the traditional average production function) are Models 1 and 2 for 1998. In general terms, we can conclude the other models estimated are not significantly different from the traditional average production function in nature.

We can take these two models and undertake further likelihood ratio tests to check the appropriateness of the model parameters and assumptions. This involves the estimation of three more models in addition to the traditional average production function (Model *.4)[26] for the two Models selected. This

[26] *.i denotes a variation (i=1,2,3 or 4) of the Model (*) in concern (either Model 1 or Model 2).

methodology is used in Battese and Coelli (1992) and involves estimating separate models with the following assumptions: $\mu=0$ (Model *.1), $\eta=0$ (Model 1.2), and $\mu=\eta=0$ (Model 1.3). This enables us to test for the suitability of each parameter, and model specifications. The results of the additional models for testing Model 1 (1998) are presented below in Table 6.2.

Table 6.6: Additional models for Model 1 (1998)

Variable	Model 1	Model 1.1	Model 1.2	Model 1.3	Model 1.4
Constant	1.6444***	1.6988***	1.5753***	1.5747***	1.5747***
	(10.43)	(10.14)	(7.909)	(7.988)	(8.581)
Visiting Team Points Scored	-0.1141***	-0.1206***	-0.1185***	-0.1186***	-0.1186***
	(-2.533)	(-2.716)	(-2.491)	(-2.527)	(-2.443)
Goalkicking Percentage	0.2572***	0.2750***	0.3492***	0.3492***	0.3492***
	(7.456)	(7.506)	(8.518)	(8.977)	(8.814)
Scrums	-0.0678	-0.1199	-0.1069	-0.1069	-0.1069
	(-0.563)	(-0.947)	(0.731)	(-0.737)	(-0.727)
Penalties	-0.0796	-0.0910	0.0224	0.0224	0.0224
	(-0.584)	(-0.645)	(0.145)	(0.148)	(0.145)
Immediate Momentum	0.0470	0.0022	-0.0063	-0.0063	-0.0063
	(0.113)	(0.053)	(-0.143)	(-0.144)	(-0.141)
Momentum	0.0246	0.0361	0.0418	0.0417	0.0417
	(1.066)	(1.479)	(1.587)	(1.569)	(1.557)
Strength	0.0311	0.0390	0.0524**	0.0524**	0.0523**
	(1.281)	(1.694)	(1.975)	(2.027)	(2.019)
σ^2	1.5819***	0.6516***	0.1557***	0.1557***	0.1612
	(5.206)	(2.892)	(10.75)	(10.96)	
γ	0.9318***	0.8214***	0.0000	0.1E-07	-
	(60.57)	(12.81)	(0.001)	(0.8E-04)	
μ	-2.4282***	-	0.0006	-	-
	(-2.816)		(0.005)		
η	-1.0401***	-1.3715	-	-	-
	(-5.815)	(-1.479)			
LLF	-92.541	-96.035	-116.415	-116.415	-116.415

Note that t-statistics are reported in parentheses below coefficient values
* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

The same process is replicated for Model 2 in 1998, and the results obtained are shown in Table 6.7.

Table 6.7: Additional models for Model 2 (1998)

Variable	Model 1	Model 1.1	Model 1.2	Model 1.3	Model 1.4
Constant	1.4878***	1.5171***	1.4811***	1.4994***	1.3910***
	(9.350)	(8.969)	(9.026)	(8.693)	(8.180)
Home Team Points Scored	-0.1485***	-0.1525***	-0.1342**	-0.1363**	-0.1410**
	(-2.377)	(-2.332)	(-2.142)	(-2.117)	(-2.137)
Goalkicking Percentage	0.2869***	0.2951***	0.3166***	0.3190***	0.3287***
	(8.237)	(8.342)	(8.814)	(8.819)	(9.120)
Scrums	-0.0466	-0.0485	-0.0434	-0.0441	-0.0437
	(-0.516)	(-0.506)	(0.450)	(0.450)	(-0.434)
Penalties	0.0833	0.0998	0.1154	0.1165	0.1197
	(0.572)	(0.655)	(0.775)	(0.753)	(0.755)
Immediate Momentum	0.0237	0.0271	0.0249	0.2569	0.0346
	(0.479)	(0.523)	(0.536)	(0.480)	(0.639)
Momentum	0.0220	0.0236	0.0098	0.0094	0.0089
	(0.677)	(0.689)	(0.340)	(0.273)	(0.258)
Strength	-0.0209	-0.0176	-0.0029	-0.0073	-0.0144
	(-0.655)	(-0.549)	(-0.083)	(-0.204)	(0.465)
σ^2	0.8280***	0.3449***	0.2763***	0.2206***	0.2140
	(4.271)	(3.703)	(2.819)	(8.798)	
γ	0.7822***	0.4665***	0.2902	0.1005	-
	(14.09)	(3.091)	(1.011)	(1.205)	
μ	-0.1610***	-	-0.5663	-	-
	(4.259)		(-0.600)		
η	-0.3468***	-0.2375**	-	-	-
	(-2.595)	(-1.999)			
LLF	-142.180	-144.309	-149.003	-149.342	-150.194

Note that t-statistics are reported in parentheses below coefficient values
* significant at 10% level, ** significant at 5% level, *** significant at 1% level.

From these results, we can test directly for the appropriateness of each distributional assumption using likelihood ratio tests. These results are displayed below in Tables 6.8 and 6.9.

Table 6.8: Likelihood Ratio Tests for Model 1 (1998)

Assumptions	H_0	χ^2 value	$\chi^2_{95\%}$ value	Decision
Model 1.4	$\gamma=\mu=\eta=0$	47.749	7.81	Reject
Model 1.3	$\mu=\eta=0$	47.749	5.99	Reject
Model 1.1	$\mu=0$	6.988	3.84	Reject
Model 1.2	$\eta=0$	47.749	3.84	Reject

Table 6.9: Likelihood Ratio Tests for Model 2 (1998)

Assumptions	H_0	χ^2 value	$\chi^2_{95\%}$ value	Decision
Model 2.4	$\gamma=\mu=\eta=0$	16.028	7.81	Reject
Model 2.3	$\mu=\eta=0$	14.324	5.99	Reject
Model 2.1	$\mu=0$	4.258	3.84	Reject
Model 2.2	$\eta=0$	13.646	3.84	Reject

Looking at the estimated models and comparing them to the stochastic frontier model estimated in Chapter 5, we can see that there are a number of conclusions we can draw about the distributional assumptions of the model. As we know from initial tests, the hypothesis that all of the additional model parameters are equal to zero (i.e. H_0: $\gamma=\mu=\eta=0$) is rejected for these two models, and thus the traditional average production function is not an appropriate representation of the data in these cases. Looking at the other results, the hypothesis that the team effects[27] follow a half-normal distribution (i.e. H_0: $\mu=0$) is rejected in both cases. We assume a truncated normal distribution for the team efficiency effects. We can also test the hypothesis that the team effects are time invariant (i.e. H_0: $\eta=0$), and we can see that the results for both models indicate that these effects are time-varying. The combination of the two hypotheses of time invariant team effects with a half-

[27] "Team effects" meaning team (in)efficiency effects.

normal distribution (i.e. H_0: $\mu=\eta=0$) is also rejected at the 5% level of significance.

As a consequence of these results, we are able to report the technical efficiencies estimated by FRONTIER version 4.1 (see Battese and Coelli, 1992, for the predictor of these efficiency measures) for Models 1 and 2 - for home teams and visiting teams respectively.

We note the negative value of the estimate of the η parameter for both models (Model 1: $\hat{\eta}$ = -1.0401, Model 2: $\hat{\eta}$ = -0.3468). With the assumed exponential model (i.e. the team efficiency effects change exponentially over time), because the value of the eta parameters are negative it would follow that the estimates of efficiency would decrease over time and become more dispersed. In other words, the efficiency of teams worsens as the year progresses. This is not an unusual result - teams always start the season equal on the competition table (i.e. on zero points) and throughout the season they disperse themselves on the competition table according to their results, which in turn depends on the contributing factors of each game. Thus these results appear intuitively attractive.

6.2 Efficiency Estimates

The estimates of efficiency that correspond to the models outlined and tested above are presented in graphical format below.

Initially, we see the estimated technical efficiencies for home teams in 1998 in Figure 6.1.

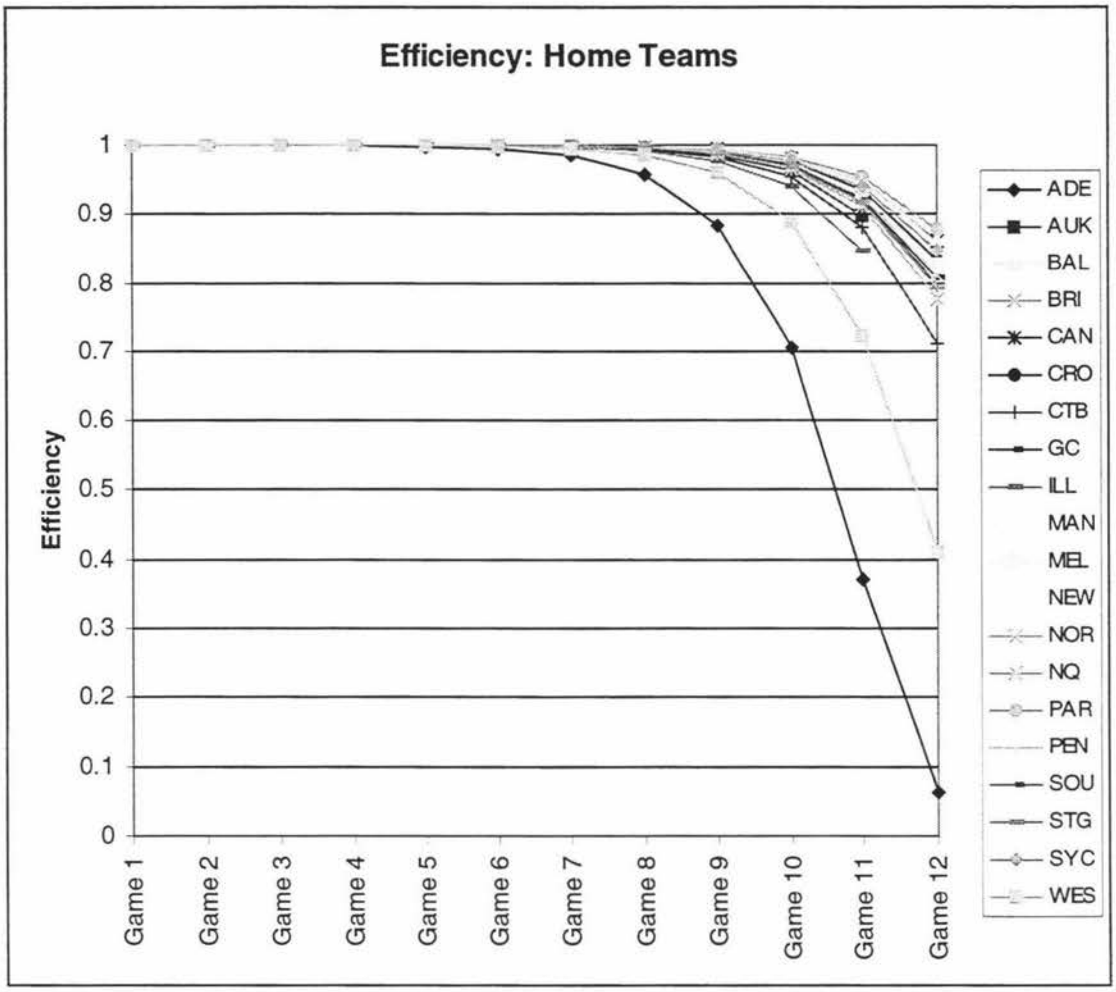

Figure 6.1: Estimated Technical Efficiencies for Home Teams in 1998[28]

The data for this table is found in Appendix I. Note that with the exception of Adelaide (ADE) and Western Suburbs (WES), the majority of teams are fairly efficient (i.e. virtually no deviation from 1) when it comes to playing at home. As we can see, there appears very little deviation from team's paths of efficiency up to Home Game 8. The reason for this lack of dispersion of efficiency measures could be that as soon as some teams have no chance of making it to the semi-finals, the efficiency of those teams deteriorates to levels lower than those teams with a chance of making it to the semi-finals. This suggests a possible variable that could be included – a variable to capture the effect of a team being unable to make the playoffs – which is not explicitly included in this

[28] Refer to Table 4.2 for interpretation of the abbreviations.

analysis, as such a variable is difficult to define. Momentum captures some of this effect in that it uses the win-loss difference, but it does not define a point where a team can no longer make the playoffs. In other words, if there is no chance of playing in the semi-finals, teams become disenchanted and do not play with as much effort as teams with a chance of post-season glory. Of course, there are teams who play for pride, and players who play for contracts for the following year, and these could possibly be reflected in the estimates of efficiency. It is worth pointing out at this stage that these measures of efficiency do not set out to measure the best team and the worst team. They measure how well a team has played relative to it's potential. Thus we can say that Adelaide performed poorly at home (as illustrated in Figure 6.1) relative to its potential in the latter stages of the 1998 season. It seems ironic at the time of writing that the Adelaide franchise was wound up by the NRL in late 1998. Another important point to note is that the relative rankings of individual teams do not change over time – although they spread out over time. This is a characteristic of models estimated using FRONTIER version 4.1 – there is no changing of rankings over time.

Indeed, we can look at some statistics for home teams presented overleaf in Table 6.10, and note that for Adelaide and Western Suburbs, neither teams have the largest negative points difference (points scored minus visiting teams points scored) however Adelaide has the poorest goal-kicking percentage (0.49), while Western Suburbs has a goal-kicking percentage that ranks near the middle of all teams (0.63). There doesn't appear to be any explicit and obvious reason why these teams' measures of efficiency deteriorate at a faster rate than other teams.

Table 6.10: Home Team Averages (Per Game) - 1998

Home Team	Points Scored	Visiting Teams Points Scored	Goal-kicking Percentage	Scrums	Penalties
Adelaide	17.75	22.08	0.49	5.42	7.00
Auckland	20.09	18.64	0.79	5.82	6.82
Balmain	17.67	16.67	0.54	7.58	8.25
Brisbane	35.83	11.50	0.78	5.92	7.00
Canberra	28.50	16.83	0.71	6.25	6.42
Canterbury	20.17	16.08	0.69	6.17	6.42
Cronulla	21.50	14.08	0.89	6.67	6.00
Gold Coast	14.92	24.75	0.50	7.75	6.83
Illawarra	17.27	24.36	0.68	5.82	7.27
Manly	22.33	17.17	0.56	5.08	8.83
Melbourne	27.08	13.50	0.71	5.67	7.08
Newcastle	24.00	15.17	0.59	7.75	7.00
North Sydney	34.33	13.17	0.76	6.92	6.08
North Queensland	17.08	16.58	0.57	6.67	7.08
Parramatta	21.33	12.67	0.58	7.17	7.08
Penrith	26.75	22.08	0.69	7.00	6.25
South Sydney	13.42	19.83	0.73	6.67	7.58
St George	22.25	17.25	0.67	5.50	8.00
Sydney City	30.17	15.50	0.76	5.67	6.25
Western Suburbs	18.58	23.25	0.63	6.50	7.67

We can also look at the corresponding estimated technical efficiencies for visiting teams in 1998, presented below in Figure 6.2. Again, this data is presented in Appendix I.

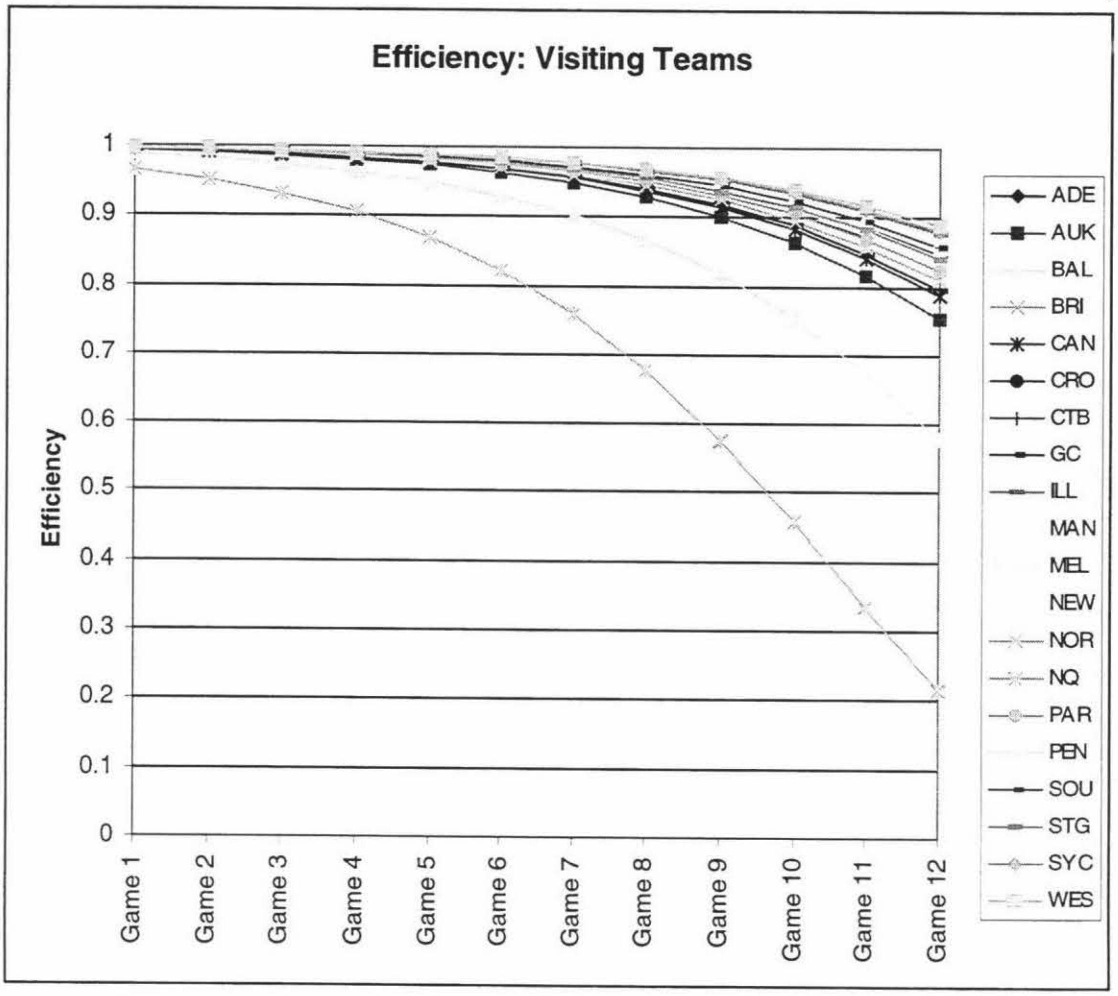

Figure 6.2: Estimated Technical Efficiencies for Visiting Teams in 1998

We note from the above figure that there is a different pattern displayed here than is displayed in Figure 6.1. It is noticeable that again two teams perform markedly poorer than the rest as visiting teams - North Queensland (NQ) and Balmain (BAL). There is a wider dispersion in efficiency for visiting teams than for home teams. It is noticeable that the movement of the efficiency scores away from each other over time happens a lot sooner for visiting teams than for home teams. This is consistent with the results found in the models of performance - that the home team plays better (in other words, the home team scores more points) than the visiting team does on average, or perhaps some teams find it easier to play at home than some teams do to play away from home.

Table 6.11: Visiting Team Averages (Per Game) - 1998

Visiting Team	Points Scored	Home Team Points Scored	Goal-kicking Percentage	Scrums	Penalties
Adelaide	15.00	29.17	0.56	6.08	6.17
Auckland	15.33	22.92	0.76	6.83	6.75
Balmain	14.08	21.92	0.66	5.42	6.17
Brisbane	21.50	14.33	0.54	5.92	4.17
Canberra	18.50	18.92	0.63	5.50	5.42
Canterbury	16.33	16.17	0.85	5.33	6.08
Cronulla	18.73	20.36	0.89	5.18	5.27
Gold Coast	9.17	29.75	0.61	6.42	6.33
Illawarra	21.83	20.50	0.65	5.08	6.00
Manly	17.91	23.18	0.59	4.82	7.55
Melbourne	18.42	17.50	0.66	6.92	5.00
Newcastle	22.83	16.58	0.63	6.17	4.92
North Sydney	20.92	17.42	0.77	5.25	5.58
North Queensland	13.00	29.75	0.32	5.92	4.75
Parramatta	17.67	16.42	0.72	6.25	4.75
Penrith	17.00	26.25	0.72	6.00	6.08
South Sydney	14.83	26.83	0.74	6.58	5.25
St George	18.25	23.58	0.61	5.67	6.83
Sydney City	27.00	16.42	0.79	5.75	6.17
Western Suburbs	12.33	43.58	0.42	6.00	5.42

When we look in Table 6.11 at the efficiency measures, we can see that North Queensland has the worst goal-kicking percentage when playing as visitors (0.32), although Balmain's goal-kicking percentage ranks near the middle of all teams (0.66). Once again, it does not appear that there is an explicit reason as to why these two teams' efficiency scores deteriorate at a faster rate than other teams.

Some overall summary statistics support the theory that the home team plays better than the visiting team does on average. If we look at the pooled statistics of the 1998 season summarised in Table 6.12, we can see the differences between home and visiting teams.

Table 6.12: Summary Statistics: 1998 Home and Visiting Models

HOME Variable	Number of Observations	Mean	Standard Deviation
Points Scored	238	17.72	2.97
Visiting Team Points Scored	238	13.11	3.52
Goalkicking Percentage	238	0.47	4.59
Scrums	238	5.93	1.51
Penalties	238	6.58	1.49

VISITING Variable	Number of Observations	Mean	Standard Deviation
Points Scored	238	13.11	3.52
Visiting Team Points Scored	238	17.72	2.97
Goalkicking Percentage	238	0.36	7.13
Scrums	238	5.23	2.02
Penalties	238	5.24	1.56

From the above statistics, we can say that on average, the home team scored more points than the visiting team, kicked a higher percentage of goals and was awarded more scrums and penalties. With a situation such as this, it would not seem unrealistic that visiting team performance would deteriorate faster when compared to home team performance. Thus the results obtained from the stochastic frontier models and the corresponding efficiency estimates make intuitive sense.

6.3 Ranking (According To Efficiency Scores)

With these efficiency scores, we can rank teams (from 1st to 20th) according to their average efficiencies playing at home and playing as visiting teams. We can also rank the teams overall by taking the average rank. The results are presented below in graphical format in Figure 6.3. Note that a high value represents a lower ranking relative to other teams (i.e. a rank of 18 places the team 18th out of 20 teams), and a low value represents a higher ranking relative to other teams.

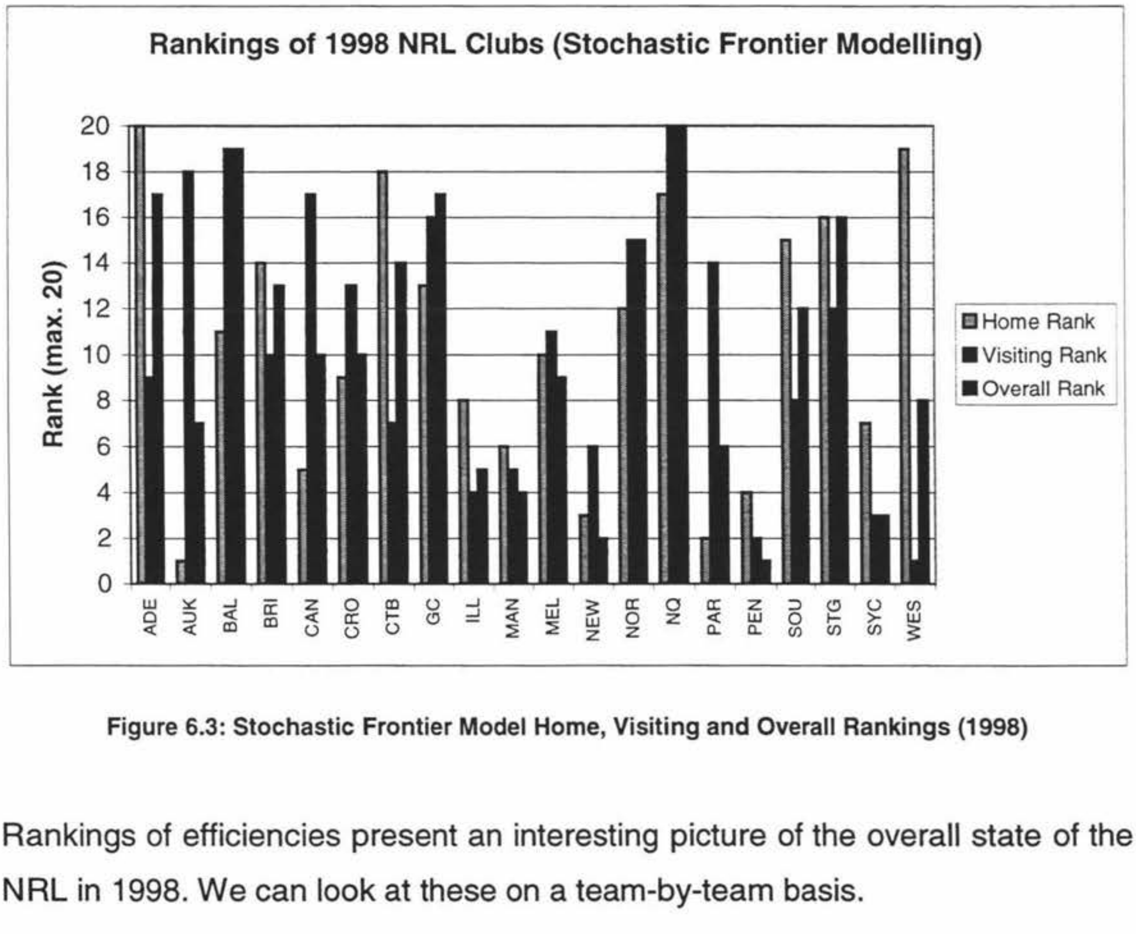

Figure 6.3: Stochastic Frontier Model Home, Visiting and Overall Rankings (1998)

Rankings of efficiencies present an interesting picture of the overall state of the NRL in 1998. We can look at these on a team-by-team basis.

Adelaide ranks as the 20th most efficient team in the NRL at home and 9th as a visitor, making for an overall ranking of 17th. These results would indicate that relative to other teams, Adelaide was the most inefficient team at home, and ranked the 9th-best in terms of efficiency as visitors. In other words, there was potential there that was not efficiently utilised both at home and as visitors, and this was reflected in their position on the competition ladder. As Adelaide was culled from the competition in late 1998, this measure is of little consequence in terms of suggesting areas for improvement.

Auckland ranked as the most efficient team in the NRL at home and the 18th most efficient team as a visitor, making for an overall ranking of 7th in terms of efficiency. It is interesting to note that Auckland were the most efficient team at home, possibly because of the perceived "difficulties" of being the sole New Zealand team in the NRL. It would seem that Auckland managed to use their inputs into the generation of points scored better than any other team at home.

Inner Sydney club Balmain ranked as the 11th best club at home, and ranked 19th as visitors, for an overall rank of 19th in the NRL in terms of efficiency. Balmain performed better at home than as visitors, and this is supported by the rankings. Balmain appeared one of the most vulnerable clubs in the NRL, as a club with poor performances and efficiency, and in a difficult situation with a view to the rationalisation of the NRL in 2000.

1998 premiers Brisbane ranked as the 14th best team in terms of home performance, and ranked 10th at home making for an overall ranking of 13th in the NRL. This indicates that Brisbane had not played as closely to their potential as over half of the NRL sides, yet they still managed to win the 1998 premiership.

Canberra ranked 5th in the NRL in terms of efficiency at home, they ranked 17th as visitors, for an overall ranking of 10th. The home result is not surprising given the difficulty visiting teams have had when playing at Bruce Stadium in recent years. 1998 seems to be no exception. As visitors, the Raiders performed relatively poorly in terms of efficiency.

Cronulla ranked as the 9th best team in terms of efficiency at home, and ranked as the 13th most efficient team as visitors, for an overall ranking of 10th. Finishing 11th on the competition table in 1998, this overall rank sums up

Cronulla's year accurately - some more efficient performances as visitors may have pushed them into a semi-finals berth.

Defeated grand finalists Canterbury had a low efficiency ranking at home (18th) and ranked 7th in the NRL as visitors, for an overall efficiency ranking of 14th. Like Brisbane, the Bulldogs managed to play below their potential and still make the grand final.

An overall rank for the Gold Coast of 17th in 1998, which was comprised of an efficiency ranking of 13th as a home team and 16th in the NRL as a visiting team was a good indication of the Gold Coast's performances. The results are not unexpected given that the Gold Coast has produced many footballers who have gone on to bigger things upon leaving the club, so they had potential. The Gold Coast club was wound up as an NRL franchise in late 1998, reducing the number of teams in the 1999 premiership to 17.

Illawarra was ranked 8th most efficient in production in the NRL as a home team, 4th as a visiting team, and was ranked 5th in the NRL overall. These results indicate that the Steelers performed closer to their potential than the majority of NRL teams. While not being as successful, they played more to their capabilities, just missing out on a semi-final berth in 1998. This result is interesting when we come to their merger partner St George. The Dragons had a ranking as the 16th most efficient team in the NRL at home, 12th as visitors, and an overall ranking of 16th. The merger between Illawarra and St George (now St George-Illawarra Dragons) looks a good match in this analysis, with players at Illawarra capable of playing close to their potential and players at St George capable of doing better in 1998. The 1999 season augers well for the new team, depending upon how well the teams knit together.

Manly, traditionally a strong team, was ranked 6th most efficient in production at home, 5th most efficient as visitors, and 4th overall in the NRL. Manly just made it into the semi-finals in 1998, exiting the playoffs with a loss to Canberra.

Again, Manly is a team that plays closer to its potential than many clubs, and this is reflected in it's point-scoring ability in 1998.

The newest franchise in the NRL, the Melbourne Storm, ranked 10th in terms of point-scoring efficiency at home, and 11th as visitors, for an overall rank of 9th. This indicates that the Storm played with the NRL average efficiency at home and away - fairly close to it's potential. Couple this with finishing 3rd on the competition table in its debut season, it is safe to say that Rugby League has a sound future in Melbourne if the present levels of efficiency are maintained.

Newcastle ranked 3rd in the NRL at point-scoring efficiency at home, 6th as visitors, and 2nd overall for 1998. Newcastle played very closely to their potential (relative to other teams in the NRL) in 1998. Indeed, finishing second on the competition table is a very good indicator of the appropriateness of this ranking.

North Sydney ranked as the 15th team overall, with a ranking of 12th in the NRL in terms of home point-scoring efficiency, and ranked 15th in point-scoring efficiency as visitors. Semi-finalists in 1998, these results indicate that the Bears have the potential (relative to other NRL teams) to perform better than their results have shown. Perhaps an improvement in efficiency could well be the catalyst for the club's first premiership since 1922.

North Queensland, the NRL's northernmost club in terms of location, ranked 17th in the NRL in terms of point-scoring efficiency at home and ranked 20th as visitors, for an overall ranking of 20th in the League. Relative to other clubs, North Queensland had the most scope for improvement in the efficiency of their performances. With the playing strength they assembled during 1998, North Queensland seemed capable of producing better results.

Parramatta ranked 2nd in the League in terms of point-scoring efficiency at home, and ranked 14th in the League as visitors for an overall rank of 6th.

Parramatta performed very well in 1998, making the semi-finals and narrowly losing to Canterbury.

Penrith ranked as the most efficient team in the NRL overall, with a ranking of 4th in terms of home point-scoring efficiency, and 2nd in terms of visiting point-scoring efficiency. Penrith had an injury-plagued year, with injuries to key players affecting them more than any other club. This meant that players with lesser ability were replacing front-line players, and the team performed (relative to other teams) closest to their potential. Eight wins from 24 matches in 1998 was not enough for semi-final qualification, but this result typifies what these measures of efficiency mean. Brisbane, the 1998 premiers, ranked 13th overall, yet won the premiership. Penrith, ranked the most efficient overall, finished 14th out of the 20 teams in 1998. Brisbane was obviously more talented, having won more games, but did not play to their full potential. Penrith, although less talented, played the closest to their potential, and this is to the credit of the coaching and management staff.

South Sydney ranked 15th in the NRL in terms of home point-scoring efficiency, and ranked 8th in terms of point-scoring efficiency as visitors, for an overall rank of 12th. South Sydney performed more efficiently (relative to other teams) as visitors than as the home team, which can be interpreted as meaning that South Sydney had a greater scope for improvement in efficiency when playing at home than as visitors.

Sydney City ranked 7th in terms of home point-scoring efficiency, 3rd in terms of point-scoring efficiency as visitors, and ranked 3rd overall in efficiency in the 1998 season. Performing to it's considerable potential was a strength of the Roosters in 1998, reaching the semi-finals and losing to Brisbane for the right to contest the grand final. Their actual point scoring was second only to Brisbane, and their results were through efficient performances as confirmed by these results.

Western Suburbs had a disappointing season in 1998, finishing last in the premiership. Their efficiency rankings are quite interesting, ranked 19th in terms of home point-scoring efficiency, a ranking of 1st in the NRL in terms of point-scoring efficiency as visitors, for an overall ranking of 8th. A ranking as low as the 19th most efficient team is not unrealistic when it is considered that on average (across the season) Western Suburbs scored 15 points per game and conceded 33 points. The ranking as the most efficient team as visitors is intuitively questionable. When we consider what this efficiency measure is actually capturing, the results become less doubtful. This measure, as mentioned before, tells us how closely to it's potential a team performs. The 19th ranking at home tells us that Western Suburbs perform relatively inefficiently compared to all but one of their counterparts at home - which makes intuitive sense with the team's results in 1998.

We can also observe the home and away efficiency rankings and compare these to the actual places each team finished in the 1998 competition, and look at the resulting rank coefficients.

Table 6.13: Home and Away Rankings and Rank Coefficients

Team	Home Efficiency Ranking	Away Efficiency Ranking	1998 Place
Adelaide	20	9	17
Auckland	1	18	15
Balmain	11	19	13
Brisbane	14	10	1
Canberra	5	17	7
Canterbury	9	13	9
Cronulla	18	7	11
Gold Coast	13	16	19
Illawarra	8	4	12
Manly	6	5	10
Melbourne	10	11	3
Newcastle	3	6	2
North Sydney	12	15	5
North Queensland	17	20	16
Parramatta	2	14	4
Penrith	4	2	14
South Sydney	15	8	18
St George	16	12	8
Sydney City	7	3	6
Western Suburbs	19	1	20
Correlation Coefficient	***0.4150***	***-0.012***	

We can see from Table 6.13 that there is a relatively strong positive correlation between efficiency in point scoring at home and overall performance in 1998. We also find that there is virtually no correlation between efficiency in point scoring away from home and overall performance. These results would tend to indicate that teams that play more efficiently at home are more successful than teams that play away from home.

We can also look at the overall point-scoring efficiency rankings, and compare these to the 1998 competition final places for teams.

Table 6.14: Overall Rankings and Rank Correlation Coefficient

Team	Overall Efficiency Ranking	1998 Place
Adelaide	17	17
Auckland	7	15
Balmain	19	13
Brisbane	13	1
Canberra	10	7
Canterbury	10	9
Cronulla	14	11
Gold Coast	17	19
Illawarra	5	12
Manly	4	10
Melbourne	9	3
Newcastle	2	2
North Sydney	15	5
North Queensland	20	16
Parramatta	6	4
Penrith	1	14
South Sydney	12	18
St George	16	8
Sydney City	3	6
Western Suburbs	8	20
Correlation Coefficient	***0.2934***	

We can see that there is a moderate positive correlation between the overall efficiency rank and overall performance in 1998. Thus, the more efficient a team is overall, the better the overall performance will be (as reflected by the position on the competition table).

Chapter 7

CONCLUSION

The analysis of production and efficiency in the Australian Rugby League (or National Rugby League) is an interesting and developing area. This is not the first attempt to model the production of sporting teams, neither is it the first attempt to use this particular method of modelling efficiency in sport. It is the first attempt, though, at modelling the production of Australian Rugby League teams, using both simple regression and stochastic frontier modelling approaches for efficiency. This chapter assesses the success of this approach and the summarises the main points drawn from this analysis.

7.1 Modelling The Determinants Of Performance

To begin with, production was defined as the difference in points scored, specifically the difference between points scored by the home team and points scored by the opposition. The inputs into the production process were game-specific variables specified as the home team's variable minus the opposition team's variable. These variables included Goal-kicking Percentage, Scrums, Penalties, Interchange Players, First Scorer (dummy variable), Lead at Halftime (dummy variable), Immediate Momentum, Momentum, Night Game (dummy variable), Strength, and Home/Away (dummy variable). Ordinary least squares regression was used to estimate models for the 1995, 1996 and 1998 years, and it was found that Goal-kicking Percentage, Lead at Halftime, Momentum and Strength were consistently significantly different from zero at the 10% level of significance or better, and all had the expected sign. This approach was similar to the study by Carmichael and Thomas (1995) for British rugby league, although with different variables.

Measures of efficiency were also calculated in a similar way to Carmichael and Thomas (1995) using the residuals from the regression equations, and the resulting rankings resulted in a moderately negative rank correlation coefficient of –0.3895. This could be interpreted as meaning that a team that played more efficiently with lower quality inputs will not perform as well as a team that plays less efficiently with higher quality inputs. This finding suggests that there was likely to have been wide variation in input quality across teams in the NRL.

7.2 Stochastic Frontier Modelling

Another approach to analyse production and efficiency, the stochastic production frontier methodology (developed by Battese and Coelli 1992, Coelli 1996) was adopted. Hofler and Payne (1996) had successfully used the methodology in a study of the NFL.

For this analysis, models were estimated with the dependent variable specified in two different ways: 1) team specific points scored (points scored by the team), and 2) the difference in points scored (home minus visiting team). The input variables were changed from being game-specific (i.e. home minus visitor) to team-specific (i.e. home or visitor) variables. The following variables were used (for home and visitor games): the opposition's team's goal-kicking percentage, scrums, penalties, immediate momentum, momentum and strength. Models were estimated for each of the three years of analysis (1995, 1996 and 1998) using the software program FRONTIER v.4.1. The models where production was specified as team-specific point scoring were the most successful with 1998 being the most suitable year for analysis using the stochastic frontier method.

The adoption of the stochastic production frontier approach to modelling production and calculating measures of efficiency could be considered partially successful. Of the four models estimated for each of the three years, only the models where production was represented as team-specific points scored (for home in 1998 and for visiting in 1998) were found to be significantly different from the traditional average production function estimated using ordinary least squares. What is surprising was that only the 1998 models produced results that significantly differed from traditional deterministic production functions. With the use of the stochastic modelling program, one noticeable concern was the restriction that measures of efficiency are only permitted to either increase or decrease exponentially over time. As it turned out in this analysis, the estimates of efficiency made intuitive sense, but this could be an area of concern in analyses where the use of efficiency estimates is not easily applicable.

7.3 Determinants Of Performance - What Matters?

In the analysis of production using the ordinary least squares regression technique, a number of variables were used and many of them were found to be important determinants of performance in the game of rugby league.

Specifically, the variables found to contribute significantly to game outcomes when we consider all games throughout the three years of observation (i.e. variables with coefficients that were significantly different from zero at the 10% level or better) are Goal-kicking percentage, Lead at halftime, Momentum, and Strength. The other variables, Scrums, Penalties, Interchange Players, First Scorer, Immediate Momentum and Night Games, were all not significantly different from zero. The four variables identified above as important variables all impacted positively on the game outcome, with Lead at Halftime the highest contributor to the final result. General conclusions that can were drawn from this analysis were: (a) that having an accurate goal-kicker was an important part of determining a game outcome, (b) having the lead at halftime could have benefitted a team substantially (by as much as 9 points in either of the three years of analysis), (c) the saying that "momentum matters" was found to be true - from this analysis, having a superior momentum (or position on the ladder) had a positive impact on the game outcome, and (d) that the greater the inherent strength (as measured by the average game outcome of the team concerned in the previous season), the greater the positive impact on the game outcome.

The constant term in the models produced interesting results, with the most notable one being the 1998 value which was 4.29 points, a value in excess of an unconverted try, and was significantly different from zero (at the 1% level). The value of the constant in this context is important - it captured the "home ground advantage" that a team may or may not have.

7.4 The Measurement of Efficiency

As mentioned before, the results generated from both the difference in points scored model and the stochastic frontier approach were interesting and made intuitive sense. The key word for many people, when one considers efficiency is "potential" - how well a team performs relative to its potential. These analyses of efficiency seek to do just that - evaluate a team's performance relative to its potential performance.

The difference in points scored (DPS) model's efficiency measures may have possibly reflected a variation in input quality across teams in 1998. It is important to be clear of the definition of this measure of efficiency – this was a measure of a team's efficiency in contests with another team – constructed from models with difference variables (i.e. difference in variable between home and away team). Thus the resulting efficiency ranking was how well a team performed in direct competition with their opposition. The resulting moderately negative rank correlation coefficient (-0.3895) could reflect a difference in input quality – a team that played more efficiently with lower quality inputs might not necessarily have performed better overall than a team that played less efficiently with higher quality inputs.

This finding is interesting when we consider the efficiency measures from the stochastic frontier modelling approach. It is also important to be clear of the definition of efficiency in this case – this was a measure of a team's point-scoring efficiency as a function of team-specific variables and the opposition's points scored. Thus this measure of efficiency complements the efficiency measure from the DPS model, in that the DPS model's efficiency measure is a measure of the game or contest efficiency, while the stochastic frontier modelling efficiency measure is a measure of a team's point-scoring efficiency.

A useful way of interpreting the stochastic frontier modelling efficiency measures is to take an example. The 1998 competition winners Brisbane were ranked the 13th most efficient team overall in the NRL, and the most efficient team overall was the competition's 14th best-performed team, Penrith. Brisbane did not play as closely to its potential as Penrith, yet managed to win 18 games. Penrith played the closest to its potential, and won 8 games. This would suggest that had Brisbane played (relatively) closer to its potential, then it may have exceeded 18 wins, but it was not necessary, given that they won enough games while performing below potential to reach the semifinals and eventually win the competition. Penrith on the other hand performed better relative to its potential, and had they not done so they may have finished worse than 14th in 1998.

It is interesting that the above example follows similar logic to the difference in points scored model's efficiency measures. It would seem to be the case from the above situation that there was considerable variation in input quality across the NRL in team-specific inputs, a finding that is consistent across the two efficiency analyses. What was equally interesting was the resulting overall rank coefficient (0.2934) - that the more efficient a team was at scoring points, the better a team would have performed. This is interesting when we consider that the game/contest efficiency findings implied that the relationship between efficiency and performance would seem to be dependent on the quality of inputs – i.e. a team that performs more efficiently may not perform better overall than teams performing less efficiently. The stochastic frontier modelling efficiency results indicate that a team that scores points more efficiently would perform better overall (as reflected in competition standings) than a team that scores points less efficiently.

If we consider both of these measures it appears that overall, the game or contest efficiency measures are better predictors of actual overall performance than point-scoring efficiency measures. This could be attributed to the "poor teams dragging their good opponents down to their level" theory in action. This is an often-mentioned comment uttered by exasperated fans, commentators and players when a top team plays a poor team and instead of thrashing their opposition, the top team "lowers itself to the other team's level" and stumbles to a mistake-riddled victory. It is feasible that a top team can be more efficient point-scoring wise, and score just enough points to win a game against a poorer team, with the possession that it gains. The higher-ranked team can also be inefficient in that it may make a lot of mistakes and provide their weaker opposition with extra possession and more chances to score – possession with which the weaker team fails to convert into points as often as the higher-ranked team. In a nutshell, the higher-ranked team may often just do enough to win the game, and not extend themselves for risk of injuries etc. These results from these analyses suggest that the "dragging us down to their level" effect possibly outweighs the point-scoring efficiency as a predictor of overall performance. This is one possible explanation – there could very well be others.

7.5 Efficiency: Policy Implications

There are a number of important policy implications to be gleaned from this analysis. These relate to boardroom decisions, potentially to the decision as to which teams should or should not play in the 2000 NRL competition (the decision made by the NRL in October 1999), as well as coaching decisions and game tactics. At the same time, these implications also relate to informal discussions and friendly banter among rugby league fans as to whose team plays closest to its potential.

When the generation of the game outcome was analysed, it was found that there were five key inputs – goal-kicking percentage, lead at halftime, momentum, strength and the so-called home ground advantage. In the analysis of point-scoring, goal-kicking percentage and strength were found to be the key inputs. Thus the importance of having an accurate goal-kicker cannot be over-emphasised. From both analyses, goal-kicking percentage carries a substantial weighting in determining game outcomes and the number of points scored. It is also notable that the inherent strength within a club is the other key input – if a club is "strong" (as measured by performance in the previous season), then it has a positive effect on the team's performance the following season. Thus it is important for club administrators and officials to retain a nucleus of a team that is successful, for it has been found to have positive effects for the season ahead.

It has been found from this study that point-scoring efficiency is not as useful as game outcome efficiency in explaining overall performance. However, the more efficient a team is at point scoring at home, the better the overall performance (as reflected by competition standings) is likely to be. Thus, it appears from this finding, along with the finding in Chapter 4 that there is evidence of a "home ground advantage" effect, that performance (and subsequently efficiency) at home is particularly important in explaining game outcomes, and overall performance.

Overall rankings are particularly interesting when we compare the rankings of both measures of efficiency. Of the game/contest efficiency rankings, four of the top eight best-performed teams in 1998, namely Newcastle (ranked 13th), Canberra (15th), Melbourne (18th) and Parramatta (20th) were ranked in the bottom ten teams in terms of game efficiency. These teams' rankings in terms of point-scoring efficiency were 2nd, 10th, 9th and 6th respectively. This would tend to indicate that these teams experienced the "dragging us down to their level" effect more so than the other four teams that made the semi-finals. As we can see, the point-scoring efficiency rankings are good in comparison, and thus they could conceivably have overcome the "dragging us down" effect with their relatively superior point-scoring efficiency.

If we look at the rankings for the stochastic frontier modelling approach, we get similarly intuitive results. Of the point-scoring efficiency rankings, three of the top eight teams in 1998, namely Brisbane (ranked 13th), North Sydney (15th) and St George (16th) were ranked outside the top ten in terms of point-scoring efficiency. Their respective rankings in terms of game/contest efficiency were 10th, 6th and 1st. In other words, these teams could have made the semi-finals because they more efficiently utilised the game/contest aspect and compensated for their relatively weaker point-scoring efficiency.

Of the top ten most efficient teams in terms of the point-scoring efficiency measures, seven were Sydney-based clubs, the three non-Sydney based clubs were Newcastle (ranked 2nd), Auckland (7th) and Melbourne (9th). Of the top ten most efficient teams in terms of game/contest efficiency, eight clubs were Sydney-based clubs, the two non-Sydney based clubs being Auckland (ranked 9th) and Brisbane (10th). This is particularly interesting given that there has been a movement in recent times to make the game more 'national' within Australia (hence the National Rugby League). From these analyses, it would appear that the majority of Sydney-based clubs are relatively efficient in terms of point-scoring, and also are relatively efficient in terms of the game/contest. The argument that there are too many Sydney-based clubs seems immaterial when we consider that the relative efficiencies of many of the Sydney-based teams are better than the efficiencies of non-Sydney teams.

The teams at the lower end of the spectrum are the teams under the microscope when we consider the NRL competition rationalisation in late 1999. The five worst performed teams in 1998 were North Queensland, Adelaide, South Sydney, Gold Coast and Western Suburbs. If we consider their game/contest efficiency measures, their rankings are 5th, 17th, 3rd, 11th and 2nd respectively. This would tend to indicate that (with the exception of Adelaide and possibly Gold Coast) these teams specialised in bringing opposition teams "down to their level". Indeed, a look at the point-scoring efficiency rankings (20th, 17th=, 12th, 17th= and 8th respectively) confirms that these teams (with the exception of Western Suburbs and possibly South Sydney) had relatively poor point-scoring efficiencies and thus concentrated more on competing with the opposition at their own style of game.

This finding is an interesting poser for league administrators. It will be particularly interesting to see whether the effect of rationalising the NRL competition will result in more high-scoring, even and exciting games. Certainly, the above results suggest that weaker teams may very well have dictated the style of play in their games with higher-ranked opposition, leading to potentially a lower-quality game. That is a subjective judgement one can only make upon observation of games involving a weaker team and a higher-ranked team, and comparison with games involving two higher-ranked teams and games involving two weaker teams. It would make an interesting comparison if such an analysis was carried out pre-rationalisation and post-rationalisation, to see whether the resulting 'more elite' competition brings about more equitable outcomes than in 1998.

7.6 Suggestions For Future Research

With improved (and more comprehensive) quality of data, this study could be reproduced using other measures of frontier modelling, including the Data Envelopment Analysis and panel data techniques, providing additional examinations of efficiency that could be compared with this study to identify additional areas for improvement.

Variables that could be added to a study of rugby league in this context could be more detailed game information, such as time in possession, number of tackles made, metres gained on attack, average general kick-in-play distance etc. These variables would add considerable explanatory power to the models estimated in this study, and may perhaps add a new dimension to efficiency measures.

The quality of inputs used in this study could be addressed through use of a play-by-play summary of the game, to identify where penalties and scrums were awarded, when interchange players entered into the game, etc. Other variables that could be looked at are injuries to key players, sin-bin and send-off offences, which again would add explanatory power, but such data is increasingly difficult to come by.

With the restructuring of the 2000 NRL competition to come into effect in 2000, scope exists to examine the differences from year to year - productive differences, performance differences or financial differences (depending upon availability of data) – from before restructuring to after restructuring. Indeed, mentioned in the previous section was one idea which could be used as an evaluation tool to evaluate the success or otherwise of the rationalisation of the NRL in 2000.

As well as productive efficiency, other areas have the potential to be examined within Australian rugby league. Areas such as the effect of off-season signings of players and coaching changes on the team (as reflected in performance), the effect of injuries on a team's performance and the historical element of rugby league – i.e. is there a cyclical pattern to a team's performance over time? Clearly, the list of applications from economics to sport, particularly rugby league, are numerous and potentially exciting and innovative areas of research.

Sport in general provides plentiful areas of research, many of which have been discussed in the literature review. As a "gymnasium" for economic theory (in other words - an area where economic theory can be tested), sport has extremely useful applications.

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Appendices

Appendix I: Stochastic Frontier Modelling Efficiency Scores

HOME TEAMS

Team	Game 1	Game 2	Game 3	Game 4	Game 5	Game 6	Game 7	Game 8	Game 9	Game 10	Game 11	Game 12	AVERAGE
ADE	0.9999	0.9999	0.9997	0.9993	0.998	0.9945	0.9846	0.957	0.8832	0.704	0.3717	0.0625	**0.829525**
AUK	0.9999	0.9999	0.9999	0.9999	0.9997	0.9993	0.9983	0.9951	0.9863	0.9621	0.8989		**0.985391**
BAL	0.9999	0.9999	0.9999	0.9999	0.9998	0.9996	0.9988	0.9965	0.9903	0.9729	0.9262	0.8122	**0.974658**
BRI	0.9999	0.9999	0.9999	0.9999	0.9998	0.9995	0.9987	0.9964	0.9897	0.9714	0.9222	0.8028	**0.973342**
CAN	0.9999	0.9999	0.9999	0.9999	0.9998	0.9996	0.9991	0.9975	0.9931	0.9806	0.9467	0.861	**0.981417**
CRO	0.9999	0.9999	0.9999	0.9999	0.9998	0.9996	0.9989	0.997	0.9915	0.9762	0.9351	0.8332	**0.977575**
CTB	0.9999	0.9999	0.9999	0.9999	0.9997	0.9992	0.9979	0.9943	0.9839	0.9554	0.8809	0.7098	**0.960058**
GC	0.9999	0.9999	0.9999	0.9999	0.9998	0.9995	0.9987	0.9965	0.99	0.9722	0.9244	0.808	**0.974058**
ILL	0.9999	0.9999	0.9999	0.9999	0.9996	0.999	0.9973	0.9924	0.9787	0.9416	0.8482		**0.977855**
MAN	0.9999	0.9999	0.9999	0.9999	0.9998	0.9996	0.9991	0.9975	0.9929	0.9803	0.946	0.8593	**0.981175**
MEL	0.9999	0.9999	0.9999	0.9999	0.9998	0.9996	0.9989	0.9969	0.9911	0.9753	0.9325	0.8269	**0.976717**
NEW	0.9999	0.9999	0.9999	0.9999	0.9998	0.9997	0.9992	0.9976	0.9933	0.9812	0.9483	0.865	**0.981975**
NOR	0.9999	0.9999	0.9999	0.9999	0.9998	0.9997	0.9988	0.9965	0.9902	0.9727	0.9259	0.8113	**0.974542**
NQ	0.9999	0.9999	0.9999	0.9999	0.9998	0.9995	0.9985	0.9958	0.9881	0.967	0.9108	0.7765	**0.969633**
PAR	0.9999	0.9999	0.9999	0.9999	0.9999	0.9997	0.9992	0.9979	0.994	0.9831	0.9535	0.8777	**0.983717**
PEN	0.9999	0.9999	0.9999	0.9999	0.9998	0.9997	0.9992	0.9976	0.9933	0.9811	0.9482	0.8646	**0.981925**
SOU	0.9999	0.9999	0.9999	0.9999	0.9998	0.9996	0.9987	0.9962	0.9894	0.9704	0.9197	0.7969	**0.972525**
STG	0.9999	0.9999	0.9999	0.9999	0.9998	0.9995	0.9986	0.9962	0.9892	0.9699	0.9185	0.7941	**0.972117**
SYC	0.9999	0.9999	0.9999	0.9999	0.9998	0.9996	0.999	0.9973	0.9923	0.9785	0.9412	0.8478	**0.979592**
WES	0.9999	0.9999	0.9999	0.9999	0.9993	0.9981	0.9949	0.9856	0.9598	0.8908	0.7235	0.4116	**0.9136**

VISITING TEAMS

Team	Game 1	Game 2	Game 3	Game 4	Game 5	Game 6	Game 7	Game 8	Game 9	Game 10	Game 11	Game 12	**AVERAGE**
ADE	0.9961	0.9945	0.9923	0.9891	0.9847	0.9785	0.9698	0.9577	0.941	0.9182	0.8876	0.8471	**0.954717**
AUK	0.9933	0.9906	0.9867	0.9813	0.9737	0.9631	0.9484	0.9282	0.9006	0.8636	0.815	0.7529	**0.924783**
BAL	0.9873	0.9821	0.9747	0.9645	0.9502	0.9305	0.9034	0.8667	0.8178	0.7543	0.6745	0.5786	**0.865383**
BRI	0.9961	0.9945	0.9922	0.989	0.9845	0.9782	0.9694	0.9571	0.9403	0.9172	0.8862	0.8452	**0.954158**
CAN	0.9944	0.9921	0.9888	0.9842	0.9778	0.9688	0.9562	0.939	0.9153	0.8835	0.8412	0.7866	**0.935658**
CRO	0.9955	0.9937	0.9911	0.9874	0.9822	0.975	0.9649	0.951	0.9318	0.9058	0.8708	0.8251	**0.947858**
CTB	0.9956	0.9938	0.9912	0.9876	0.9826	0.9755	0.9656	0.952	0.9332	0.9077	0.8737		**0.959864**
GC	0.9946	0.9924	0.9893	0.9849	0.9788	0.9702	0.9582	0.9418	0.9192	0.8886	0.848	0.7954	**0.93845**
ILL	0.997	0.9957	0.994	0.9914	0.988	0.9831	0.9762	0.9666	0.9533	0.9351	0.9103	0.8771	**0.963983**
MAN	0.9958	0.9941	0.9917	0.9883	0.9835	0.9768	0.9674	0.9544	0.9366	0.9123	0.8798		**0.961882**
MEL	0.9961	0.9945	0.9922	0.989	0.9844	0.9781	0.9693	0.957	0.9401	0.917	0.8859	0.8448	**0.954033**
NEW	0.9968	0.9954	0.9936	0.9909	0.9872	0.9819	0.9746	0.9644	0.9503	0.9309	0.9047	0.8697	**0.9617**
NOR	0.995	0.993	0.9901	0.9861	0.9804	0.9724	0.9614	0.946	0.925	0.8964	0.8584	0.8089	**0.942758**
NQ	0.9658	0.952	0.9329	0.9064	0.8703	0.8217	0.7578	0.676	0.5755	0.459	0.3343	0.2147	**0.705533**
PAR	0.9955	0.9936	0.991	0.9874	0.9822	0.9749	0.9649	0.9509	0.9316	0.9055	0.8705	0.8246	**0.947717**
PEN	0.9972	0.996	0.9943	0.992	0.9887	0.9841	0.9777	0.9687	0.9562	0.939	0.9156	0.8843	**0.96615**
SOU	0.9965	0.995	0.993	0.99	0.9859	0.9803	0.9723	0.9612	0.9458	0.9248	0.8964	0.8588	**0.958333**
STG	0.996	0.9944	0.992	0.9888	0.9842	0.9777	0.9687	0.9562	0.939	0.9155	0.884	0.8423	**0.953233**
SYC	0.9971	0.9959	0.9942	0.9918	0.9884	0.9836	0.977	0.9677	0.9548	0.9371	0.9131	0.8809	**0.965133**
WES	0.9973	0.9961	0.9946	0.9923	0.9891	0.9847	0.9785	0.9698	0.9578	0.9412	0.9185	0.8882	**0.967342**